Decision Support Systems 145 (2021) 113519

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Disconfirmation effect on online review credibility: An experimental analysis

Ashish Kumar Jha [a,*], Snehal Shah [b]

[a] Trinity College Dublin, Ireland
[b] S.P. Jain Institute of Management and Research, India

ARTICLE INFO

Keywords:
Disconfirmation effect
Review credibility
Online reviews
eWOM
Experiment method

ABSTRACT

The rise of e-commerce has led to the increased reliance of users on electronic word-of-mouth (eWOM) to evaluate the products and services offered. Previous research has attempted to determine which reviews are more credible than others, as credible reviews tend to impact readers more than non-credible ones. However, one of the research questions in this domain that has not been addressed so far is the impact of circumstances of review writing itself, which may influence the way the review is written and affect its credibility. In this paper, we describe a controlled experiment to study the impacts of a user's exposure to past reviews and the user's own product experience on the perceived credibility of reviews written by the user. We have employed attitude-behavior linkage theories and the disconfirmation effect to study this phenomenon. Our results indicate that *disconfirmation*, or the difference between a user's own experience and expected experience, has a significant impact on the way a user writes reviews and hence on the review's perceived credibility with the subsequent readers of the review. We find that disconfirmation and perceived review credibility follow a *U-shaped* relationship, in which perceived credibility is high for the highest and lowest values of disconfirmation.

1. Introduction

The digital economy has pushed a large part of economic activity online. A large proportion of purchases for products ranging from soaps to electronic gadgets now takes place online. The increasing reach of digital stores can be gauged by the estimation that overall sales on e-commerce platforms in the USA in 2020 would exceed USD 700 billion [1]. The increase in relevance and demand for online shopping is also being pushed by the stay-at-home orders being enforced during the current COVID-19 pandemic. Due to the proliferation of online stores as a preferred shopping medium, online product reviews have also increased as a source of information for consumers [2,3]. Consumers use the product reviews found online to complement their understanding of the product or service being offered, as an additional feedback medium [2,4].

Given the rising importance of reviews in consumer decision-making [5,6], it is important that the reviews are perceived to be credible. Research has shown that a lack of credibility in reviews negatively impacts the acceptability of a platform [7]. Multiple studies have examined the perceived credibility of reviews from the perspective of a review reader [8]. This line of research attempts to determine the constituents of a credible review. These studies have identified that important factors affecting the perceived credibility of anonymous reviews include the profile picture of the review writer, the content of the review, and the valence of the review compared to the cumulative average product or service rating, to name a few [9]. Driven by this information, e-commerce platforms strive to develop portfolios of more credible reviews. Platforms do this by nudging review writers to include such credibility inducing elements in their reviews [10]. While these policies are based on recognizing what constitutes a credible review and promoting those elements, the impact of review writing circumstances on the perceived credibility of reviews has been overlooked by both academia and industry.

As stated in the preceding paragraph, we found that most of the existing studies on review credibility analyze review text [9] and assume the credibility of a review to be exogenous to the review writing process [11–13]. While it can be reliably assumed that most review writers try to write fair and credible reviews (from their perspectives), it remains a fact that some reviews are perceived to be more credible than others. This indicates that the factors influencing a review writer impact the review's perceived credibility. This brings us to our research question: How do past reviews, as a stimulus presented to the review writer,

* Corresponding author.
E-mail addresses: akjha@tcd.ie (A.K. Jha), Snehal.shah@spjimr.org (S. Shah).

https://doi.org/10.1016/j.dss.2021.113519
Received 12 May 2020; Received in revised form 5 February 2021; Accepted 7 February 2021
Available online 10 February 2021

influence the perceived credibility of the written review? We feel that though credibility is a perceptual entity [14], the review writing process, specifically, the conditions under which a review is written, has a significant impact on the content of the review and, in turn, the perceived credibility of the review. While there have been studies on review writing context [15,16] as well as review credibility [17,18], there is a lack of work connecting the review writing context to review credibility, a gap this study aims to fill. A nuanced understanding of such factors shall enable the e-commerce platforms to nudge review writers toward writing credible reviews by providing the right stimuli on their platform and hence raise the overall quality of reviews on their platform. The overall purpose of this study is to test how the conditions under which the review is written influence the perceived credibility of the written review. More specifically, this paper explores two dimensions of this relationship with perceived credibility: a) the influence of one's own product experience and others' evaluations of the product and b) influence of *disconfirmation*—the gap between one's own experience and the expectations inferred from others' reviews.

Research in human behavior has established that the human mind is a complex tool, impacted by myriad factors while performing any act. [19].While acknowledging that multiple factors could affect the decision to write a certain kind of review, we test the credibility of written reviews under the influence of disconfirmation. The expectation could be driven by a host of factors, but one of the most important of these factors that impacts a user's expectation is the wider public experience of the product as visible through the product's public rating and reviews [18]. As past reviews represent the views of others, they also add to social influence, i.e., influence from other humans who took the same action—reviews influenced in turn by previous reviews. We base our theoretical grounding in literature on the attitude–behavior linkage that helps us trace how the attitudes of review writers and various other factors, including past reviews, impact the writing of reviews.

The questions raised in this paper have been addressed through a laboratory experiment based method. Drawing on the data collected from over 200 subjects, our study found that review credibility depends on the previous reviews to which a review writer has been exposed. Analyzing our data through the theoretical lens of the disconfirmation effect, we also found that disconfirmation between the review writer's own experience and others' experiences has a significant effect on the credibility of the review written by the user. The relationship between disconfirmation and credibility follows a *U-shaped* curve, such that very high and very low disconfirmation leads to higher perceived credibility of a review as compared to average values of disconfirmation. Our research adds a new dimension to the information systems (IS) research stream of review credibility by introducing the psychological stimuli of past reviews as one of the potential determinants of the perceived review credibility.

2. Background[1]

The theoretical background of this paper draws on two major streams of literature. The first of those is the work in the domain of *electronic word-of-mouth*, or eWOM. We eWOM literature to establish the theoretical grounding of our work and develop a comprehension of how review credibility has been treated in previous research. The second domain of research that we have developed in succeeding sections is the construct of attitude–behavior linkage theory, of which two aspects are salient here: a) social influence, as manifested by the social pressures experienced by the review writer, and b) the disconfirmation effect, as indicated by the expectation–experience mismatch.

2.1. eWOM and review credibility

eWOM has been an integral part of e-commerce for over two decades now. In the context of e-commerce, eWOM often takes the shape of online product and service reviews when customers, or other product users, provide their feedback on the product or service used [20]. Numerous researchers have studied the importance of reviews in electronic commerce and the deep impact it has on sales through online channels [21]. Previous studies established that online reviews enable subsequent customers to understand and evaluate a product better [22]. Positive reviews, hence, lead to increased sales and reputations [20]. Research in the domain of online reviews has established that not all reviews are equal. Certain aspects of reviews make some reviews seem more helpful [17], believable [17] or trustable [18] to readers.

One such trait is review credibility, as perceived credible reviews are expected to have a much higher impact on readers and enhance the overall trust quotient of the e-commerce platform [17]. The credibility of a review has been defined as the believability or trust that a reader has in the review that they are reading [17,23]. Past research on online review credibility has examined the determinants of review credibility through multiple perspectives. Some of the factors that past research has identified as having an impact on review credibility are source credibility, review consistency, review sidedness and argument quality [17].

Table 1 lists of work done in the domain of review credibility. As the summary suggests, most work has studied the credibility of reviews from the perspective of a review reader by identifying factors like review valence and sidedness, reviewer profile and images, review order and

Table 1
A non-exhaustive summary of literature in the domain of review credibility and eWoM.

Paper	Core Topic	Main Theory/ Contribution	Method
Karimi & Wang [24]	Review helpfulness and trust	Reviewer's profile image significantly impacts the perceived helpfulness of reviewers written by the user	Secondary data-based analysis
Banerjee et al. [18]		Source credibility theory-based determinants identified for reviewer trustworthiness	Secondary data-based analysis
Jha and Shah [25]	Social influence in review	Past reviews influence the kind of sentiments present in a review writers review	Lab experiments
Ho et al. [26]		Past ratings have an impact on future ratings for a product on e-commerce websites	Secondary data-based analysis
Zhou & Guo [13]		Past reviews, in terms of the order of reviews, impacts the helpfulness of future reviews	
Jensen et al. [27]	Review credibility	Language expectancy theory-based measures of lexical complexity and two-sidedness of review impacts review credibility	Lab experiment
Cheung et al. [17]		Argument quality, argument sidedness are important determinants for review credibility	Secondary data based analysis
Qiu, Pang & Lim [9]		Review credibility is impacted by the conflicting aggregation of ratings shown to a user	Lab experiment
Filieri [23]		Consumers primarily use cues related to the message content and style and review extremity and valence to assess trustworthiness	Interviews of online reviewers
Shan [28]		Role of self-generated and system-generated information in enhancing the credibility of online reviews	Lab experiment

[1] There is a vast amount of research across disciplines in eWOM, online reviews and e-commerce. This section does not attempt to provide a comprehensive literature review of these topics. (See Cheung and Thadani, 2012, and Qahri-Saremi and Montazemi, 2019, for recent literature reviews.) In this section, we position our work with regard to its relevant background.

aggregation. While past research has studied the impact of social influence on review helpfulness and sentiments, the impact on review writer and its implication on the perceived credibility of review has not been studied so far.

In the context of review credibility and otherwise, there has been a growing stream of research on the impact of context upon online reviews and ratings. Jha and Shah [25] analyzed the influence of exposure to past reviews on newly written reviews. Ho et al. [26] specifically analyzed the impact of context user ratings posted on online review platforms. Hu and Li [16] also found evidence of online reviews being dependent on the context of writing the review. Ma and Khansa [15] dove deep into the phenomenon to study the impact of past reviews on subsequently written reviews. While all these studies have analyzed the impact of the review writing context on various facets of reviews, the direct relationship between the context and the credibility of reviews needs to be analyzed in detail.

2.2. Attitude–behavior linkage theories

Social psychology researchers have studied the attitude–behavior link with great interest [29]. *Attitude* refers to the consistency or predictability of response toward an action [30]. Over time, multiple studies revealed a weak relationship between the two constructs leading many investigators to study the intervening variables that influence this linkage [30]. For example, studies have shown that individuals are less likely to behave consistently with their attitudes if they feel constrained by the context situational context [31]. Of particular interest to this study are the two situational dimensions presented by Smith and Swineyard [32] that influence the attitude–behavior linkage. These are a) social demand characteristics and b) norms of acceptable behavior. The first dimension relates to certain social demands of the context that influence attitude, while the second dimension covers aspects of behavioral norms and role requirements that may influence the linkage. Coincidentally, the social influence theory popularized in the IS literature that forms the basis of some hypotheses in this study refers to the social pressures experienced by an individual in much the same way as the situational constructs are described in the attitude–behavior linkage [29]. Where it primarily differs is in its application to a context. Customers or in our case, review writers, are in an online e-commerce platform reading reviews written by others, instead of a being in a physical face-to-face environment.

Similarly, the concept of disconfirmation, central to this paper, based on the expectancy-disconfirmation theory (EDT) established in the marketing literature [33,34], has its roots in the situational construct described in Smith and Swineyard [32]. This dimension is an unexpected external event that can create an inconsistency in an otherwise predictable attitude–behavior link. EDT refers to the difference between customer expectations of a product and the actual experience, thereby impacting satisfaction [35]. This gap creates a sense of discomfort in the minds of individuals prompting them to adjust their thinking. In the context of our study, it pertains to the inconsistency created due to the expectation–experience mismatch. Here, the expectation is considered as an external event derived from reading others' reviews.

Past studies in the IS domain have identified multiple factors that form customer expectations. They are formed by individuals, based on their prior assumptions, marketing information or word-of-mouth publicity of the given product or service [36]. One of the critical factors that helps shape the expectation is word-of-mouth communication in offline or online channels [36]. Research in marketing has established that positive word-of-mouth, i.e., positive reviews, accrues more easily with products that exceed their expected quality [36]. On the other hand, negative reviews are dominant for products that fail to perform as expected, even if they were performing similarly to the other available options [33]. Given its nuanced effects, we focused on the gap between the expectations formed by online reviews of other users and one's own experience to form the basis of the disconfirmation linkage explored in this paper. Fig. 1 explains the disconfirmation effect as operationalized in this study.

It is noteworthy how the gap between expectation and experience—the core concept of disconfirmation in this study—resembles the service quality framework developed by Parsuraman et al. [37]. Researchers concur service quality "measures how well the service level delivered matches customer expectations" [38]. To this extent, this paper's operationalization of disconfirmation has an apparent similarity. However, the two concepts differ in one important way. Essentially, the service quality model espoused by Parsuraman et al. [37] outlines *how* gaps are created between customer expectations and marketer efforts to provide quality, thereby influencing satisfaction outcomes. While this research, through the size and direction of disconfirmation, explores *why* a gap is created and *how* it influences others' perceptions of review credibility, not one's own satisfaction.

3. Hypotheses development

As noted earlier, in the domain of social psychology and marketing, the attitude–behavior consistency link has intrigued researchers [29,39]. While multiple moderators have impacted the relationship (e.g., [39]), the direct experience of an object, a variable of interest in this study, was found to strongly moderate this relationship [40]. The direct experience of a product provides a dependable reference from the past [41]. It is also shown to form strong attitudes by developing confidence, clarity and certainty that maintain an attitude [41]. In a subsequent paper, the authors also found those attitudes that were developed through direct experience were more likely to leave stronger imprints in the memory [42].

In the context of this study, the review writer who has had her own prior experience of the product is prompted to convert attitude into purposeful behavior in writing a review [29]. In the absence of a direct interface with the source in an online setting, the review written by the source with direct experience is likely to transfer the qualities of clarity, confidence and certainty into their review writing behavior [42]. When these qualities are transferred, it is presumed that, irrespective of whether the review is positive or negative, the source credibility as demonstrated from the written text will have significance to the reader. In essence, the message becomes the proxy for the credibility of the source when the source has had a direct experience of the product. Specifically, the hypothesis states,

H1. *: Review writers' product experiences will have significant effects on the perceived credibility of the reviews they write.*

eWOM continues to be an important source of input for online shoppers [18,43]. In the e-commerce domain, researchers have long recognized the role of friends, strangers and referent others in influencing consumer decision making [44]. In IS literature, *social influence theory* refers to the social pressure experienced to change one's behavior [45]. As mentioned in Section 2.2, it relates to some of the situational dimensions influencing the magnitude of the attitude–behavior link. According to Deutche and Gerard [46], social influence can be of two types: informational and normative. *Informational influence* is related to the extent to which individuals are willing to accept information received from others as factual and valid. On the other hand, *normative influence* is the degree to which individuals conform to the expectations of referent others.

To develop the next hypothesis, we argue that, in the absence of one's own experience, individuals are likely to depend on the cues received from others' experiences—both informational and normative. The logic would be as follows: As per the informational influence theory, one will be guided to pay attention to the factual information in others' writing as they choose to write one's own review [47]. Further, not having had direct experience, one will also pay attention to aspects such as whether there is a generally accepted view and whether a consensus is emerging, in other words, relying on the dominant view as derived from

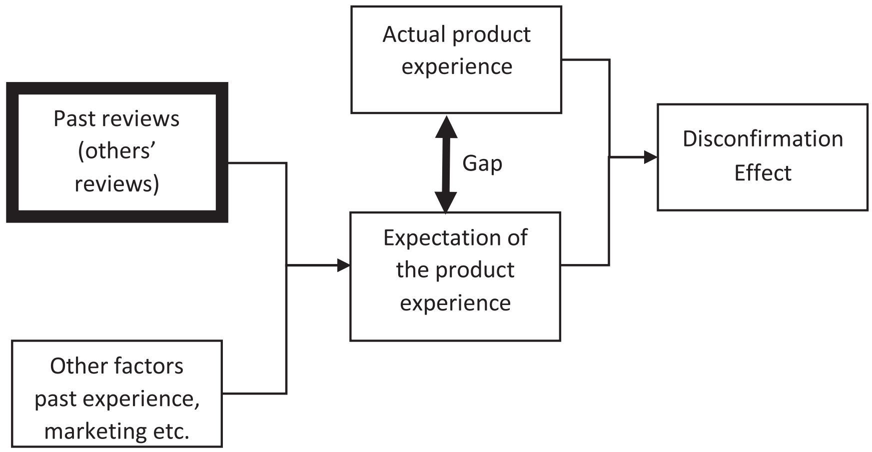

Fig. 1. Disconfirmation effect and its operationalization in this paper.

interpreting the social cues in others' writing [48]. Individuals may be driven by both aspects of social influence, because adopting such a view may make them believe they have come closer to a more accurate product evaluation (informational influence) or help them to develop their own virtual social identity (we thank the reviewer for this valuable insight). Taken together, the following hypothesis suggests that, in the absence of one's own experience and analysis of it, the informational and normative aspects of social influence theory provide relevant inputs to a writer in creating a credible review. Hence, the next hypothesis states:

H2. *: A writer's exposure to others' product reviews will have a significant effect on the perceived credibility of the writers' review.*

Hypotheses 2a and 2b postulated below are intended to capture the nuanced effects of social influence theory, which we infer is a manifestation of the situational dimensions impacting the attitude–behavior link. The above hypothesis assumes others' reviews to affect the author of a new review uniformly. However, that may not be the case. A review writer may react differently to positive and negative components of a review. IS literature refers to such cues as *sentiments*. More specifically, as defined by Munezero et al. [48] a sentiment is a "more or less enduring predisposition in a personality to respond with positive or negative affect to specific object or entity" (page 3). Moe and Schweidel [43], Sridhar and Srinivasan [49] and Ho et al. [26] provided substantial evidence validating the relationship between sentiments generated by others' opinions and customer decision choices. It is interesting to note that negative sentiments have a stronger effect than positive sentiments [26]. This is also true in the eWOM domain, even though it is rather rare to see negative opinions as demonstrated by the J-curve of product ratings [43].

The next set of hypotheses link an individual's review-writing behavior to the evaluation of the nature of sentiments to which an individual is exposed. Fundamentally, in a social setting, humans are primarily driven to identify with the dominant view so as not to be labeled as an outlier in a particular social context [50]. Given this propensity to fit in, Hypothesis 2a suggests that, when exposed to others' negative reviews, a writer conforms and writes a negative review. On the other hand, when exposed to others' positive reviews, a writer conforms and writes a positive review. Having established that in the eWOM space, negative reviews are perceived as more credible, we hypothesize that a writer's exposure to negative sentiments creates a stronger set of conditions for the written review to be seen as more credible, as compared to the positive sentiment condition. Therefore, Hypotheses 2a and 2b are:

H2a. *: Exposure to others' negative reviews will lead to higher perceived credibility in a new review.*

H2b. *: Exposure to others' positive review will lead to lower perceived credibility in a new review.*

Hypothesis 1 established the link between one's own product experience and the perceived credibility of a resulting review. The reasoning supporting this relationship is that the review writer who has experienced the product herself is likely to write a message that is certain, clear and therefore likely to be seen as credible. In such situations, since the involvement in the experience is much greater, Petty and Caciappo [51] argued that the attitude–behavior link is much greater to warrant writing a review that is perceived as credible, leading to a change in behavior [52]. Subsequently, Hypothesis 2 has proposed, through the mechanism explained by social influence theory—a manifestation of the situational constructs of attitude–behavior linkage—that a review writer is persuaded to make an earnest attempt to write a socially acceptable and potentially credible review, as perceived by readers [45].

Taking this further, the next hypothesis tests for the moderating effect of one's product experience on the link between others' reviews and perceived credibility. It suggests that we as individuals are not willing to give up control of the situation derived from the clarity, confidence and certainty that emerge from our direct experience of the product [41]. We are not driven entirely by the social constructs in which we live. Our response to the stimuli is a combination of our own agency through direct experience and social influence—taking into consideration what others think of the situation. To operationalize this notion, the hypothesis states,

H3. *: The relationship between others' reviews and the perceived credibility of a new review will be moderated by the writer's product experience.*

The paper now shifts focus to what is deemed to be a very relevant construct in the eWOM domain: the disconfirmation effect [53]. In this study, it is the difference between one's own experience of a product and expectations formed through reading others' reviews on online platforms. Earlier, we have associated its manifestation in the literature with the situational context dimensions of an unexpected external event causing inconsistency, thereby influencing the operationalization of the attitude–behavior link. The basic premise of these sets of hypotheses is that individuals are prompted to act when they encounter a discrepancy between what is expected and what is experienced. Cognitive evaluation like this generates different levels of emotions, especially when the gap between expectation and experience is large in either direction, positive or negative. There is evidence to support this notion. Research has shown enhanced levels of discussions over movies and newspaper articles have more emotional content [53]. Moreover, consumer behavior theorists have demonstrated that highly dissatisfied or highly satisfied customers write more or provide elaborate feedback than those who are not in those extreme zones [53].

This study argues that, in the event of a discrepancy between experience and expectations, the conflicting scenario condition under which one writes a review will impact the perceived credibility of the review. The hypothesis states,

H4. : *Disconfirmation (the difference between the review writer's experience and experience of others that form expectations) will have a significant effect on the perceived credibility of one's review.*

Research on disconfirmation in online reviews is gathering momentum. Ho et al. [26] established a linear effect between the experience of disconfirmation and the decision to write a review and assign ratings. Although we acknowledge the contribution made earlier, we think the relationship between the two constructs is more complex than what is already explored [25]. In the event of a disconfirmation, individuals face an experience–expectation mismatch, resulting in a "sense of psychological discomfort." Individuals cope with this discomfort by changing their behavior to reduce the dissonance [53]. However, this adjustment, we argue, is contingent on the extent of the mismatch: A response depends on one's assessment of where one falls on the mismatch continuum.

Based on Anderson's [53] work on product evaluation and customer satisfaction, we propose that a customer cognitively divides the mismatch continuum into zones in order to determine a response strategy. If, for instance, the gap between the experience of the product and expectation is not very large, one is likely to remain true to one's experience. Coincidentally, since one is closer to the expectations of others, one's intended behavior will naturally adjust to assimilate or "fit in" with the dominant view [53], which in this case, is aligned to one's own view as well. Based on this premise, we hypothesize that when the gap between one's own experience and expectation is low, one is likely to remain true to that experience and write a review that is seen a credible. However, if the gap is wide enough, one is more likely to employ the strategy of *contrast effect*, which means to move toward one's own experience and away from the expectation in an exaggerated manner—simply put, moving toward the extreme [25]. This may be done with the motivation to showcase oneself as an expert or to acknowledge a feeling to 'stand out from the crowd'. When choosing to remain true to one's own experience, rather than moving toward the mean, one's writing naturally becomes more truthful, honest and believable. So, putting both of these effects together, whether the consumer is in a low-disconfirmation zone or a high-disconfirmation zone, we argue that reviewer behavior will follow a curvilinear relationship between disconfirmation and perceived credibility. More specifically,

H4a. : *Disconfirmation in product experience and perceived credibility of reviews have a U-shaped relationship such that extremely high and extremely low values of disconfirmation lead to higher perceived credibility of reviews.*

Hypothesis 4 posits that if the gap between expectations as formed by others' reviews and one's own experience is not very large, customers will assimilate. On the other hand, if the gap is in the extreme (in either direction), then the customer may employ a contrast behavior. In testing for the moderating effect of others' reviews, this curvilinear relationship may be impacted in such a way that, even if the dissonance is at the extreme ends, instead of having a contrast behavior, the customer regresses toward the mean, i.e., toward the dominant view.

We posit that this may occur for two reasons. First, given the disconfirmation at extreme ends, the potential reviewer is nonetheless grappling with higher levels of cognitive dissonance that must be resolved. Second, with the moderating effect of others' reviews, the reviewer feels a pull toward the dominant view. So, in a way, the reviewer faces double pressure to conform. Our hypothesized effect finds support in the seminal paper by Oliver [33], which states that "consistent evidence in favor of the predictive superiority of the assimilation model. … showed that the contrast effect is elusive." The moderation hypothesis, therefore, states that:

H5. : *Relationship between disconfirmation in product experience and perceived credibility of review is moderated by writer's exposure to others' past review.*

Fig. 2 shows the complete research model and the hypotheses as described in the preceding sections. As shown in the figure, the review writing process is influenced by different kinds of factors- the experience of the user of the product as well as the past reviews that the said user is exposed to before writing the review. The third factor is the disconfirmation.

4. Data and method

4.1. Experiment design

We used laboratory experimentation as the preferred method of study in this paper. A review of the literature shows that this is the preferred method in such studies (see Table 1). In this experiment, we used a high-end smartphone as a stimulant product. The choice of the smartphone was made as most premium smartphones are popularly bought online in India [54]. Also, the rise of smartphone popularity ensured that most of our experiment subjects were aware of the product, and product-level bias was eliminated. We conducted the experiment over a six-month period (February–August 2017) in a leading business school in India where the participants were drawn from the pool of students, staff and teachers who volunteered to take part in a study. Each participant was compensated with an Amazon coupon of 100 Indian rupees (equivalent to USD 25 in PPP terms). To emulate the real review writing experience, the subjects were free to write a review or not after experiencing the product and looking at the stimuli. The subjects were not incentivized to write reviews specifically. The subjects were exposed to the stimuli factors (as discussed below) and provided a customized platform to write their reviews. The reviews were then independently assessed for their credibility. This allowed the researchers to study the impact of the stimuli on the credibility of reviews as perceived by neutral readers.

The experiment was designed as a two-factor experiment in which the factors were a) user experience of the product and b) past reviews shown to users before writing their own reviews. We also included two control cases in which past reviews were not shown to participants. Table 2 shows the experimental conditions used in the study.

The participants were chosen from the list of volunteers based on a preliminary survey: Volunteers without prior online shopping experience were eliminated. The rest were invited to proceed through to the next step of the experiment, compensated with online shopping vouchers (for INR 100). We had a male dominant (183 males, 78.9% of 232 respondents in total) participant pool, generally reflective of the online user demographics in India. We found that all the respondents were smartphone users ($N = 232$).

4.2. Experiment stimulus

The experiment stimulus was designed to eliminate bias and ensure that all subjects had a similar understanding of the product being reviewed and its features. It is reasonable to assume that different individuals will have different product experiences with the same product, because of their preferences and biases. This would limit the control in our experiment. Hence, we used a narrative-based model of stimulus in this experiment [55]. The narrative-based model of providing stimuli was driven by the requirement for participants to have uniform experience stimuli in order to maintain the control of laboratory conditions [25]. Such methods have been previously deployed in experimental research where experiences needed to be controlled [25,55]. As Daugherty et al. [56] have established, narrative-based methods provide the rigor essential to ensure uniform stimuli for all subjects. Narrative, being a mode of indirect experience, would have a lesser effect than

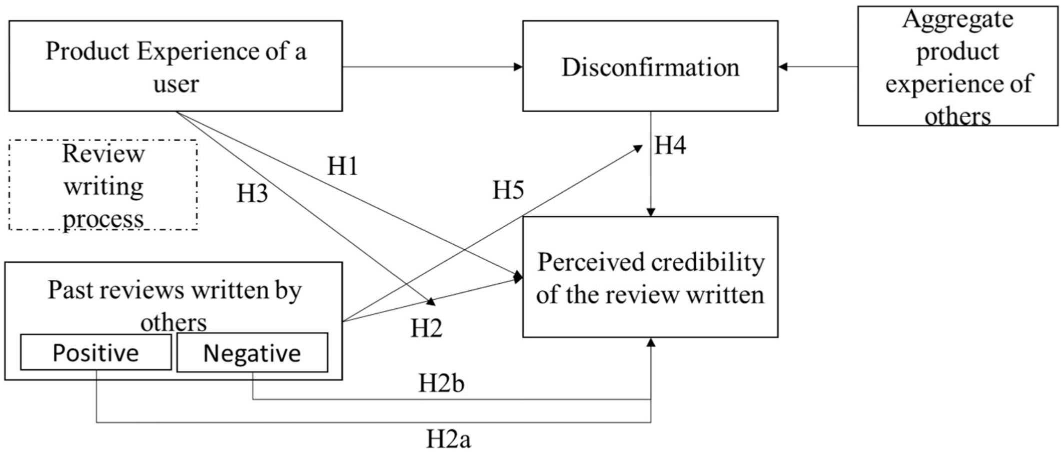

Fig. 2. Research model showing the hypotheses of the study.

Table 2
Experimental conditions.

Experiment Group	Stimuli 1: User experience	Stimuli 2: Past reviews
1	Positive	Not shown
2	Positive	Positive
3	Positive	Negative
4	Negative	Not Shown
5	Negative	Positive
6	Negative	Negative

direct experience on the subjects [52]. This adds to the robustness of our analysis, as our results would be suppressed rather than exaggerated due to the use of narratives.

To simulate product experience, a detailed description of a typical product experience was given to the participants in a narrative style [55]. A detailed description of the product (smartphone) was provided (as mentioned in Table 3). The product description was provided for both good and bad products presented to the subjects. A uniformly described product experience for the good and bad products along with the physical experience of the product is the best mechanism to make the potential reviewers experience the product in a controlled environment. The study used the fictitious name of the phone to ensure no brand-level bias was introduced in the study. Since previous studies have established that the operating system (OS) is an important consideration in smartphone preferences [58], we masked the OS of the phone so that the default OS could not be recognized. This ensured that OS bias was eliminated. The subject would only be exposed to the material provided by the researchers. Hence, the expectation would be influenced only by the previous user reviews and not any other individual specific factor that may otherwise be a confounding factor in formation of individual's expectation of any product or service.

Table 3
Examples of stimuli used in the study.

Stimuli	Level	Sample
Experience	Positive	I used the mobile phone and found that the quality of sound from the new type C headphone is even better than advertised. I also realized that speed of charging has increased so much so that phone gets 70% charged in under 1 h. The response of the touchscreen is better than any other phone I encountered so far as well as the quality of the camera images that it captures.
	Negative	After using the mobile phone, I found that I am having trouble connecting to the headphone as the mobile has no 3.5 mm headphone jack. The mobile also is not able play favourite game and heats up quite quickly. There is a problem to restart the phone, it takes quite some time and you are able to restart the phone only after multiple attempts. As a photography enthusiast and one of the reasons for buying this phone was its advertised camera quality. However, the phone camera does not perform as well as other phone cameras of competitor brands, especially in low light when the images comes quite pixelated.
Past Reviews	Positive	Tekas means Tekas. No stars matter at all. Quality Unmatched like always. If it is a Tekas, nothing else is left to say. Either it is a Tekas or just another mobile phone:)
	Negative	Waste of money. Better to buy Samsung phone instead. Tekas 4 had 1 gb of ram, Tekas 5 has 2 GB of ram. Better to buy Oneplus 3 at Rs 30,000 with 6gb of ram. This is fact.

The second factor of past reviews was curated by showing the users a selection of 10 very positive and 10 very negative reviews to generate extreme stimuli. The most positive and negative reviews were selected from a larger set sourced from real reviews on amazon.com and were rated by 30 coders regarding sentiment. The 10 reviews with the most positive and negative sentiment scores, respectively, were chosen as the stimuli. Each participant was exposed to the conditions and was asked to write a review of the product. These reviews became the primary dataset for studying perceived credibility in this research. Table 3 shows a snapshot of the stimuli used in the study.

4.3. Method

The first stage in the analysis was to assign a credibility score to the reviews written by the experiment subjects. Previous literature has established that credibility is a perceived phenomenon and is dependent on how a reader interprets the credibility based on their understanding from a variety of factors in the review [27]. Hence, we recruited five research assistants[2] who were asked to rate the reviews on four parameters of review credibility as established by Cheung et al. [17]. Through this exercise, we ensured the following:

a. The credibility scores reflected the perceived credibility as observed by neutral readers.

[2] The RAs were postgraduate management students at a business school where one of the authors was employed. The RAs were trained on the aspects of survey design and e-commerce and were trained on filling the credibility questionnaire. About 10% of the filled questionnaires were tested by the other author to ensure the questionnaire were filled correctly and the interpretations of RAs were as expected.

b. The credibility scores are free of bias and represent the truly perceived credibility judged by readers with the same cultural and linguistic understanding.

Cohen's kappa score of the similarity of five RAs was 0.85, which was considered acceptable for the purpose of this exercise [57]. After ensuring that the credibility scores for none of the reviews deviated from each other significantly, we took the average of the five RA scores as the credibility score for the review. In a similar fashion, we also computed the sentiment of each review, which was a necessary control for the analysis. Apart from review sentiment and the experiment factors, i.e., past reviews and product experience, we also used an array of control variables to study the credibility of reviews. These control variables were gender, age, currently owned smartphone (and its OS), smartphone usage history (i.e., how many years the respondent has used smartphones), smartphone usage count (i.e., number of smartphones used), online review history (i.e., frequency of review writing on online platforms) and preferred OS. The OS of the respondents' owned phone was used as a control variable, as individuals can be very particular about their preferred OSes, and this can affect their ratings on products with different OSes [58]. We calculated disconfirmation by computing the difference between the average past product rating (to signify others' experiences that form one's expectations) and the individual product rating (which acts as a proxy for one's own experiences).

Table 4A provides the means, standard deviations and Pearson correlation of the variables in the study. Table 4B provides a brief description of the dependent variable with respect to the experiment factors. One important factor in ensuring the internal validity of a randomized experiment like this is ensuring randomized assignments of subjects to groups. We conducted checks for randomization using a host of demographic and behavioral variables presented in Table 4C. These variables include smartphone usage history, frequency of e-commerce usage, gender, age, history of review writing and preferred operating system.[3] Results in Table 4C indicate sufficient randomization. We conducted ANOVA and Tukey's HSD tests on all the variables to seek significant differences among the six groups, but no differences were found.

We used ordinary least squares (OLS) regression and tobit regression to study the effects of different factors on perceived credibility. As previously mentioned, the two major factors that we study are the influence of a user's own product experience (*prod_experience*) and past reviews visible to the user (*past_review*). We used tobit regression to understand the relation between the target variable, *Credibility*, and the explanatory variables, as the target variable is censored. In this study, the *Credibility* variable is both left-censored and right-censored. *Censoring* indicates that the values beyond a set threshold take the set threshold value. In this study, *Credibility* is left-censored at 0 and right-censored at 7. This indicates that the values of *Credibility* cannot go below 0 or above 7. Since this is an artificially imposed restriction due to Likert scale rating, tobit regression was thought to be the best solution to compare the effects with OLS regression.

5. Results and analysis

The first analysis we conducted was a two-way ANOVA test to check for the effects of the two factors, i.e., product experience and past reviews, on the credibility of subsequently written reviews. The result of the ANOVA test, provided in Table 5, shows a significant effect of the two factors being studied.

To test the impact of the factors and validate our hypotheses, we used hierarchical regression, through which we were able to discern the effect of a group of additional variables through the variance partitioning method. This method has been widely used in social sciences research to understand the effect of an additional set of variables [59,60]. As described earlier, we used tobit regression as the preferred analytical method. However, we also reported OLS regression coefficients to establish a baseline and increase the robustness of our results. In the interest of parsimony, we have not shown the results of analysis with only control variables.[4] Tables 6 and 7 show the results of the analysis. Models 1a and 1b show the OLS and tobit regression results respectively, for models without the disconfirmation effect variable or the interaction effect.

Table 7 shows coefficients and standard errors for Models 2a and 2b that include, in addition to variables shown in Models 1a and 1b, variables for the disconfirmation effect and the Interaction term. Model 2 shows the base OLS model without including interaction effect, while models 2a and 2b show OLS and tobit coefficients for the complete model, including interaction effects.

To test the validity of the model, we computed the variance inflation factor (VIF) to eliminate the possibility of autocorrelation. The VIF for all models was below 7, and hence we can assume the absence of autocorrelation in the models. We also performed the Breusch–Pagan test to identify the presence of any heteroscedasticity in the error distribution of the model. The null hypothesis of homoscedasticity could not be rejected. The estimates for the test are mentioned below the tables for OLS models.

Based on the results as reported in this section, we did not find support for Hypothesis 1. In both Tables 6 and 7, we found the coefficient of the category of product experience to be a non-significant predictor of perceived review credibility ($p > 0.1$). This indicates that a review writer's product experience does not affect the perceived credibility of the resulting review. Our results show that credibility is independent of the product experience, and both positive and negative product reviews (i.e., written under positive and negative product experiences, respectively) can lead to equally credible reviews. This result demonstrates that motivations and psychological drivers for writing reviews are not driven by a specific type of experience. Individuals with both positive and negative experiences would be equally inclined to share their experiences with the wider public, and hence we should not expect different outcomes in terms of perceived credibility.

We do, however, find support for our second hypothesis. H2 predicted that exposure to others' reviews would have a significant effect on the perceived credibility of reviews written under their influence. Tables 6 and 7 both show that the variable *Category* of past reviews is significant ($p < 0.01$). We also found that the coefficient of the variable is positive (0.262, Model 2b). This indicates higher perceived credibility of reviews written under the influence of negative past reviews (as the variable *past reviews* is reverse-coded, *2* signifies negative past reviews, and *1* signifies positive past reviews). These results add to the existing literature on the impact of negative sentiments showing that negative sentiments have a higher impact than positive sentiments [60]. Hence, we find support for Hypotheses 2a and 2b. We performed a factor-variable regression to analyze the impact of different past reviews on perceived credibility. Table 8 shows the results of the analysis. We find that compared to the base case (no past reviews), both positive and negative past reviews have lower perceived credibility, but negative past reviews lead to more credible reviews compared to positive past reviews reaffirming our findings from Tables 6 and 7.

The results in Tables 6 and 7 also indicate that product experience moderates the relationship between the impact of others' past reviews and the perceived credibility of reviews written by a user. The relationship is positive and significant (coef = 0.344, $p < 0.01$). Factor-variable regression results in Table 8 show a higher moderation of positive past reviews by negative product experience. This signifies that while product experience in itself may not have a significant effect on

[3] All these variables were operationalized as categorical variables.

[4] The authors can provide the first stage (i.e., control variables only) regression coefficients on request.

Table 4A
Descriptive statistics and correlation matrix of the variables.

S.no.	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1	Product rating	2.96	1.420	1							
2	Overall credibility	3.11	1.601	−0.003	1						
3	Disconfirmation	−0.28	1.477	0.504**	0.048	1					
4	Product experience	1.50	0.501	−0.773**	0.006	−0.459**	1				
5	Past review	1.03	0.810	−0.066	−0.046	0.229**	−0.021	1			
6	Age	2.03	0.657	0.164*	0.147*	0.029	−0.105	−0.051	1		
7	Gender	0.79	0.409	0.036	0.148*	−0.061	−0.095	−0.069	0.301**	1	
8	Current mobile	1.00	0.066	0.044	−0.050	0.108	−0.066	0.003	0.003	−0.034	1
9	Smartphone usage history	3.72	0.538	0.052	−0.003	0.034	−0.121	0.032	0.101	0.182**	−0.034
10	Smartphone usage count	2.14	0.525	−0.027	0.123	0.042	−0.066	−0.062	0.061	0.177**	0.017
11	Preferred OS	1.96	0.682	0.034	0.045	0.003	0.038	−0.036	0.206**	0.029	−0.004
12	Online review history	0.44	0.497	0.064	0.128	0.094	−0.017	−0.049	0.046	0.139*	0.058
				9	**10**	**11**	**12**				
9	Smartphone usage history			1							
10	Smartphone usage count			0.184**	1						
11	Preferred OS			−0.104	−0.225**	1					
12	Online review history			0.042	0.165*	−0.122	1				

**Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed).

Table 4B
Descriptive statistics of the experiment data.

		Overall credibility		
Product experience	Past review	Mean	Standard deviation	**N**
Good	None	3.58631	1.398475	35
	Positive	2.46094	1.46079	40
	Negative	3.3125	1.522965	41
Bad	None	3.18694	1.827791	37
	Positive	3.13542	1.696075	40
	Negative	3.04701	1.543567	39

the perceived credibility of reviews, negative experience probably involves stronger emotions magnifying its effect in the presence of positive past reviews (coef = 0.07, $p < 0.05$), causing the resulting reviews to be perceived as being more credible.

Figs. 3 and 4 present a graphical view of the moderation analysis. Fig. 3 shows how the credibility of the review varies with the product experience of the review writer with past reviews they have seen, as a moderating variable. This plot indicates that the perceived credibility of the review differs significantly when the review writer has seen past reviews. This is additional support in favor of Hypothesis 3. Fig. 4 also shows how one's product experience moderates the effect of seeing past reviews on the perceived credibility of the review one writes. The variation of the perceived credibility at different levels of product experience supports Hypothesis 3.

In Fig. 3, the line for no past review (past review = 0) shows an interesting result that was not hypothesized. We found that, in the absence of any past review to bias the review writer, the credibility of written review is high. It shows that the presence of past reviews significantly biases the subsequent review writing process and, in an attempt to write something that fits the previously written reviews, possibly the review writer loses originality and hence the credibility of the review. The results in Table 8 and in the figures shown here demonstrate that there is a difference in the perceived credibility of reviews when a review writer with a positive experience is exposed to negative past reviews. This leads us to our next hypotheses that explain this phenomenon, disconfirmation.

To test Hypotheses 4, 4a and 5, we needed to create a variable to analyze disconfirmation. As specified in the sections on theory and hypotheses, disconfirmation has been defined as the difference between the expected and actual experience of the user. The expectation, in turn, is based on the average experience of past users to which a user has been exposed. For instance, if a product is rated as 5 stars on an e-commerce platform, a user expects the product to be great, but if their experience is worth only 2 stars, then the disconfirmation is equivalent to 3 stars, the difference between their actual and expected experiences. To actualize this variable, we took the difference between the user rating on a 5-point scale and the aggregate past ratings that the user saw. Since our hypothesis also includes a possible U-shaped relationship, we also used a

Table 5
Results of two factor ANOVA test.

Tests of between-subjects effects			
Dependent Variable: Overall Credibility			
Source	df	Mean Square	F
Corrected model	5	5.374***	2.148
Intercept	1	2253.93***	900.789
Category of product experience	1	0.0001	0.000
Category of past review	2	6.836*	2.732
Product exp. * Past review	2	6.68*	2.669

R Squared = 0.045 (Adjusted R Squared = 0.024).
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$

Table 4C
Results of randomization check on data.

Group		Smartphone history	*E*-commerce frequency	Gender	Age	Review history	Preferred OS
Product Experience	**Past Review**						
Positive	None	3.74	3.17	1.91	2.22	0.54	2.0
Positive	Positive	3.75	3.27	1.80	2.12	0.42	1.92
Positive	Negative	3.85	3.07	1.78	1.97	0.39	1.87
Negative	None	3.70	3.15	1.80	1.97	0.35	1.95
Negative	Positive	3.60	2.97	1.72	1.91	0.45	2.0
Negative	Negative	3.61	3.10	1.71	2.0	0.48	2.0
F- Value (*P*-value)		0.98 (0.43)	0.47 (0.80)	1.06 (0.38)	1.14 (0.36)	0.72(0.63)	0.21 (0.95)

Table 6
OLS and Tobit regression coefficients for Model 1 (excluding interaction and disconfirmation).

	Model 1a- OLS		Model 1b- Tobit	
	Estimate	Std. Error	Estimate	Std. Error
Intercept	3.023*	1.598	3.45**	1.621
Category of product experience	0.080	0.249	0.046	0.347
Category of past review	0.465***	0.176	0.658***	0.109
Product rating	0.049	0.095	0.054	0.088
Age category	0.418***	0.142	0.334***	0.095
Gender category	0.007	0.217	0.137	0.457
Preferred OS category	−0.142	0.128	−0.082	0.126
Ecommerce frequency	−0.091	0.096	−0.051	0.224
Phone ecommerce	0.184	0.123	0.165	0.121
Current mobile	−2.292**	1.039	−1.91***	0.984
Smartphone history	−0.194	0.181	−0.191	0.186
Smartphone count	0.074	0.173	0.091	0.135
Adjusted r-squared	0.58	**Log likelihood**		−340.584
F-statistic	16.7			
BP test	10.364			

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

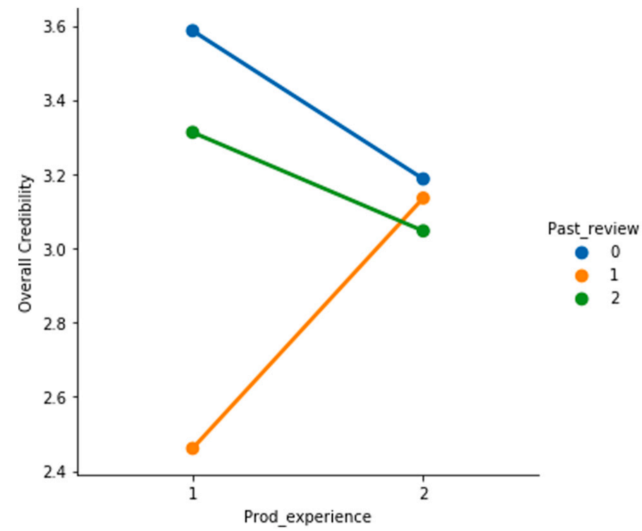

Fig. 3. Interaction effect of product experience and past reviews on overall credibility.

squared term of the variable[5] in our analysis, as shown in Table 7 in Models 2a and 2b. We found support for both Hypotheses 4 (coef =0.187, $p < 0.01$) and 4a (coef = 0.193, $p < 0.01$). This indicates that disconfirmation has a strong impact on the perceived credibility of the reviews written by the user and does follow a U-shaped curve as the positive coefficient of the squared term signifies.[6] From our results in

Table 7
OLS and Tobit regression coefficients for Model 2 (with interaction and disconfirmation).

	Model 2		Model 2a		Model 2b	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Intercept	3.863***	1.35	3.895***	1.422	3.505***	0.7496026
Category of product experience	0.016	0.219	0.017	0.221	−0.182	0.323
Category of past review	0.364***	0.078	0.387***	0.089	0.262***	0.089
Product rating	−0.022	0.079	−0.047	0.084	0.024	0.082
Age category	0.295***	0.102	0.337***	0.113	0.287	0.115
Gender category	0.121	0.204	0.193	0.184	0.042	0.185
Preferred OS category	−0.066	0.115	−0.073	0.107	−0.167	0.148
Ecommerce frequency	−0.008	0.092	−0.005	0.081	−0.013	0.071
Phone ecommerce	0.188*	0.117	0.195*	0.105	0.225*	0.108
Current mobile	−2.228**	1.008	−2.125**	1.045	−3.147***	1.088
Smartphone history	−0.144	0.247	−0.179	0.132	−0.229	0.452
Smartphone count	0.049	0.226	0.053	0.142	0.064	0.116
Disconfirmation	0.185***	0.058	0.163***	0.057	0.187***	0.049
Disconfirmation^2	0.116**	0.089	0.112**	0.084	0.193**	0.108
Product exp. * Past review			0.352**	0.176	0.344**	0.153
Disconfirmation*Past review			0.216***	0.087	0.225***	0.091
Adjusted r-squared	0.495		0.586	**Log Likelihood**		−344.540
F-statistic	21.12		24.31			
BP Test	10.63		11.304			

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 8
Factor variable regression coefficients.

	Estimate	Pr(>|t|)
Intercept	3.5863***	< 2e-16
Prod experience (negative)	−0.3994	0.28542
Past review (Positive)	−1.1254***	0.00237
Past review (negative)	−0.2738*	0.05274
Prod experience (negative): Past review (positive)	1.0739**	0.03782
Prod experience (negative): Past review (negative)	0.1339*	0.09478

Adjusted r-square = 0.024.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

[5] U-shaped curves are tested by the presence of significant squared terms. This is because squared terms test the quadratic effect and hence have a curvilinear graph showing a U-shaped or inverted U-shaped relationships. See Haans et al. [63] for further details on analyzing U-shaped relationships.

[6] The presence of a significant linear component along with a quadratic component of disconfirmation indicates a U-shaped relationship with diverging arms.

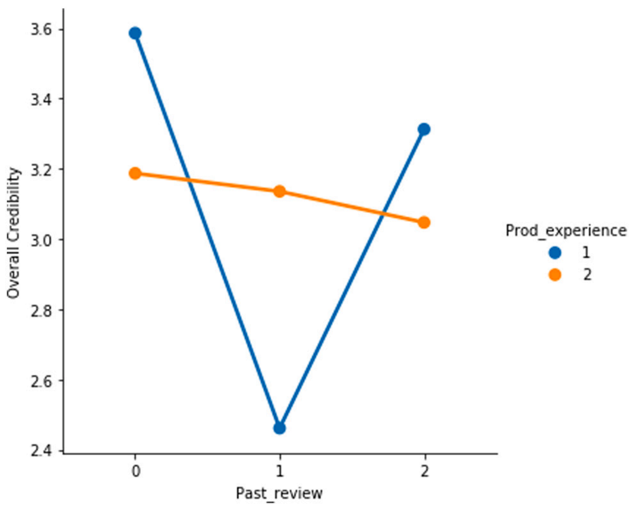

Fig. 4. Interaction effect of product experience and past reviews on overall credibility. Note- '0' indicates the absence of past reviews and 1 and 2 respectively stand for positive and negative past reviews and product experience.

Table 8 and Fig. 3, we also found that the effect is heightened when the review writer faces negative disconfirmation, i.e., negative past reviews and a positive experience. This plot also shows that when the review writer is faced with disconfirmation, the perceived credibility of the resulting review is higher. We also find support for Hypothesis 5, as Table 7 indicates. Disconfirmation is a significant moderator of the relationship between past review and perceived credibility (coef = 0.225, $p < 0.01$). To study this moderation more closely, we also plotted the graph of disconfirmation and past reviews with overall credibility in Fig. 5. For additional robustness in the complete model, we have also presented the results for the full model by excluding Hypothesis 5, i.e., the disconfirmation interaction term. This is presented in Model 2 in Table 7. The continued significance of Hypothesis 4, i.e., the impact of disconfirmation effect on credibility, shows the independent impact of disconfirmation beyond its moderation effect.

Fig. 5 represents the hypothesis that higher disconfirmation leads to higher perceived credibility. It also brings forth an interesting finding that, at lower levels of disconfirmation, perceived credibility seems to increase significantly. This would be the result of a review writer trying too hard to make a review stand out despite having an experience similar to others.

5.1. Robustness analysis of results

To ensure robustness in the primary analysis, we have ensured that autocorrelation is not a significant factor in the study (VIF < 3 for all analyses). Our use of tobit regression also ensures that censored data does not impact the results. A Breusch–Pagan test revealed that heteroscedasticity is not present in our analysis. To ensure the robustness of our results emerging from the choice of an experiment as a method, we also employed falsification, or sanity, checks [61]. While we have studied the impact of past reviews on the perceived credibility of reviews written under their influence, we do not expect the different groups of review writers to write more or less credible reviews based on OS preference or frequency of e-commerce use. For both these hypotheses, we get rejections with $p > 0.1$, and hence we conclude that the outcome of credibility does is not affected by OS preference or e-commerce usage frequency. Therefore, we can conclude that our analysis passes the sanity check.

The second set of issues from which any quantitative study may suffer is *alternative explanation.* The first of these alternative explanations is the preference for a specific OS. Studies have identified the connection that users feel with their preferred OS [58]. Hence, it is possible that users write more credible reviews for the phone with their preferred OS. To control for this effect, we asked users to report their preferred OS as well as the OS they think the phone had that they reviewed. We found that the variable *preferred OS* is insignificant in the analysis of the perceived credibility of reviews, as reported in Table 7. To dive deep into this, we performed a supplementary analysis in which we divided the data into two groups: one with the same preferred and assumed OS and one with different preferred and assumed OSes. We ran an ANOVA to test the difference in the perceived credibility of reviews written by the two groups of users and found that the two groups were statistically indistinguishable ($p > 0.2$), with the mean of the two groups being 3.46 and 3.54, respectively. We also ran a similar statistical subsample analysis between the two groups of users who had more experience with online shopping and users who had less experience, to eliminate the possible explanation of experienced users writing more comprehensive and credible reviews [62]. We performed a similar ANOVA analysis on these groups, and the results showed that the perceived credibility of reviews written by these two groups were 3.55 and 3.57, respectively, with ANOVA being statistically insignificant ($p > 0.5$).

6. Discussion and conclusion

All our proposed hypotheses, except Hypothesis 1, found support in our data. The results indicate that while the perceived credibility of reviews is not affected by product experience significantly, it is impacted by past reviews. Product experience also impacts the credibility of reviews written under their influence, though not directly, but rather as a moderating variable and through the disconfirmation variable. In this section, we discuss the theoretical and practical implications of our results as well as their limitations.

6.1. Theoretical implications

The construct of review credibility in the eWOM domain has received considerable attention in the past decade [17]. By going beyond the content of the review and exploring the impact of review writing conditions on the perceived credibility of reviews, this paper makes unique contributions to enhance the theoretical understanding in this space. Building upon past research by Jha and Shah [25] and Ho et al. [26], this study found that social influence in terms of past reviews visible to a review writer has a significant impact on the review writer. This study extends the concept of social influence in the domain of reviews by establishing the social influence of past reviews on review writers as a significant determinant of the perceived credibility of following reviews. Conceptually, the paper theorizes a unique U-curved relationship between disconfirmation and perceived credibility, which, to our knowledge, has not been established so far. Going further, basis Festinger [35], the paper theorizes a "cognitive tug-of-war" played in the minds of consumers indicating that, when disconfirmation is in the extreme zones, consumers perceive higher credibility in written reviews. Finally, it also finds this effect to hold true when disconfirmation is at a minimum, perhaps indicating that review writers try extra hard to sound authentic when their experiences are similar to aggregate views.

6.2. Managerial implications

Heeding the conclusions presented here and aligned with previous research, we suggest that e-marketers present negative past reviews along with positive reviews in order to significantly impact the credibility of future reviews. Furthermore, we also suggest that e-marketers seek the optimal formula for influencing consumers to engage in behavior change. They may wish to focus on providing an "e-psychological space" by giving an opportunity to rely on one's own agency (direct experience) along with the freedom to process what others have

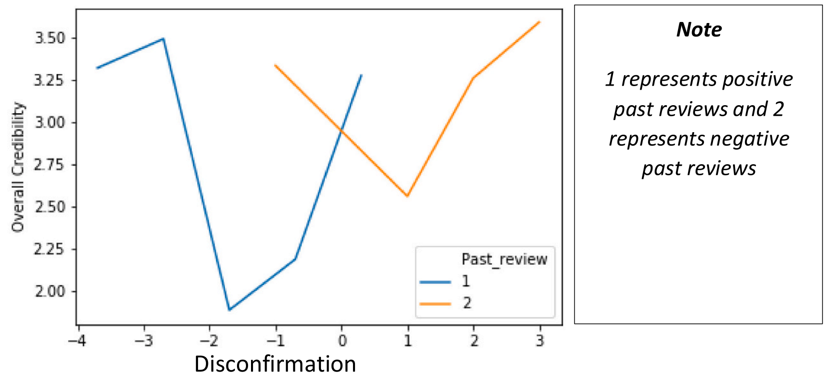

Fig. 5. Impact of disconfirmation and past reviews on credibility.

said about the concerned product or service.

With regard to the practical implications of this important theoretical underpinning, the e-marketers may want to follow the following steps: a) assess the disconfirmation zones of their consumers; b) bucket the consumers into different zones while paying particular attention to those who are in the extreme zones on both sides and in the middle where the disconfirmation is at a minimum; c) recognize that these customers outlined in b) are their ambassadors, as they are likely to perceive eWOM communication more credible compared to others—-positive reinforcements including targeted promotional campaigns can yield better outcomes with this customer segment; and d) employ a different marketing strategy of mixing negative with positive reviews for consumers in other zones, as that will influence perceived credibility more favorably.

6.3. Limitations

The nature of the experiment design limits us from choosing a vast array of situations that may be present in the domain. We have used smartphones as a context for the study, as smartphones are one of the most popular products purchased online with a high degree of familiarity for all respondents. We believe future research could use natural experiments or surveys to study this phenomenon in detail for other product combinations as well.

Another limitation of the current study is the narrative-based stimuli method, which ensured uniform stimuli for all participants but restricted varied responses to the same product and limited individual psychological traits to evaluate the products independently. Like all experimental studies, we have studied the extreme cases of positive and negative experiences to illustrate how these stimuli influence individuals. Users are more likely to see a mix of positive and negative stimuli in an e-commerce website that may subdue the effects mentioned in this paper. As most review writing platforms expect the review writer to have bought and experienced the product, we have not created a "no direct experience" case in our experiment. A future study could include that to study fake or non-experiential reviews.

A subsequent follow-up study linking the different stimuli to different review elements (e.g., facts and images) would complete the link between stimuli-review–element-review credibility. Another extension of this study could analyze the impact of the credibility of the review writing platform itself, as different platforms could be perceived to have different levels of credibility. Hence, a comparative platform analysis would enable analyzing platform-level effects in the perception of reviews. A final limitation of the study is its geographical representation of subjects. The study was conducted in India with Indian subjects, and cross-cultural analysis in different countries would be required to ensure the generalizability of these results.

6.4. Conclusion

We feel that the current research adds significant depth to the field of study of online reviews. Due to a rise in customer preferences, as well as the COVID-19 pandemic forcing people to stay indoors, the rise of online shopping is only going to increase in the coming years. The rise of shopping on online platforms also implies that customers will see and be influenced a lot more by the reviews for the products mentioned on the pages. Hence, it becomes imperative for both the platform owners as well as the sellers of the products to identify how the review writers write their review as subsequent readers tend to value more credible reviews higher whether positive or negative. It is in this space that our paper makes a significant contribution by initiating a discussion on the psychological factors that determine perceived credibility and adding an enhanced degree of richness to both the theoretical as well as the practical aspects of this study.

Acknowledgment

The authors would like to thank the editors and the anonymous reviewers for constructive comments throughout the review cycle. The authors also want to thank their colleagues at Trinity College Dublin and SPJIMR for providing constructive comments on the early version of the article.

CRediT authorship contribution statement

Ashish Kumar Jha: Conceptualization, Methodology, Data Curation, Software, Formal Analysis, Writing - original draft, Writing - review & editing; **Snehal Shah:** Conceptualization, Methodology, Data Curation, Investigation, Writing - original draft, Writing - review & editing.

References

[1] A. Lipsman, U.S. Ecommerce, Mobile and social commerce fuel ongoing Ecommerce Channel shift, NY 2019 (2019). https://www.emarketer.com/content/us-ecommerce-2019.
[2] J.A. Chevalier, D. Mayzlin, The effect of word of mouth on sales: online book reviews, J. Mark. Res. 43 (2006) 345–354.
[3] S. Bhattacharyya, I. Bose, S-commerce: influence of Facebook likes on purchases and recommendations on a linked e-commerce site, Decis. Support. Syst. 138 (2020) 113383.
[4] X. Li, L.M. Hitt, Price effects in online product reviews: an analytical model and empirical analysis, MIS Q. (2010) 809–831.
[5] I.E. Vermeulen, D. Seegers, Tried and tested: the impact of online hotel reviews on consumer consideration, Tour. Manag. 30 (2009) 123–127.
[6] J. Benitez, L. Ruiz, A. Castillo, J. Llorens, How corporate social responsibility activities influence employer reputation: the role of social media capability, Decis. Support. Syst. 129 (2020) 113223.
[7] J. Nieto, R.M. Hernández-Maestro, P.A. Muñoz-Gallego, Marketing decisions, customer reviews, and business performance: the use of the Toprural website by Spanish rural lodging establishments, Tour. Manag. 45 (2014) 115–123.

[8] N. Hu, I. Bose, N.S. Koh, L. Liu, Manipulation of online reviews: an analysis of ratings, readability, and sentiments, Decis. Support. Syst. 52 (2012) 674–684.
[9] L. Qiu, J. Pang, K.H. Lim, Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: the moderating role of review valence, Decis. Support. Syst. 54 (2012) 631–643.
[10] Averun, Product Review With Images, Magento Marketpl, 2019. https://marketplace.magento.com/averun-magento2-module-review-images.html.
[11] S. Sen, D. Lerman, Why are you telling me this? An examination into negative consumer reviews on the web, J. Interact. Mark. 21 (2007) 76–94.
[12] R. Filieri, E. Raguseo, C. Vitari, What moderates the influence of extremely negative ratings? The role of review and reviewer characteristics, Int. J. Hosp. Manag. 77 (2019) 333–341.
[13] S. Zhou, B. Guo, The order effect on online review helpfulness: a social influence perspective, Decis. Support. Syst. 93 (2017) 77–87.
[14] J.K. Burgoon, T. Birk, M. Pfau, Nonverbal behaviors, persuasion, and credibility, Hum. Commun. Res. 17 (1990) 140–169.
[15] X. Ma, L. Khansa, Y. Deng, S.S. Kim, Impact of prior reviews on the subsequent review process in reputation systems, J. Manag. Inf. Syst. 30 (2013) 279–310.
[16] Y. Hu, X. Li, Context-dependent product evaluations: an empirical analysis of internet book reviews, J. Interact. Mark. 25 (2011) 123–133.
[17] C.M.-Y. Cheung, C.-L. Sia, K.K.Y. Kuan, Is this review believable? A study of factors affecting the credibility of online consumer reviews from an ELM perspective, J. Assoc. Inf. Syst. 13 (2012) 618.
[18] S. Banerjee, S. Bhattacharyya, I. Bose, Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business, Decis. Support. Syst. 96 (2017) 17–26.
[19] J.R. Anderson, P.L. Hagerdorn, J. Gunstad, M.B. Spitznagel, Using coffee to compensate for poor sleep: impact on vigilance and implications for workplace performance, Appl. Ergon. 70 (2018) 142–147.
[20] J.Q. Zhang, G. Craciun, D. Shin, When does electronic word-of-mouth matter? A study of consumer product reviews, J. Bus. Res. 63 (2010) 1336–1341.
[21] X. Li, C. Wu, F. Mai, The effect of online reviews on product sales: a joint sentiment-topic analysis, Inf. Manag. 56 (2019) 172–184.
[22] J. Yang, R. Sarathy, J. Lee, The effect of product review balance and volume on online Shoppers' risk perception and purchase intention, Decis. Support. Syst. 89 (2016) 66–76.
[23] R. Filieri, What makes an online consumer review trustworthy? Ann. Tour. Res. 58 (2016) 46–64.
[24] S. Karimi, F. Wang, Online review helpfulness: impact of reviewer profile image, Decis. Support. Syst. 96 (2017) 39–48.
[25] A.K. Jha, S. Shah, Social influence on future review sentiments: an appraisal-theoretic view, J. Manag. Inf. Syst. 36 (2019) 610–638.
[26] Y.-C. Ho, J. Wu, Y. Tan, Disconfirmation effect on online rating behavior: a structural model, Inf. Syst. Res. 28 (2017) 626–642.
[27] M.L. Jensen, J.M. Averbeck, Z. Zhang, K.B. Wright, Credibility of anonymous online product reviews: a language expectancy perspective, J. Manag. Inf. Syst. 30 (2013) 293–324.
[28] Y. Shan, How credible are online product reviews? The effects of self-generated and system-generated cues on source credibility evaluation, Comput. Human Behav. 55 (2016) 633–641.
[29] R.B. Cialdini, R.E. Petty, J.T. Cacioppo, Attitude and attitude change, Annu. Rev. Psychol. 32 (1981) 357–404.
[30] A.W. Wicker, Attitudes versus actions: the relationship of verbal and overt behavioral responses to attitude objects, J. Soc. Issues 25 (1969) 41–78.
[31] L.G. Warner, M.L. DeFleur, Attitude as an interactional concept: social constraint and social distance as intervening variables between attitudes and action, Am. Sociol. Rev. (1969) 153–169.
[32] R.E. Smith, W.R. Swinyard, Attitude-behavior consistency: the impact of product trial versus advertising, J. Mark. Res. 20 (1983) 257–267.
[33] R.L. Oliver, Effect of expectation and disconfirmation on postexposure product evaluations: an alternative interpretation, J. Appl. Psychol. 62 (1977) 480.
[34] R.L. Oliver, A cognitive model of the antecedents and consequences of satisfaction decisions, J. Mark. Res. 17 (1980) 460–469.
[35] H. TANG, X.J. LIN, P. Pun, S. Kuan, Why do online buyers engage in electronic word-of-mouth? an expectancy, J. Manag. Inf. Syst. E-Commerce 4 (2017) 12–25.
[36] R.L. Oliver, J.E. Swan, Equity and disconfirmation perceptions as influences on merchant and product satisfaction, J. Consum. Res. 16 (1989) 372–383.
[37] A. Parasuraman, V.A. Zeithaml, L.L. Berry, A conceptual model of service quality and its implications for future research, J. Mark. 49 (1985) 41–50.
[38] R.C. Lewis, B.H. Booms, The marketing aspects of service quality, Emerg. Perspect. Serv. Mark. 65 (1983) 99–107.
[39] A.R. Davidson, S. Yantis, M. Norwood, D.E. Montano, Amount of information about the attitude object and attitude–behavior consistency, J. Pers. Soc. Psychol. 49 (1985) 1184.
[40] D.T. Regan, R. Fazio, On the consistency between attitudes and behavior: look to the method of attitude formation, J. Exp. Soc. Psychol. 13 (1977) 28–45.
[41] R.H. Fazio, M.P. Zanna, On the predictive validity of attitudes: the roles of direct experience and confidence 1, J. Pers. 46 (1978) 228–243.
[42] R.H. Fazio, J.-M. Chen, E.C. McDonel, S.J. Sherman, Attitude accessibility, attitude-behavior consistency, and the strength of the object-evaluation association, J. Exp. Soc. Psychol. 18 (1982) 339–357.
[43] W.W. Moe, D.A. Schweidel, Online product opinions: incidence, evaluation, and evolution, Mark. Sci. 31 (2012) 372–386.
[44] M.K.O. Lee, N. Shi, C.M.K. Cheung, K.H. Lim, C.L. Sia, Consumer's decision to shop online: the moderating role of positive informational social influence, Inf. Manag. 48 (2011) 185–191.
[45] L. Rashotte, Social influence, Blackwell Encycl, Sociol, 2007.
[46] M. Deutsch, H.B. Gerard, A study of normative and informational social influences upon individual judgment, J. Abnorm. Soc. Psychol. 51 (1955) 629.
[47] X. Xu, How do consumers in the sharing economy value sharing? Evidence from online reviews, Decis. Support. Syst. 128 (2020) 113162.
[48] M.D. Munezero, C.S. Montero, E. Sutinen, J. Pajunen, Are they different? Affect, feeling, emotion, sentiment, and opinion detection in text, IEEE Trans. Affect. Comput. 5 (2014) 101–111.
[49] S. Sridhar, R. Srinivasan, et al., Journal of Marketing 76 (5) (2012) 70–88.
[50] R.B. Cialdini, N.J. Goldstein, Social influence: compliance and conformity, Annu. Rev. Psychol. 55 (2004) 591–621.
[51] R.E. Petty, J.T. Cacioppo, The Elaboration Likelihood Model of Persuasion, in: Commun, Springer, Persuas, 1986, pp. 1–24.
[52] C. Wu, D.R. Shaffer, Susceptibility to persuasive appeals as a function of source credibility and prior experience with the attitude object, J. Pers. Soc. Psychol. 52 (1987) 677.
[53] R.E. Anderson, Consumer dissatisfaction: the effect of disconfirmed expectancy on perceived product performance, J. Mark. Res. 10 (1973) 38–44.
[54] Indo Asian News Service, Online Smartphone Sales in India Grow 26% in Q2 of 2019: Counterpoint, Hindustan Times. https://www.hindustantimes.com/tech/online-smartphone-sales-in-india-grow-26-in-q2-of-2019-counterpoint/story-5EFvQP5iuLusdfXiHeLWGL.html, 2019.
[55] E. Moyer-Gusé, R.L. Nabi, Explaining the effects of narrative in an entertainment television program: overcoming resistance to persuasion, Hum. Commun. Res. 36 (2010) 26–52.
[56] T. Daugherty, H. Li, F. Biocca, Consumer learning and the effects of virtual experience relative to indirect and direct product experience, Psychol. Mark. 25 (2008) 568–586.
[57] M. Winkler, A.S. Abrahams, R. Gruss, J.P. Ehsani, Toy safety surveillance from online reviews, Decis. Support. Syst. 90 (2016) 23–32.
[58] T.-C. Lin, S.-L. Huang, C.-J. Hsu, A dual-factor model of loyalty to IT product–the case of smartphones, Int. J. Inf. Manag. 35 (2015) 215–228.
[59] A.K. Jha, I. Bose, Innovation in IT firms: An investigation of intramural and extramural R&D activities and their impact, Inf. Manag. 53 (2016), https://doi.org/10.1016/j.im.2015.09.002.
[60] H. Rui, Y. Liu, A. Whinston, Whose and what chatter matters? The effect of tweets on movie sales, Decis. Support. Syst. 55 (2013) 863–870.
[61] X. Luo, S. Tong, Z. Fang, Z. Qu, Frontiers: machines vs. humans: the impact of artificial intelligence chatbot disclosure on customer purchases, Mark. Sci. 38 (2019) 937–947.
[62] M. Zhang, X. Wei, D.D. Zeng, A matter of reevaluation: incentivizing users to contribute reviews in online platforms, Decis. Support. Syst. 128 (2020) 113158.
[63] R.F. Haans, C. Pieters, Z.L. He, Thinking about U: theorizing and testing U-and inverted U-shaped relationships in strategy research, Strateg. Manag. J. 37 (2016) 1177–1195.

Ashish Kumar Jha is an Associate Professor in the field of Business Analytics at Trinity Business School. His research revolves around the areas of technology innovation and social media analysis. Ashish uses statistical and analytical techniques to understand how firms and consumers interact on social platforms and its effects for both firms and their consumers. He received his PhD from Indian Institute of Management in Calcutta in India in field of Management Information Systems. His papers have been published in many top journals of the field including JMIS, DSS, I&M, IJPE, CAIS among others. He has also presented his work at numerous top conferences of field including ICIS, ECIS among others. Ashish has been a part of research groups working on robotic process automation in IT services industry.

Snehal Shah is a Professor of Organisation Behavior, Chairperson of the Fellow Program (Doctoral Studies) and Head of Research at SP Jain Institute of Management & Research, India. Her research interests are in the field of Diversity and Inclusion with specific focus on corporate governance and career choices. Her other research interests include eastern wisdom traditions and intersectionality of OB concepts in other management domains. Snehal has published papers in journals like Journal of Management Information Systems, Journal of Applied Psychology, Journal of Organisation Behavior and Journal of Management Development. She has also been invited to present papers at top conferences such as Academy of Management annual meeting, Marketing Science etc. and invited to write book chapters. Snehal has served as a reviewer for top journals in the field of Organisation Behavior and Information Management.