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Does Impulsive Posting Hurt or Help? The Effects of Conflicting Online Information on Attitude Uncertainty and Behavioural Consequences: The Moderating Role of Peer Social Network Support

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Abstract: Prior research suggests that consumers may find prematurely written online information trivial, nondiagnostic, and most likely to be neglected. This article examines the effects of impulsive posting caused by the incentive algorithm of e-commerce on attitude uncertainty and behavioural consequences. Impulsive posting comprises two perspectives: consumer-generated reviews (i.e., perceived tentativeness and irrelevance of conflicting online reviews) and corporate-generated responses (i.e., perceived depersonalisation of incongruent managerial responses). Our central premise is that facilitating the processing of conflicting information by a systematic route induced by accountability warrants more cognitive resources and amplifies the use of nonoptimal information during attitude formation. Thus, confidence decreases when the information that underlies the attitude is difficult to determine, leading to attitude uncertainty and reverse intentions (i.e., site stickiness and purchase intention).

Keywords: conflicting online reviews; managerial responses; impulsive posting; site stickiness; attitude uncertainty; dual-process theory

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1. Introduction

Consumers may find prematurely written online information trivial and nondiagnostic. However, it could potentially influence their decisions due to early information engendered from a pre-emptive emotion based on uncertainty [1]—specifically when an e-commerce algorithm requires consumers to post a review once a product is delivered to receive a financial reward [2], or a corporation to post a response to maintain shop awareness. As an example, leading global e-commerce platforms such as Amazon have launched an "early reviewer program" [3], while the Alibaba Group (Taobao and Lazada) has applied the same strategy called "coin back". According to Ifie's empirical research [4], 4.3% of the selected products are reviewed tentatively. In behavioural psychology, such a motivation undermines the information quality, in which a low temporal contiguity [5] impedes people from forming a greater involvement to develop a comprehensive opinion towards an object.

Within the growing body of literature on conflicting online reviews [6–8], the scant research on contextual factors calls for greater attention [4,9,10]. To fill the practical academic gaps, the current study constructs a model that explains the phenomenon based on relevant studies from consumer- and corporate-generated information. For consumer-generated reviews, the most closely related works related to our research are on the dilution effect [11]. Extant research has revealed the confounding results of the dilution effect on attitude certainty through the addition of tentative reviews [4] and irrelevant reviews [10] to a set of positive reviews. Thus, we took the initiative to reconcile the inconsistencies with the contradictory events through an underlying mechanism of a systematic route of information processing.

In addition, for corporate-generated responses, the most closely related works are on the role of personalised offerings [12]. Specifically, prior studies have found that an apologetic or appreciative strategy is a relatively cost-effective way to counter negative emotions with psychological compensation without committing to any service solution [13]. However, we argue that facilitating the processing with a systematic route demands more of a cognitive effort to recognise the apology script as a depersonalised response, leading to an adverse inference or a service failure. A relevant question arises: how does contradictory information that is tentative, irrelevant, and depersonalised influence attitude and behavioural consequences? Could a peer social network support moderate the main effects? Our research addresses this question by extending the dual process theory to investigate how consumers perceive the impact of consumer- and corporate-generated online information.

Drawing on the dual process theory (the heuristic–systematic processing model: HSM) [14], the present study bridges the theoretical gaps and contends that the motivation to process systematically can decrease attitude certainty when there is contradictory information. In turn, this can cause decision discomfort and adverse behavioural intentions (i.e., site stickiness and purchase intention). In particular, we investigate how the proposed impact of contradictory information on attitude uncertainty is moderated by peer social network supports. Lastly, we contend that the contradictions within or across multiple reviews are different to our context because systematic processing enables a joint evaluation [15]. Thus, this research provides new insights into the literature on information processing and sheds light on how firms should engage in incentive marketing.

In the next section, we review the relevant literature that contributed to our conceptual framework and hypotheses. Then, the output and empirical analyses are presented based on structural equation modelling (SEM). Finally, we discuss the findings' theoretical and managerial implications.

2. Theoretical Background

The Heuristic–Systematic Processing Model

According to the literature on dual-process theories, the heuristic–systematic model (HSM) [14] explains the mechanism of persuasive information processing in a more flexible and perplexing way than the elaboration likelihood model (ELM). Chaiken [14] has proposed two concurrent modes of information processing. Under the systematic processing route, consumers are motivated to strive for resolving rather than retaining the issue by expending cognitive effort on processing content-based cognition. In the heuristic processing route, consumers tend to exert minimal effort in judging information validity and rely more on reliable and accessible non-content cues derived from the categorial script of the communicator.

Although there is a likelihood of concurrence between the two processing routes [16], the systematic processing route is unlikely to be subject to error due to the precondition of motivation being unbiased [17]. Specifically, some researchers argued that inconsistent online reviews point to the need for cognition and justification, in which the emergence of a systematic processing route can attenuate the heuristic route [18] and, even so, still explain a low-importance condition [19]. Moreover, research studies support the fact that a single processing mode is recommended to avoid biased effects [9]. Thus, we employ the systematic route to investigate our conceptual framework in consumer- and corporate-generated conflicting information. Based on the evidence mentioned above, these are the key reasons:

- The nature of the motivational variable of contradiction;
- An intention to construct a parsimonious model by avoiding the occurrence of both processing routes that may lead to bias effects.

Based on the theoretical premise, the present study proposes that motivation to process contradictory information induced by accountability to increase confidence warrants more cognitive resources to systematically process and incorporate unpredictable information during attitude formation. In turn, the discrepancy between actual and desired confidence increases as the information underlies an attitude that is difficult to characterise (i.e., perceived tentativeness, irrelevance, and depersonalisation), leading to attitude uncertainty. Consistent with the attitude certainty paradigm, motivation as a precondition can determine the information processing to solve attitude uncertainty [20]. Furthermore, we infer that motivating people with a systematic processing route enables them to detect an apologetic script throughout all reviews as depersonalised managerial responses and infer it as service failure. Consistent with the rationality of attribution theory [21], people tend to form adverse inferences about service quality, psychological reactance, and susceptibility as a result of negative emotional content in online reviews or the recognition of an iterative response that is not useful [22,23].

Taken together, our view is that people tend to incorporate nonoptimal information during attitude formation when they are motivated to process systematically to increase their confidence. Specifically, confidence decreases as contradictory information undermines an attitude, causing attitude uncertainty and temporarily submerging the user into a state of decision discomfort. As a result, adverse behavioural intentions are expected. We develop hypotheses from the relevant literature in the next section.

3. Hypothesis Development

3.1. Perceived Tentativeness of Conflicting Online Reviews and Attitude Uncertainty

Perceived tentativeness of online reviews is defined as a written review that implicitly or explicitly appears to be noncommittal to product or service experiences [24]. In psychology, the concept of tentativeness refers to pre-emptive information with "a less valid explanation (and) become(s) obsolete when more reliable findings occur" [25].

Previous research has proposed a conceptual link between tentativeness and uncertainty [4,25]. In consumer research, Kevitz and Simonson [26] show that a tentative choice is perceived as a poor indicator of a missing attribute value, which causes option evaluation. Furthermore, it has been shown that perceived tentativeness from linguistic cues can dilute the extremity of emotional words [27]. Snehasish and Chua [24] further reveal that perceived tentativeness from linguistic cues cannot increase the algorithmic process to detect fake reviews. Specifically, Ifie [4] demonstrates that people tend to form attitude uncertainty and purchase intention when adding a tentative review to a set of positive reviews.

Drawing upon the attitude certainty paradigm [20], two-sided information can form a motivation to increase one's confidence to increase attitude certainty. Unlike the previous works with the salience hypothesis [4], the dual process theory [14] provides an extant viewpoint through a motivation to engage in systematic processing. There are reasons to support the notion that motivating people to process contradictory information systematically tends to decrease their confidence when the information is tentative. First, people tend to become more accountable when the motivation to process is to increase confidence. When presented with conflicting information, people are motivated to process information integratively by incorporating nondiagnostic information, which decreases their confidence and product belief [28]. Further, it has been found that the effect of inconsistency attracts special attention even with a low-importance condition [19]. Accordingly, to the extent that tentative information is conflicted and hence more likely to be perceived as having unpredictable outcomes, conflicting tentative information cannot yield confidence during attitude formation, which leads to attitude uncertainty. More specifically,

Hypothesis 1 (H1): *Perceived tentativeness of conflicting online reviews is positively associated with attitude uncertainty.*

3.2. Perceived Irrelevance of Conflicting Online Reviews and Attitude Uncertainty

Perceived irrelevance of online reviews refers to a written review that is non-product-related (i.e., about package delivery, marketing information, product availability) [29] and most likely to fail the criteria of information accessibility and diagnosticity [30].

Past research has shown that irrelevant information dampens confidence in processing [31]. Based on the perceptual salience of diagnostic attributes, Hutchinson and Alba [31] find that confidence is expected to decline because analytical processing should be significantly inhibited by irrelevant information. Xia and Shudharshan [32] show that, when people are prepared for an interruption, they spend more time processing irrelevant rather than relevant information.

Research rooted in the dilution effect supports our hypothesis development. Meyvis and Janiszewiski [29] find that irrelevant attributes weaken people's judgmental extremity and product belief. Shoham, Moldovan, and Steinhart [10] argue that the negative impact of the dilution effect can be reversed under a mechanism of confidence in information completeness, especially when there is the addition of irrelevant negative information to a set of positive reviews. We further propose that when irrelevant reviews are presented contradictorily, it can weaken rather than strengthen confidence in product beliefs and information completeness.

Based on these arguments, there are reasons to support the notion that, when people are motivated to process contradictory information to increase their confidence, they tend to incorporate irrelevant attributes and develop attitude uncertainty. First, it has been suggested that people tend to find it difficult to neglect irrelevant attributes when they are deliberately processing information [33]. As a result, we expect that the contradiction of irrelevant information cannot yield positive confidence. Instead, the discrepancy between actual and desired confidence develops attitude uncertainty. More specifically,

Hypothesis 2 (H2): *Perceived relevance of conflicting online reviews is positively associated with attitude uncertainty.*

3.3. Perceived Depersonalisation of Incongruent Managerial Responses and Attitude Uncertainty

Perceived depersonalisation of managerial response refers to the opposite of manager-generated responses that deliver relevant information, tailored resolutions, and individualised interactions that resonate with consumers' preferences written in online reviews. Our definition is consistent with recent efforts [34], defining personalisation as the adaptation to meet users' needs. In fact, depersonalised managerial responses are commonly observed in a standardised apologetic or appreciative message giving an acknowledgement but not a commitment [13,35] when staff do not promise accommodative strategies.

Previous works have shown that consumers tend to have a negative perception towards corporate monologues because they come across as unnatural and insincere [35–37]. Similar reactions to the concept of depersonalised managerial responses can be found across different types of managerial responses. Wang and Chaudhry [22], for instance, find that a boilerplate response causes psychological reactance and unfavourable inference towards the intention of framing. Consistent with this notion, Liu, Wang, Gao, and Gallivan [38] have examined the effect of rote responses, finding that a standardised apology throughout all reviews has a negative impact on subsequent positive reviews due to the low quality of information. By contrast, Sheng, Wang, and Amank-Amoah [39] provide inclusive findings for engagement in future ratings.

There are reasons to believe that people become more sensitised to depersonalised managerial responses that are incongruent with the corresponding reviews when they exert more cognitive effort and infer them as service failures. First, it has been suggested that people tend to perceive a prescripted apology as insincere [36] and attribute it to a firm's service failure. Second, a defective managerial response that requires people to take further action can intensify subsequent negative emotions [40]. Accordingly, we speculate that people with a systematic motivated route tend to recognise the pattern of prescripted information and perceive depersonalised managerial responses as uninformative and unhelpful, which can be attributed to service failure. Thus, confidence decreases as the information underlying an attitude is uninformative, thus leading to attitude uncertainty. More formally,

Hypothesis 3 (H3): *Perceived depersonalisation of incongruent managerial response is positively associated with attitude uncertainty.*

3.4. Attitude Uncertainty and Decision Discomfort

Attitude (un)certainty refers to a lack of confidence or metacognitive assessment, reflecting the degree to which individuals believe that their attitude is either clear or correct towards an attitude object [20].

Prior research has manifested the state of uncertainty as "a dynamic state of discomfort," which is derived from a lack of confidence or knowledge in evaluating inconsistent or inadequate information regarding predicting the outcome of a purchase situation [41]. Within consumer psychology, the effect of contradictory information was observed to influence the relationship between attitudinal ambivalence and psychological discomfort [42–44]. Specifically, Hwang, Choi, and Mattila (2018) found a positive relationship between consumers' uncertainty and decision discomfort when evaluating mixed reviews. Based on these arguments, there are reasons to support the notion that motivating people to process contradictory information with a systematic route can develop attitude uncertainty to a stage of decision discomfort. As supported by Rucker, Petty, and Briñol [45], when presented with inconsistent or incongruent information, people engage in deeper information processing, enhancing their confidence if the information is relevant. In addition to that, it has been suggested that confidence in information completeness decreases attitude certainty when people are sensitised to missing information [4]. This research suggests that a motivation to process contradictory information can erode attitude certainty and develop decision discomfort. More specifically,

Hypothesis 4 (H4): *Attitude uncertainty is positively associated with consumers' decision discomfort.*

3.5. Decision Discomfort and Behavioural Responses

Decision discomfort is defined as "the degree of psychological (and physiological) ease, contentment, and well-being that one feels about a specific decision" [46]. In this context, we infer that decision discomfort from evaluating contradictory information could reconcile paradoxical studies: (a) site stickiness as a proxy for higher purchase intention if considering greater involvement [47] and (b) the duration or depth of the visit cannot warrant a positive attitude [48].

Previous studies show that information quality is one of the predictors of site stickiness [49]. Bhat, Bevans, and Sengupta [49] documented that site stickiness is the ability to attract and retain people through overall usefulness that can manifest as the degree of site stickiness over time. Consistent with the cognitive lock-in paradigm, it supports the notion that people tend to be less likely to stick to a site when they perceive less value or when they perceive a low level of ease of learning, influencing purchase intention [50,51]. Other evidence has suggested that asymmetrical information resulting in perceiving higher risk can cause a lower propensity of flow experience [52], lower confidence, and thus lower purchase intention [43,53]. Specifically, Hong and Lee [54] elaborated that discomfort experienced leads to an unfavourable attitude toward an attitude object, which has a negative impact on purchase intention.

Based on these arguments, there are reasons to believe that people use a state of decision discomfort as a justifiable reason to permit themselves to execute adverse intentions (i.e., site stickiness and purchase intention). An avoiding approach allows people to terminate negative emotions and regain confidence in alternative sites. Moreover, as suggested by the effect of decision quicksand, experiencing decision discomfort could awaken people from overcorrection [55]. More specifically,

Hypothesis 5 (H5): *Decision discomfort is negatively associated with site stickiness.*

Hypothesis 6 (H6): *Decision discomfort is negatively associated with purchase intention.*

Hypothesis 7 (H7): *Stickiness is positively associated with purchase intention.*

3.6. The Moderating Role of Peer Social Network Support

Social support theory is a fundamental theorem for a protective mechanism against emotional difficulties [56] through exchanging sources (e.g., relevant information related to product or service specification or knowledge) [57] within a social network under mutual obligations [58]. Xu, Zhou, Ye, and Zhou [57] argue that social support can enable conflict resolution, in which the protective mechanism is then replaced with confidence in social support information. Specifically, there are two primary characteristics of messages and social interaction in e-commerce: informational and emotional support [59,60]. In our context, we infer that informational support, such as practical solutions from someone on a social networking site, would serve as further diagnostic input to resolve conflicting information and regain attitude certainty.

Prior studies have shown that social support is a buffer that moderates difficulties from potential stressors [58]. In online marketing literature, people regain confidence, attitude certainty, and behavioural intentions through the accessibility of peer social network support [56,60]. Liang and fellow researchers [60] find that social support significantly impacts relationship quality, influencing the continuous intention to use the website and conduct social commerce. Xu, Zhou, Ye, and Zhou [57] showed that social support from either direct or indirect experience can lead to a lowering of psychological security barriers. More recently, Chen, Zhu, and Mantrala [61] have revealed that peer social support can translate into seller performance.

Based on these arguments, we contend that people tend to seek conflict resolution when they are motivated to process information systematically. Thus, consumers with a high level of peer social network support could find more informational support that is diagnostic and relevant to mitigate the impact of contradictory information on attitude uncertainty. As supported by Taylor and fellow researchers [62], informational support provides diagnostic information, knowledge, or strategies to tackle the problem. More specifically,

Hypothesis 8a (H8a): *Peer social network support moderates the impact of perceived tentativeness of conflicting online reviews on attitude uncertainty, such that the relationship is weaker when information support is high rather than low.*

Hypothesis 8b (H8b): *Peer social network support moderates the impact of perceived irrelevance of conflicting online reviews on attitude uncertainty such that the relationship is weaker when information support is high rather than low.*

Hypothesis 8c (H8c): *Peer social network support moderates the impact of perceived depersonalisation of managerial responses on attitude uncertainty such that the relationship is weaker when information support is high rather than low.*

4. Research Methodology

4.1. Research Settings

We selected the largest e-commerce platforms in Thailand (i.e., Lazada and Shopee) to examine the impact of consumer- and corporate-generated conflicting information. Empirical data have reported that 4.7% of selected product reviews on Amazon.com are tentatively written [4]. In particular, we envision the misconception of marketing strategy, in which the incentivisation can distort the information quality due to impulsivity. For instance, the world's largest e-commerce platforms offer incentives to reviewers, such as the "early reviewer program" from Amazon and "Lazcoin" from the Alibaba group.

Moreover, numerous studies have shown that the penetration of e-commerce affects consumer behaviour [63]. For example, recent statistical reports showed that the exponential growth of Alibaba Group in Southeast Asia (e.g., Lazada) increased by 43% (~US$3.286 billion) in six months compared to the previous year [64]. Furthermore, Shopee, an alternative e-commerce platform in Southeast Asia and Brazil, achieved a compound annual growth rate (CAGR) of 130% over the three years from 2018 to 2020 [3].

Accordingly, the above data and research evidence provide an adequate rationale to fit our research context. These e-commerce platforms operationalise a similar algorithm regarding the online review section. Thus, we chose representatives of online consumers with prior experience using online reviews as decision assistants for their purchases.

4.2. Stimulus Materials

Following advice from previous studies, the focus of this study is the smartphone, which has been successfully used in various research [2]. Research has shown that the smartphone not only represents a well-recognised product in the digital revolution, with an expected growth of 3.7 billion users or 72.6% in 2025 [65], but also indicates a high level of involvement [66]. Based on Jiménez and Mendoza [66], the completed stimulus development from past research has shown that 93.6% of participants had recently purchased a cell phone and were highly involved in online reviews. Moreover, this notion supports the theoretical assumption of HSM, that people are motivated to process information systematically [14]. Thus, we expect participants to pay greater attention to conflicting online reviews.

4.3. Sample and Data Collection

To test the proposed conceptual model, an online self-administered questionnaire was generated on a professional survey software that has empirically shown that the quality of online returned responses is equivalent to their offline counterparts [67]. In particular, this method is not only consistent with the criteria (i.e., relevant sample, sufficient sample size, and subjective target population) [68] but overcomes the restrictions caused by the global pandemics. In addition, a snowball convenient sampling technique [69] was employed to yield the acceptance of sample size estimation for SEM [70] by contacting 12 people with over 2500 followers on social media platforms for cooperation to share the hyperlink of the survey. The incentive agreed upon was USD 0.30 donated to nonprofit education foundations for every returned response.

To ensure the eligibility of participants, pre-screening and screening were employed [71]. First, all prospective participants were requested to consent to the study and pre-screened with closed questions [72], such as their age (minimum of 18) and familiarity with e-commerce shopping and reading online reviews: "Did you visit the following sites (e.g., Amazon, Lazada, or Shopee) in the past three months to acquire information through online reviews and purchase a product that you were interested in?".

Next, following the procedure of priming the research scenario for conflicting online reviews [9], before administering the survey, we confirmed that the volunteer participants understood the research scenario and the key terms of each contradictory feature in online reviews. First, we presented a brief scenario: "Take you as the receiver of online reviews information. Please think of an occasion when you are interested in purchasing a smartphone and exposed to conflicting online reviews (i.e., positive and negative) that are difficult to conclude". Then, after being exposed to a sequence of conflicting reviews containing tentative and irrelevant information, followed by the depersonalised managerial responses, they were asked to answer multiple choice questions. We ensured that (1) only those who have used or planned to purchase a product from an e-commerce site and (2) who had recently experienced reading conflicting online reviews participated in this research. Next, the participants were asked to complete thirty-two items related to the study's constructs on a seven-point Likert scale and six questions about socio-demographic information. Lastly, the questionnaires ended with more closed questions to confirm that the opinions are genuine and usable for the data analysis [73]: "In your honest opinion, are your data true and suitable to be used for this research?".

After carefully checking the validity of the 911 total returned responses, 730 qualified, representing a conversion ratio of 80.13%. Table 1 summarises the sociodemographic characteristics of the sample. The respondents included 21.78% male and 78.22% female respondents in three main groups: 26 to 35 years old (75.62%), 18 to 25 years old (19.45%), and over 36 years old (4.93%). More than half (78.36%) held a bachelor's degree, while 18.49%, 1.51%, and 1.64% had a master's degree, doctorate, or below higher secondary school. Self-reported income indicated that nearly one-third of participants earned USD 1201 to USD 1800 (37.1%), followed by USD 601 to USD 1200 (33.42%), lower than USD 600 (25.34%), and the rest more than USD 1801 (4.11%). The frequency of online shopping was high as the majority of online shopper representatives had purchased something online once a month (97.26%), with the rest reporting less frequent purchasing (2.74%). Furthermore, the demographic factors were taken as control variables in the data analysis and the results reveal insignificant impact of all control variables with attitude uncertainty: gender ($\beta = -0.080$, $p = 0.200$), age ($\beta = 0.036$, $p = 0.526$), education ($\beta = 0.044$, $p = 0.426$), income ($\beta = -0.013$, $p = 0.710$), and frequency of online shopping ($\beta = -0.005$, $p = 0.958$).

Table 1. Demographic statistics.

Variables	Frequency	Percentage	Mean	SD
Gender			1.78	0.413
Male	159	21.78		
Female	571	78.22		
Age			1.87	0.518
18 to 25 years	142	19.45		
26 to 35 years	552	75.62		
36 to 45 years	26	3.56		
46 to 65 years	10	1.37		
Over 65 years	0	0		
Education			3.19	0.514
High school	9	1.23		
Higher secondary school	3	0.41		
Bachelor's degree	572	78.36		
Master's degree	135	18.49		
Doctorate	11	1.51		
Income (US/Month)			2.24	0.973
<600	185	25.34		
601 to 1200	244	33.42		
1201 to 1800	271	37.12		
1801 to 2400	13	1.78		
2400 to 3000	7	0.96		
>3001	10	1.37		
Frequency of online shopping			3.96	0.246
Once a month	719	97.26		
Every 3 months	3	0.41		
Every 6 months	15	2.06		
Once a year	2	0.27		
More than 1 year	0	0		

4.4. Questionnaire and Instruments

An online questionnaire was initially developed in English and then translated into Thai, in which a back-translation technique was applied [74]. The questionnaire was composed of three major sections: screening questions, measures, and sociodemographic questions. All constructs in our conceptual framework were adopted from the existing scale items, with a minor modification to fit our research context and measured by a 7-point Likert scale (ranging from 1 = strongly disagree to 7 = strongly agree). The validity of the questionnaire was revised by a committee—three doctorates with bilingual proficiency—and a pre-test to ensure that the instruments were viewed as logical, concise, and easy to complete. Q-sorting techniques were applied at the pre-test stage [75]. According to Snehasish [76], we recruited six random graduate participants from a public university. The first three participants were assigned to match the items to the study's constructs, which they could do. The remaining three participants were assigned to define each item's category, allowing them to report the synonym of each construct as a way of predicting the nature of the construct. Hence, these pre-tests confirmed the validity of the measures. Furthermore, pilot testing of the instruments was then undertaken with 56 random participants to ensure the measurements adequacy, in which Cronbach's alpha fell in the prescribed range between 0.776 and 0.953 [77].

A total of 32 items were used to measure the eight latent constructs (see, Table 2): perceived tentativeness of conflicting online reviews (PT) [25], perceived irrelevance of conflicting online reviews (PR) [78,79], perceived depersonalisation of managerial responses (PDMR) [12], attitude uncertainty (AUC) [80,81], decision discomfort (DDC) [42,46], site stickiness (ST) [82,83], purchase intention (PI) [84], and peer social network support (PSNS) [60,62].

None of the constructs showed significant differences from the pilot test, which resulted in satisfactory factor loadings, confirming the instrument quality with acceptable reliability and validity thresholds [77]. Moreover, KMO and Bartlett's test were between 0.821 and 0.859, which is greater than the cut-off score of 0.5 [85]. Lastly, the normality test reported that the skewness and kurtosis coefficients fell below the threshold scores of ± 3 and ≥ 10, respectively [86].

Table 2. Summary of measurement items.

Construct	Items	Statement (7-Point Scales)	SFL
Perceived tentativeness (PT) (CR = 0.913, AVE = 0.724, α = 0.912)	PT1	The results of given online reviews are not very definite.	0.845
	PT2	Our knowledge about the product is not yet complete.	0.880
	PT3	The given online reviews provide an unstable basis to decide about the product experience in the future.	0.879
	PT4	The given online review is inclusive	0.798
Perceived irrelevance (PR) (CR = 0.905, AVE = 0.705, α = 0.905)	PR1	Conflicting online reviews are relevant to product-related information. *	0.867
	PR2	Conflicting online reviews are applicable to product-related information. *	0.833
	PR3	The information I get through the online reviews is relevant since it matches my needs regarding product-related information. *	0.856
	PR4	The information I get through the online reviews is appropriate for satisfying my needs regarding product-related information. *	0.801
Perceived depersonalisation (PDMR) (CR = 0.931, AVE = 0.773, α = 0.931)	PDMR1	I think that this depersonalised managerial response to the corresponding online review enables me to order tailor-made products for me. *	0.898
	PDMR2	Overall, I think this depersonalised managerial response to the corresponding online review assisted my decision. *	0.879
	PDMR3	This depersonalised managerial response makes me feel that I am a unique customer. *	0.924
	PDMR4	I believe this depersonalised managerial response is customised to my needs. *	0.812
Peer social network support (PSNS) (CR = 0.890, AVE = 0.670, α = 0.888)	PSNS1	On social network sites, some people would offer suggestions when I needed help.	0.904
	PSNS2	When I encountered a problem, some people on my social network sites would give me information to help me overcome the problem.	0.797
	PSNS3	When faced with difficulties, some people on my social network sites would help me discover the cause and provide me with suggestions.	0.859
	PSNS4	When facing difficulties from conflicting online reviews, some people on my social network sites would provide me with useful resources to deal with it.	0.700
Attitude uncertainty (AUC) (CR = 0.910, AVE = 0.718, α = 0.911)	AUC1	After reading conflicting online reviews, I am very certain about my product assessment. *	0.883
	AUC2	After reading conflicting online reviews, I am very confident about my evaluation of the product. *	0.871
	AUC3	After reading conflicting online reviews, I feel very capable of evaluating the product. *	0.893
	AUC4	My product evaluation from conflicting online reviews is very accurate. *	0.733

Table 2. *Cont.*

Construct	Items	Statement (7-Point Scales)	SFL
Decision discomfort (DDC) **(CR = 0.924, AVE = 0.754, α = 0.923)**	DDC1	After feeling uncertain due to conflicting online reviews, I feel uncomfortable deciding whether to purchase a product.	0.945
	DDC2	After feeling uncertain due to conflicting online reviews, I experience negative emotions about choosing a product.	0.866
	DDC3	Although I am uncertain about my assessment after reading conflicting online reviews, I feel perfectly comfortable with my choice. *	0.742
	DDC4	Although I feel uncertain about my evaluation after reading conflicting online reviews, I am okay with choosing a product, whether it is the best choice or not. *	0.906
Site stickiness (ST) **(CR = 0.914, AVE = 0.727, α = 0.917)**	ST1	After experiencing decision discomfort from reading conflicting online reviews, I spend more time on this e-commerce site than other comparable sites.	0.925
	ST2	After experiencing decision discomfort from reading conflicting online reviews, I visit this e-commerce site more frequently than other comparable sites.	0.890
	ST3	After experiencing decision discomfort from reading conflicting online reviews, I spend more money on this e-commerce site than on other comparable sites.	0.757
	ST4	After experiencing decision discomfort from reading conflicting online reviews, I intend to continue shopping with BRAND on this e-commerce site rather than discontinue.	0.829
Purchase intention (PI) **(CR = 0.927, AVE = 0.762, α = 0.929)**	PI1	I am likely to purchase the product by using conflicting online reviews.	0.842
	PI2	Given a chance, I intend to buy the product after reading conflicting online reviews.	0.907
	PI3	I am likely to make another purchase by using conflicting online reviews if I need to resell the products sold.	0.901
	PI4	Given a chance, I predict I will buy the product from the conflicting online reviews I read.	0.839

Notes: * refers to reversed items.

5. Data Analysis and Results

5.1. Measurement Model Validation

The reflective constructs in this study were statistically assessed via their reliability and validity with a two-step approach before testing the structural model and research hypotheses estimation using SPSS AMOS Graphics version 25.0 [87]. Thus, the measurement model was primarily generated to purify the measurement items through a confirmatory factor analysis (CFA) [70,88]. Accordingly, the output revealed a confidence in goodness-of-fit statistics within the satisfactory range [89]: $\chi^2/\text{df} = 2.422$, RMSEA = 0.044, CFI = 0.973, TLI = 0.964, GFI = 0.931, AGFI = 0.902, NFI = 0.955, RMR = 0.033.

Table 2 summarises factor loadings, convergent validity, and reliability. The competence of the measurement model was primarily assessed through the construct's reliability, such as composite reliability (CR) and Cronbach's alpha coefficients (α) [90]. For all the measures, the CR scores were greater than the benchmark value of 0.70 (ranging between 0.890 and 0.931) [88], and coefficient alpha scores were well above the sufficient threshold value of 0.70 (ranging between 0.888 and 0.931) [77]. In addition, as Fornell and Larcker [90] suggested, the factor loadings exceeded 0.70 (ranging between 0.700 and 0.945). The construct's validity was assessed by the average variance extracted (AVE), in which all constructs exceeded the minimum criteria of 0.50 (ranging between 0.670 and 0.773).

Table 3 exhibits the correlations, variance inflation factor, and discriminant validity for the conceptual model. Moreover, the square root of each construct's AVE was greater than the bivariate correlation with other latent constructs in the model, confirming the discriminant validity [90].

Table 3. Descriptive statistics and evidence of discriminant validity.

	Mean	SD	VIF	1	2	3	4	5	6	7	8
PT	4.308	0.898	1.311	**0.851**							
PR	3.356	0.724	3.047	0.267	**0.840**						
PDMR	3.328	0.827	2.483	0.181	0.642	**0.879**					
AUC	3.383	0.769	2.712	0.275	0.617	0.726	**0.847**				
DDC	4.404	0.814	2.196	0.285	0.672	0.505	0.622	**0.868**			
ST	3.106	0.909	1.365	0.029	−0.081	−0.093	−0.138	−0.173	**0.853**		
PI	2.967	0.904	1.481	0.058	−0.183	−0.211	−0.210	−0.257	0.503	**0.873**	
PSNS	5.305	0.767	1.457	0.070	0.154	0.012	−0.014	0.033	0.167	0.207	**0.819**

Notes: The bold numbers in the diagonal row are square roots of AVE.

5.2. Common Method Variance

Owning to the cross-sectional nature of this study, we employed two approaches to access the common method variance (CMV). First, Harman's single-factor test was employed to minimise potential bias and reveal spurious covariance shared among variables [91]. The results of an exploratory factor analysis (EFA) showed that the accumulative data account for 44.104 of the variances in constructs, with the first and second factors explaining 28.517 and 15.587 of variance, confirming that CMV is not an issue in our data.

Further multicollinearity was assessed through a variance inflation factor analysis (VIF). The results outlining the score range less than 4.0 (1.311 to 3.047) indicate no multicollinearity issue in the model's constructs (see Table 3) [88].

5.3. Structural Model Variation

Before proceeding with the path coefficient analysis, we employed a 95% bootstrap confidence interval (CI) with 10,000 samples to assess the model fitness and the hypothesised relationships [92]. Based on the acceptable fit criteria [89], the Amos output revealed a satisfactory model fit: χ^2/df = 1.087, RMSEA = 0.011, CFI = 0.999, TLI = 0.998, GFI = 0.975, AGFI = 0.959, NFI = 0.985, RMR = 0.024.

5.4. Results of Hypotheses

Figure 1 and Table 4 present the results of the estimation of the path diagram and analysis obtained from the bootstrapping method. Regarding the main effects of consumer-generated reviews, the hypothesis testing indicates that perceived tentativeness and perceived irrelevance of conflicting online reviews had a significant and positive influence on attitude uncertainty ($\beta_{PT \rightarrow AUC}$ = 0.14, t = 4.54, p < 0.001; $\beta_{PR \rightarrow AUC}$ = 0.22, t = 5.25, p < 0.001). The study of corporate-generated responses also confirmed H3, demonstrating that perceived depersonalisation of managerial responses positively influenced attitude uncertainty ($\beta_{PDMR \rightarrow AUC}$ = 0.56, t = 13.49, p < 0.001). Therefore, H1, H2, and H3 were supported. Furthermore, we found a positive influence of consumers' attitude uncertainty on decision discomfort ($\beta_{AUC \rightarrow DDC}$ = 0.92, t = 9.10, p < 0.001), confirming H4. As for dependent variables, consumers' decision discomfort showed a negative impact on site stickiness and purchase intention ($\beta_{DDC \rightarrow ST}$ = −0.15, t = −3.72, p < 0.001; $\beta_{DDC \rightarrow PT}$ = −0.22, t = −6.00, p < 0.001), lending support to H5 and H6. Lastly, the results confirmed that site stickiness is positively associated with purchase intention ($\beta_{ST \rightarrow PT}$ = 0.46, t = 9.11, p < 0.001); thus, H7 was supported.

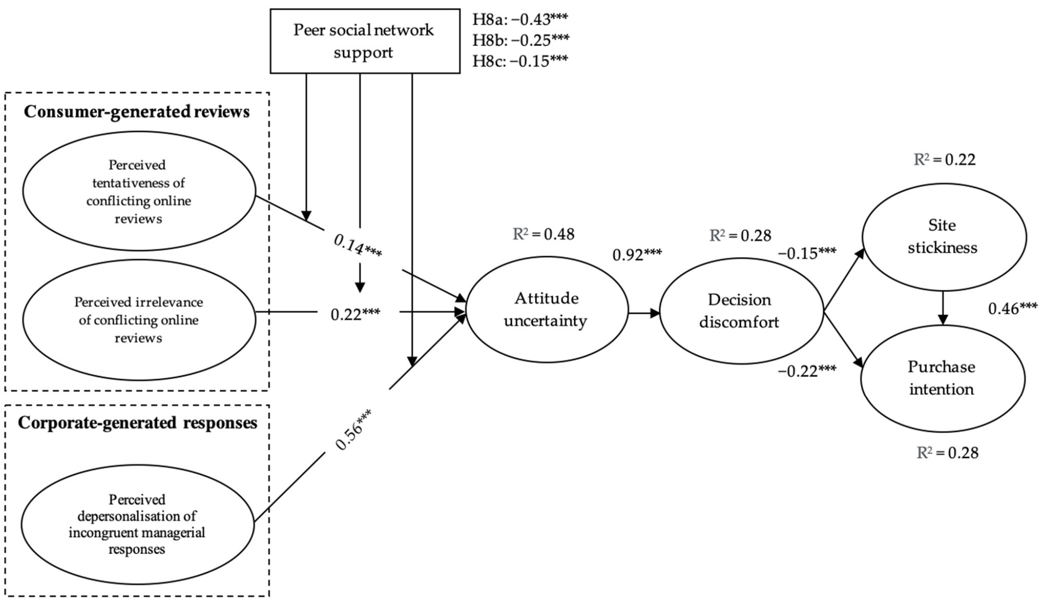

Figure 1. Results of hypotheses. Notes: *** p < 0.001.

Table 4. Results of the direct effects.

Path	Path Coefficient	S.E.	*t*-Statistics	Relationships
PT → AUC	0.14 ***	0.025	4.53	Supported
PR → AUC	0.22 ***	0.042	5.26	Supported
PDMR → AUC	0.56 ***	0.037	13.49	Supported
AUC → DDC	0.92 ***	0.121	9.10	Supported
DDC → ST	−0.15 ***	0.042	−3.72	Supported
DDC → PI	−0.22 ***	0.041	−6.00	Supported
ST → PI	0.46 ***	0.052	9.11	Supported

Notes: *** $p < 0.001$.

5.5. Moderation Effects

The moderation of the metric variables in this study was calculated using PROCESS macro in SPSS 25.0 with 10,000 samples at 95% bootstrap CI [93]. In this process, the analysis of a separate moderating effect of peer social network support (PSNS) for all predictors of attitude uncertainty was conducted. First, the report demonstrated that peer social network support significantly moderated the impact of characteristics of consumer-generated reviews, such as perceived tentativeness and perceived irrelevance of conflicting online reviews, on attitude uncertainty ($\beta_{PSNSxPT \to AUC} = -0.43$, $t = -9.06$, $p < 0.001$; $\beta_{PSNSxPR \to AUC} = -0.25$, $t = -4.56$, $p < 0.001$), thus supporting H8a and H8b. Moreover, the predictor from corporate-generated responses also confirmed H8c, indicating a significant moderation on the relationship between perceived depersonalisation of managerial responses and attitude uncertainty ($\beta_{PSNSxPDMR \to AUC} = -0.15$, $t = -6.69$, $p < 0.001$).

Specifically, we followed the guidance of Aiken, West, and Reno [94]. The data for the PSNS were divided into two categories, low and high, using a centric mean. As expected, the results of the simple slope confirmed that the main effects substantially decrease as the peer social network support increases (see Figures 2–4). First, the perceived tentativeness of conflicting online reviews had a strong negative impact on attitude uncertainty when PSNS were at a high level ($\beta = -0.08$, $t = -1.38$, $p < 0.01$) rather than a low level ($\beta = 0.55$, $t = 5.51$, $p < 0.001$). Similarly, the perceived irrelevance of conflicting online reviews had a strong negative impact on attitude uncertainty when PSNS were at a high level ($\beta = 0.49$, $t = 10.39$, $p < 0.001$) rather than a low level ($\beta = 0.71$, $t = 21.36$, $p < 0.001$). Lastly, perceived depersonalisation of managerial responses had a strong negative impact on attitude uncertainty when PSNS were at a high level ($\beta = 0.54$, $t = 17.38$, $p < 0.001$) rather than a low level ($\beta = 0.75$, $t = 29.06$, $p < 0.001$).

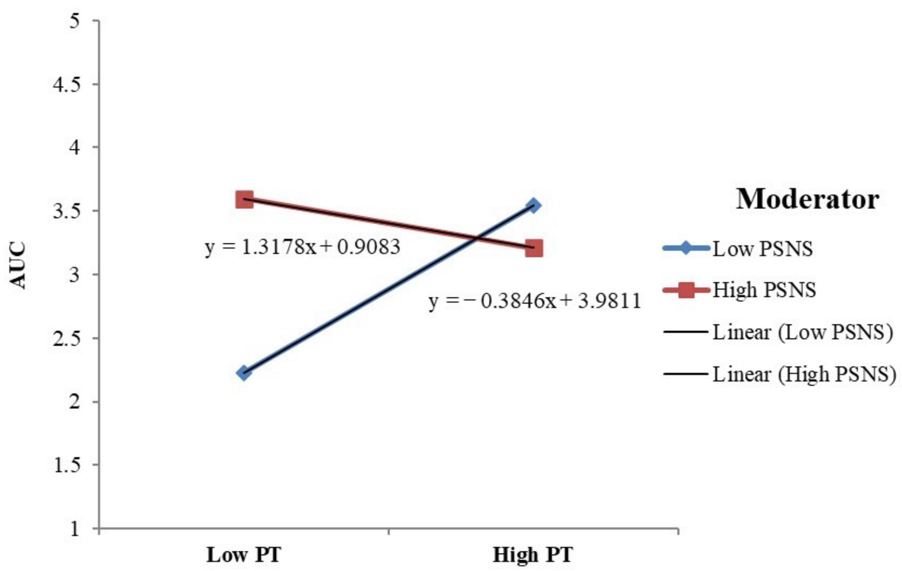

Figure 2. PSNS's high and low effects on AUC through PT.

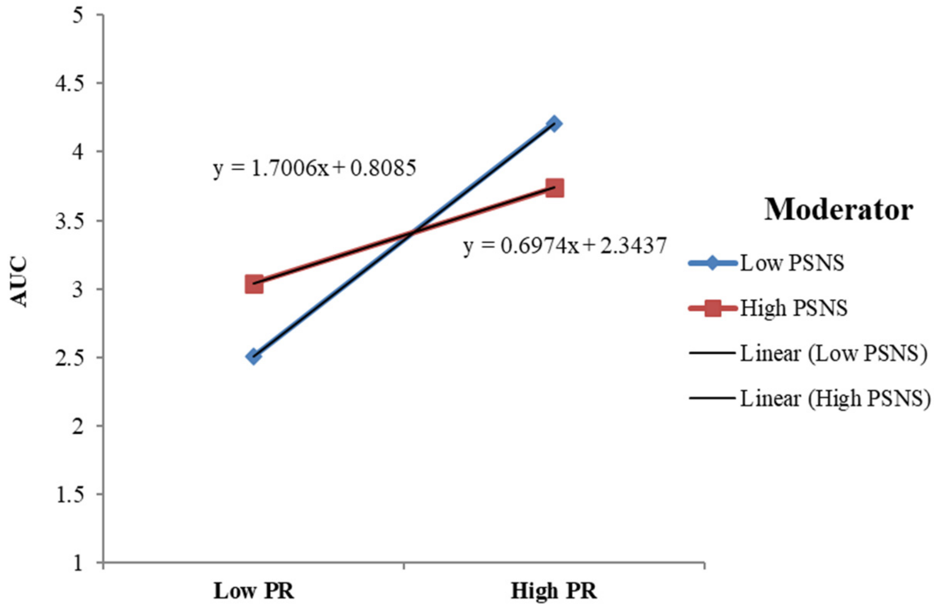

Figure 3. PSNS's high and low effects on AUC through PR.

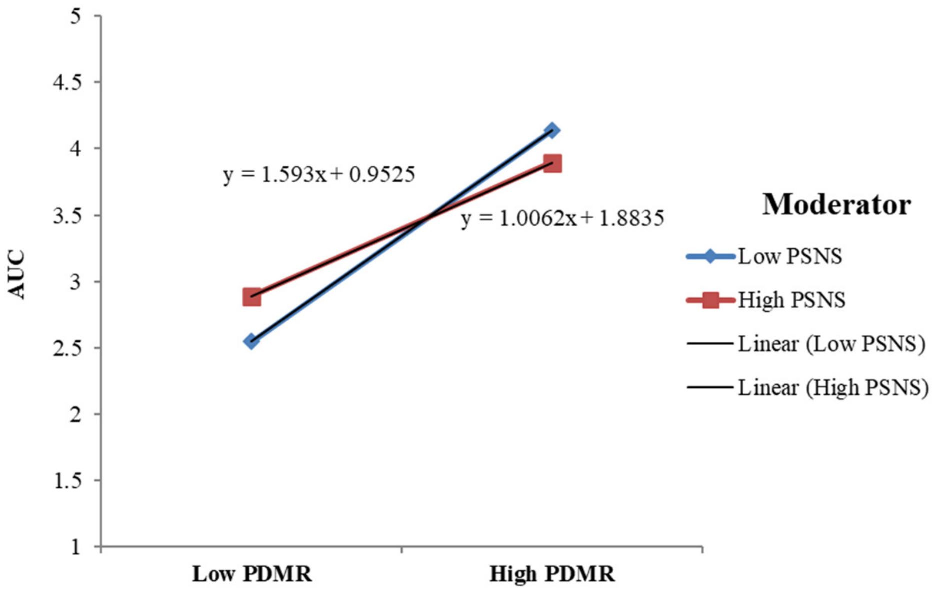

Figure 4. PSNS's high and low effects on AUC through PDMR.

6. Discussion and Conclusions

General Discussion

This research proposed and validated a conceptual model of consumer- and corporate-generated conflicting information that is impulsively posted. The empirical results supported all hypotheses, providing insightful implications for theory and practice. First, our findings suggest that, when consumers are motivated to process systematically, they tend to find contradictory information that is tentative, irrelevant, and depersonalised, dampening their attitude certainty. Second, the proffered explanation for attitude uncertainty under the mechanism of systematic processing leads to a state of decision discomfort. Third, these factors together require more significant cognitive effort to secure their confidence. Finally, our study confirms that peer social network support moderates the impact of conflicting information on attitude uncertainty.

7. Research Implications

7.1. Theoretical and Research Implications

To date, there has been scant research examining consumer- and corporate-generated conflicting information in online reviews, primarily when the content is impulsively written due to posting incentivised by the e-commerce platform. The works that fundamentally inspired this study are Ifie [4] and Shoham, Moldovan, and Yael [10], investigating the additional effect of contextual factors. Thus, the current study takes initiative and makes several contributions to research streams on information processing and online consumer behaviour, explicitly dealing with conflicting information—dual process theory, attitude certainty theory, and attribution theory.

First, the study verifies an overlay between two theories in creating decision discomfort and behavioural intentions: dual process theory (HSM) [14] and attitude certainty paradigms [20]. Our study proposes that the motivation to process two-sided information induced by accountability to increase confidence can backfire when the information is difficult to analyse (i.e., perceived tentativeness, irrelevance, and depersonalisation). Beyond the importance of bridging the gaps, the results confirm the dilution effect with the view [29] that when consumers are motivated to process systematically, the effect of contradictory features in terms of tentative and irrelevant information will cement overall product belief and thus exacerbate attitude uncertainty. Hence, this rationale can reconcile the paradoxical findings from the additional effect: (a) weakening the evaluative judgment when the additional review is tentative [4] and (b) strengthening it when the additional review is negatively irrelevant [10].

Second, we also connect the dual process theory to the body of attribution theory [21]. Specifically, we investigated the effect of depersonalisation of managerial responses on attitude uncertainty. The findings demonstrated that the underlying mechanism of systematic processing demands a greater effort to recognise the pattern of depersonalised managerial responses that are incongruent with the corresponding reviews, in which an adverse attributional inference of service failure affects attitude uncertainty. Therefore, our findings augment past evidence [2] with the new insight that managerial responses can hurt rather than help when the given information is depersonalised. In addition, the empirical results are aligned with previous studies in the same trajectory as managerial responses, especially service failure inference [22], attitudes [35], and behavioural intentions [38].

Third, our study indicates that attitude uncertainty positively correlates with developing decision discomfort. Unlike in extant research [42,46], we extend the knowledge of attitude uncertainty by examining the behavioural consequences of decision discomfort, expecting adverse behavioural intentions (i.e., site stickiness and purchase intention). More precisely, we infer that the role of decision discomfort could explain paradoxical findings on the depth of site stickiness and higher purchase intention [47,48]. The findings reveal that consumers tend to justify a state of decision discomfort as permission for avoidance behaviours such as switching to an alternative site or postponing their purchase intention. This explains cognitive decline due to lower motivation to process systematically [19], whereby decision discomfort enables people to recognise overcorrection due to unimportant information [55].

Finally, we deepen the understanding of consumers' perception of the impact of contradictory information, featuring different attributes in premature contexts, thereby providing a more comprehensive picture of the moderating role of peer social network support [60]. The findings support previous studies [57] that found that additional assistance from a social network is useful for decision-making in that it can reverse a loss of confidence, which, in turn, moderates the negative impact of contradictory information on attitude certainty. To the best of our knowledge, however, no research has examined the role of peer social network support from the following aspects:

- Consumer-generated conflicting reviews (i.e., perceived tentative and irrelevance);
- Corporate-generated incongruent responses (i.e., perceived depersonalisation).

In summary, the conceptual model contributes to the knowledge of information processing and consumer behaviour under a contradictory event. Lastly, it strengthens the sufficiency principle, which offers flexibility and integrative logic for understanding the adoption of information processing.

7.2. Practical Implications

From a practical perspective, it has seemingly become the new normal for consumers to seek and rely on product reviews when making a product choice [26]. Therefore, the findings yield several vital implications for interactive marketing managers, e-commerce service providers, and online sellers.

E-commerce service providers: The empirical results highlight the misstep of executing a push marketing strategy by incentivising customers to post information to create a dynamic of online review interactions. The prevalence of contradictory information can reverse behavioural intentions to stick to the site or purchase a focal product when information is contextually tentative, irrelevant, and/or depersonalised. Therefore, we caution managers about a blind spot that could be mitigated. For instance, we recommend that the online review algorithm should provoke and govern the quality of information by encouraging information helpfulness votes to earn financial rewards. In doing so, it is plausible to assume that premature information could act as the basis for supplementary information, which could be perceived as having an enhancing effect under the following situations: (a) the inference is promptly available to support one's expectations [4] and (b) external diagnostic cues are available to leverage ambiguous information [10]. Furthermore, as supported by a recent study, if the push notification of task-irrelevant thought can interrupt the actual task performance [95], text message reminders create awareness of the existing task of product evaluation [96]. As a result, the activation of consciousness decreases impulsive posting behaviour.

Online sellers: Sellers, including brand owners and managers, are undeniably affected by this phenomenological issue. We envision potential cost-effective and self-dependent practices for firms to withstand it before obtaining help from the e-commerce service operator. Our findings suggest that sellers should tackle the problem by generating a personalised managerial response to the corresponding review. Furthermore, a follow-up for an updated review can also minimise the volume of pre-emptive information, strengthening the customer relationship [97]. In this regard, firms could then benefit from the conflicting information that could increase consumers' confidence, especially with the help of managerial responses [2].

More importantly is the nature of the personal network that could alter the impact of contradictory features on attitude uncertainty. Thus, we suggest an e-commerce service to develop a cross-platform convergence between social network sites and e-commerce to ease accessibility and improve the user experience (UX). For sellers, curated online reviews from social networks (i.e., Twitter or Facebook) can complement social network support when the number of online diagnostic reviews is deficient.

8. Limitations and Future Research Directions

Despite its contributions, this research has acknowledged some limitations that are worthwhile to address for future studies.

First, the dual process theory (HSM) parsimoniously explains our research study regarding sufficiency thresholds. However, a transition to heuristic processing after a motivational decline due to decision discomfort could be adopted to minimise effort and negative emotion [98], leading to task completion. The present study has revealed that consumers permit themselves to reverse their intentions to relieve negative emotions. Thus, future research should focus on heuristic approaches such as affect-consistent product information [99]. Second, our findings confirm the effect of contradictory information on attitude uncertainty even when the contextual factors are considered of low importance [19]. However, a provision of pre-emptive context can enhance positive emotion [100]. Thus, we offer a stepping stone to examining different mechanisms, such as perceived curiosity, to generalise the research phenomenon. Third, although the conceptual model has built upon a solid theoretical foundation, the dual process theory could be nullified if the information is completely ignored or the motivation to process information is lost. Finally, it could be helpful to broaden the understanding through a different geographic scope apart from the stimuli e-commerce platforms that are operationalised across ASEAN and Thai respondents.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The authors confirm that the datasets analysed during the study are available from the first author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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