How Does the Authenticity in an Online Review Affect Its Helpfulness? A Decision Tree Induction Theory Development Approach

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Abstract

Drawing on multi-dimensionality of authenticity, this study focuses on the role of two distinct authenticities: nominal and expressive. We propose that the type of authenticity in a review will vary based on the reviews' lexical density (word level) and breadth (sentence level). Using the decision tree induction approach, the main and interaction effects of the dimensions and forms of authenticity are examined for their effect on review helpfulness. The preliminary analysis of 470 reviews demonstrate that the lexical density form of expressive authenticity is a predominant predictor of online review helpfulness. Additionally, the effects of expressive authenticity depth, nominal authenticity breadth and depth on online review helpfulness, vary based on the expressive breadth. The decision tree induction approach provides new theoretical insights that extends the frontiers of authenticity and practical implications on online review helpfulness.

Keywords: authenticity, nominal, expressive, online review helpfulness, decision tree induction

1. Introduction

Online reviews, also referred to as electronic word of mouth (eWOM), play a prominent role in consumers' decision-making process in digital and mobile commerce. Opinion-sharing websites such as Yelp.com enable consumers to share their personal experiences, emotions, attitudes, and feelings on products and services in the form of reviews (Heydari et al., 2015). Consequently, in recent years, user-generated consumer reviews posted on such websites have increased dramatically (Fitzpatrick, 2019). This vast number of online reviews creates significant information overload for the reader (Zhang et al., 2022) reducing the value of the reviews (Ghose & Ipeirotis, 2010; Lee et al., 2017). One way to address this problem is to differentiate between helpful and unhelpful reviews. Prior studies have identified various factors that influence online review helpfulness (Rietsche et al., 2019). These factors include reviewer-related reputation (Chua & Banerjee, 2016), experience (Huang et al., 2015), and information disclosure (Ghose & Ipeirotis, 2010); review-related factors such as rating (Yang et al., 2017), readability (Singh et al., 2017); affect (Willemsen et al., 2011), and anger versus anxiety (Yin et al., 2020; Yin et al., 2014).

The ability of readers to establish the veracity of review influences how they consider reviews as helpful in collaborative consumption. However, the psychological process of evaluating a review involves identifying cues in the review that indicate its truthfulness. Consider the following reviews.

Review A: "**Great spot** *located adjacent to Axelrad*. Came right at opening time and there were already a few people. You *order at the counter* and they *bring your order to you*, so it would be a **good idea** to know what you want before you reach the *counter*. The *guy taking* my *order*, I wish i had gotten *his name*, *he* was **so friendly**, and we bonded over the **deliciousness** of *Mikes Hot Honey*. We decided to *sit outside*. It's *connected to Axelrad's patio*, so you've got some **cool** *seating options*. I sat in a *swing* while we waited for food. The pizza was **SOO GOOD**. it was **fresh**, **perfect** amount of bite to the crust and **perfect** toppings. The *chicken alfredo* was **good**, but nothing **spectacular**. I also got a *Luigi's philly* to take to my husband at work, and he said it was an **amazing** *sandwich*."

Review B: "*Luigi's* is our **go to spot** for a *slice of pizza* in *Houston*! We have been here a few times now and have yet to have a **bad experience**. This time we tried the *caprese*, which I **really enjoyed**. It came with **fresh** *tomatoes*, *buffalo-style mozzarella*, & *basil*. The last time I remember my **favorite slice** being the *margarita*! You **can't go wrong** with either choice. If you are in a **cheesy mood**, I would go with the *caprese* since it has the *mozzarella*. I **finally tried** their *gelato*, and it **lived up to my expectations**! It was

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super creamy which I **really liked**. The flavor we ordered wasn't labeled but had both *chocolate & caramel* in it. I **can't wait** to come back again for more *pizza* and *gelato* **sometime soon**!"

Upon close examination, one may notice that review "A" consists of information (italicized) on the location, the interior and exterior setting, menu items offered by the business, and few expressive words (bold). Review "B" however, consists of more expressive words related to the business, products, or service when compared to Review A. Each cue provides different pointers of distinct authenticities that aid a reader in assessing the helpfulness of a review. We argue that the different cues identified in Reviews A and B represent different dimensions of authenticity, which is a marked departure from extant literature. Hitherto, prior IS research has considered authenticity as a unidimensional concept. As illustrated in the preceding examples, there are distinct forms of authenticity (i.e., expressive and nominal) that have not been examined in the context of online reviews. Therefore, the current study poses the following research question: *How do the different dimensions of authenticity affect online review helpfulness?*

Using data from Yelp.com, we employ decision tree (DT) induction approach (Osei-Bryson and Ngwenyama (2011), to explore the conditional relationships between the various forms of distinct authenticities and online review helpfulness. Our preliminary findings demonstrate that lexical breadth of expressive authenticity is a predominant predictor of online review helpfulness, and the significance of expressive authenticity depth (sentence level), nominal authenticity breadth, and depth vary based on the expressive authenticity breadth. Theoretically, the dimensions explored in this study highlight the role of consumers' perception of authenticity and its influence on review helpfulness. Practically, our findings can benefit managers of online review platforms. Although voting methods can be used to identify helpful reviews from the readers' perspective, it may take time for a review to be voted (Zhang & Tran, 2010). If helpful reviews can be identified earlier, they can be used to proactively describe a business which in turn helps the readers (Yin et al., 2014). Additionally, the findings provide insights for online review platforms when deploying filtering algorithms to differentiate helpful from unhelpful reviews.

2. Literature Review

2.1. Online Review Helpfulness

In the context of current research, 'online review' refers to user-generated review of a business posted on a third-party website (Mudambi & Schuff, 2010). Online review helpfulness is the extent to which consumers rate a user-generated review of a business as useful in facilitating consumers' decision-making process (Yin et al., 2014). Online reviews and their helpfulness have received wide attention since the inception of various e-commerce and review-based platforms. Scholars have identified multiple review, reviewer, and platform-based factors that impact a review's helpfulness (Malik, 2020). One study found varying effects of reviewer characteristics and review characteristics on review helpfulness, in which the level of word count was found to be a good predictor of review helpfulness (Huang et al., 2015). A study that examined the influence of consistency of a reviewer's pattern of ratings on review helpfulness found that reviews that have highly biased ratings in the past receive more helpful votes in the future (Gao et al., 2017). From a social influence perspective, a study found that the order of review negatively relates to the helpfulness, and the negative effect is inversely proportional to the reviewer's expertise (Zhou & Guo, 2017).

The effects of sentiment and the linguistic content embedded in a review on review helpfulness has also received attention from researchers (Rietsche et al., 2019). For example, Kim et al. (2006) concluded that the sentiment of the review i.e., positive or negative is a good predictor of online review helpfulness. The information disseminated in the expressed sentiments within a review may influence the helpfulness score. Yin et al. (2014) found that reviews that posit emotional anxiety are perceived as more helpful than reviews depicting anger. Qazi et al. (2016) determined review helpfulness using opinion mining and sentiment analysis at two levels. The word level analysis approach involves keyword spotting, lexical breadth, and statistical methods, whereas the concept level considers multi-word expressions instead of treating words such as "cloud computing" as two different words. Qazi et al. (2016) suggest that the average number of concepts per sentence has a varying degree of impact on helpfulness. Is the varying degree of impact a function of the authenticity of the reviews? Past research has often considered authenticity as a homogeneous concept (Rietsche et al., 2019). Regardless of the emotionality in a review, its authenticity should be observed to influence consumer processing of the review. We investigate this theoretical gap in this study.

2.2. Theoretical Background- Authenticity and Online Reviews

Prior research has examined the veracity of reviews through such lens as honesty, truthfulness, bias, and authenticity (Rietsche et al., 2019). Authenticity allows for distinguishing what is real from what may be imaginary. Extensive research in various disciplines such as management and the tourism industry has underlined the importance of authenticity in online reviews. For example, Safaaa et al. (2017) examined how the term 'authenticity' is used in commercial and tourism brochures and its relevance to actual travel experience. The findings suggest that the term 'authenticity' should reflect the appropriate meaning to the objects and experiences present in the promotional brochures. Defining authentic reviews as post-purchase reviews and fictitious reviews as imagination-based reviews, Banerjee et al. (2017) examined the potential of linguistic analysis to distinguish between authentic and fictitious reviews. Kovács et al. (2014) ascertain that consumer assign higher value ratings to organizations regarded as authentic (i.e., consumers perceive Mom-and-pop and specialist restaurants as authentic compared to chain-operated or non-family-owned restaurants). Overall, authenticity has been regarded as a single construct in most studies.

2.3. Multi Dimensionality of Authenticity

Recently, Le et al. (2021) underscored the importance of authenticity in consumer reviews. The results establish authenticity as a multi-dimensional concept with various levels. The concept of authenticity impacts every aspect of an individual's daily life, from products, architecture, furniture, food and dining (Kovács et al., 2014). Dutton (2003) defines authenticity as a multi-dimensional entity, i.e., if one is not particular about the dimension of authenticity that is being judged then, the word "authenticity" makes no sense. Therefore, at the broadest level authenticity is subjected to limitations, as it can be judged differently based on the application and/or the context. For example, a reviewer from USA may judge "authentic Italian pizza" differently from a reviewer who resides in Italy (Newman & Smith, 2016). Due to these limitations, several researchers are motivated to identify various dimensions of authenticity by categorizing the judgements based on structural similarities. Newman and Smith (2016) proposed two general dimensions that describe the type of entity that is being judged or evaluated and the source of information that is consulted for the evaluation. Here the first dimension captures the entity (location, artwork, product, service) that is being judged by the evaluators and the second dimension captures the criteria that the judges use to evaluate the entity, i.e., objective beliefs versus subjective beliefs. To depict the impact of objective statements and subjective statements on online review helpfulness, this study focuses on two authenticity dimensions; nominal authenticity and expressive authenticity (Newman & Smith, 2016).

2.3.1. Nominal Authenticity versus Expressive Authenticity

Nominal authenticity (NA) has been defined as "the correct identification of the origin, authorship or provenance of an object" (Dutton, 2003, p. 259). For example, NA distinguishes between the artwork that was created by original painter and that which was not.

In the current study, we define NA as the extent to which the information in the review describes a business or a product or service allows the reader to verify the origin of the information. For example, consider a review 'ABC place is located at XYZ road.' Through this review the reviewer or the author is establishing NA by explicitly locating the place they visited. Upon reading this review a reader, through various informational sources, could verify the information in the review. The effect of NA on a reader's helpfulness perception of a review is not established in prior IS literature.

Expressive authenticity (EA) is defined as the "true expression of an individual's or a society values and beliefs" (Dutton, 2003, p. 259). In the current context, we define EA as the extent to which a reviewer effectively expresses their feelings about a business or a product, or service that aid in the verification of a review. For example, consider a review 'The ambience of ABC is so good. I love the décor and the staff are very friendly'. The review consists of subjective expressions such as 'so good', 'love' and 'very friendly'. A review with extensive EA tends to be more subjective and contentious, influencing the process of establishing veracity of the review and subsequent online review helpfulness perception. However, the effect EA on online review helpfulness is theoretically unknown.

Given that the multidimensional view of authenticity has not been investigated in prior IS research, and the need to optimize NA and EA, we employ an inductive approach to examine the interactive effects of the various dimensions on online review helpfulness.

3. Methodology

A dataset of 470 online reviews was extracted from Yelp.com, a popular online review platform. The data consists of online reviews from 23 restaurants located in and around two major cities in southern United States. Restaurants were selected randomly from the Yelp search results. Approximately 20 reviews spanning from 2018 to 2021 were collected from each restaurant. A sample of a Yelp review is shown in Figure 1, where the review readers are able to vote the review as helpful using the useful button.

Figure 1. Sample Yelp Review

The collected reviews were coded for further analysis. The challenge of identifying NA and EA is that they can be expressed using different terms; therefore, we initially identified terms that describe NA and EA authenticity. Technology assisted approaches such as Linguistic Inquiry and Word Count (LIWC) may provide authentic score in a review automatically. However, as the current research involves two distinct dimensions of authenticity, LIWC will not be useful or appropriate. Therefore, we manually measured NA and EA through direct inspection, guided by definitions of the different concepts. This classification technique can be considered as manual content analysis as it involves human knowledge and interpretation to identify key themes emerging from the data (Moore & Zuev, 2005). Upon close examination, we found informative words that describe the business, and that the expressions of reviewers can be deep but narrow. Therefore, to examine the interaction effect of NA and EA dimensions across word level occurrence and sentence level occurrence, we categorized each dimension into breadth and depth subgroups based on the word level and sentence level occurrence respectively (Swart et al., 2017). These variables are computed as follows.

NA Breadth = (Number of informational words and or word pairs) / (Total number of words in a review - Number of words subtracted from each word pair) *100

NA Depth = (Number of sentences conveying informational items) / (Total number of sentences in a review) *100

EA Breadth = (Number of expressive words or word pairs) / (Total number of words in review - Total number of words subtracted from each word pair) *100

EA Depth = (Number of sentences possessing expressive items) / (Total number of sentences in a review) *100

Word pair represents a pair of words which are in general considered as one word. For example, the word “Sea food” is treated as a word pair (Qazi et al., 2016)

4. Decision Tree Induction Technique

A decision tree (DT) uses a tree structure to represent a given decision problem such that every non-leaf node is associated with one of the decision variables, and every branch from a non-leaf node is associated with a subset of the values of the corresponding decision variable, and each leaf node is associated with a value of the target (or dependent) variable. The process of generating a DT from a given data set is referred to as decision Tree induction.

DT induction approach provides insights on conditional relationships between independent variables and a target variable (Osei-Bryson & Ngwenyama, 2011). DT also facilitates abduction, deduction, and induction processes which allow researchers to postulate hypotheses (abduction) based on empirical observations and statistically test them (induction) to generate a theoretical model (Osei-Bryson & Ngwenyama, 2011). In this research, DT is generated using IBM statistical package for the social sciences (SPSS) v27 application. SPSS offers various growing algorithms such as quick unbiased efficient statistical tree (QUEST), classification and regression tree (CRT), and chi-squared automatic interaction detection (CHAID) to split and classify the variables forming a tree structure. It is possible that the generated DT may differ from one algorithm to the other. To address this issue, we generated several tree’s using various algorithms with 10-fold cross validation. All trees are pruned to avoid overfitting. A common pattern i.e., EA breadth and EA depth forming as root node and subsequent node respectively is observed in the sixteen of the twenty generated decision trees. The DT that best explains the interaction effect of independent variables, i.e., different dimensions of authenticity of the review on the target variable, i.e., online review helpfulness is retained (Andoh-Baidoo et al., 2012) and is presented in the Figure 2.

5. Results

Figure 2 depicts the retained DT subjected to 10-fold cross validation which provided true positive cases of 86.6 percent with 72.6 percent overall accuracy. In the DT, each variable is discretized into two classes: Yes and No based on the helpfulness percentage and N is the number of cases associated with the condition component of the rule. These rules are also used to generate a set of propositions which we discuss in detail in the next section.

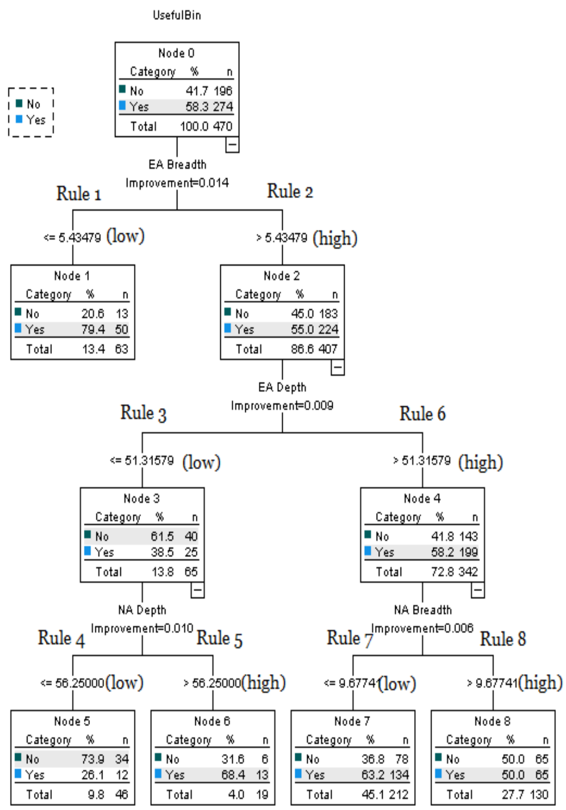

Figure 2. Decision Tree

From Figure 2, Rule 1 can be interpreted as: If the independent variable EA breadth is lower than or equal to 5.43 (Low) then the review can be classified as helpful with 79.4% probability and 63 cases. Similarly, Rule 2 can be interpreted as: If the independent variable EA breadth is greater than 5.43 (High) then the review would be classified as helpful with 55% probability and 407 cases. On careful analysis the reader will observe that Rules 3 and 4 have a similar structure i.e., they emanate directly from the internal node EA breadth. Rules 3 and 4 are called sibling rules (Osei-Bryson and Ngwenyama, 2011), as they involve the entire set of branches from the internal node EA breadth through the branch when EA breadth is high. The corresponding rule ID emanated from the DT are described in Table 1.

6. Propositions

From the set of sibling rules as shown in the Table 1, we generated sibling rule hypothesis (propositions) (Osei-Bryson and Ngwenyama 2011). A sibling rule hypothesis could be directional or non-directional; in either case they are derived using a set of sibling rules. For example, Rules 2 and 3 constitute a set of sibling rules.

Having this pair of rules, one could generate and indirectly test the directional hypothesis: given that EA breadth is high, then EA depth has a positive impact on review helpfulness. We could indirectly explore the validity of the above sibling rule hypothesis by testing the surrogate hypothesis given that EA breadth is high, a review is helpful if EA depth is high. Acceptance of this surrogate hypothesis would suggest that the given sibling rule hypothesis might be valid and should be accepted (see Table 2).

Table 1. Rule set of Decision Tree

Rule ID	Condition	Helpfulness (%)	N
1	EA Breadth = Low	Yes: 79.4; No: 18.9	63
2	EA Breadth = High	Yes: 55.0; No:45.0	407
3	EA Breadth = High & EA Depth = Low	Yes: 38.5; No: 61.5	65
4	EA Breadth = High & EA Depth, NA Depth = Low	Yes: 26.1; No:73.9	46
5	EA Breadth = High, EA Depth = Low & NA Depth = High	Yes: 68.4; No: 31.6	19
6	EA Breadth = High & EA Depth = High	Yes: 58.2; No: 41.8	342
7	EA Breadth, EA Depth = High & NA Breadth = Low	Yes: 63.2; No: 36.8	212
8	EA Breadth, EA Depth & NA Depth = High	Yes: 50; No: 50	130

As, our research is at nascent stage we called the hypotheses propositions and tested them with the proposed methodology.

Proposition 1: Low EA breadth will have a positive impact on review helpfulness.

Proposition 2: If EA breadth is High, then High EA depth will have a positive impact on online review helpfulness.

Proposition 3: If EA breadth is High and EA depth is Low, then High NA depth will have a positive impact on online review helpfulness.

Proposition 4: If EA breadth and EA depth are High, then Low NA breadth will have a positive impact of online review usefulness.

One of the benefits of using DT induction as the classification technique to examine the association between authenticity and online review helpfulness, is the use of DT induction for theory development. The set of propositions presented above can be subjected to statistical testing. Those that pass the test can be further tested using empirical data from other contexts, thereby enhancing the generalization of the findings from the context where the data was originally captured. Hence, DT induction is useful for inductive theory development.

Table 2. Sibling rule propositions for DT

Condition event				
	Rule	N	Frequency (f)	Proposition (P)
	EA Breadth = Low	63	0.79	P1
	EA Breadth = High	407	0.55	
Backend Rule	**Frontend Rule**			
EA Breadth = High	EA Depth = Low	65	0.38	P2
	EA Depth = High	342	0.58	
EA Breadth = High & EA Depth = Low	NA Depth = Low	46	0.26	P3
	NA Depth = High	19	0.68	
EA Breadth & EA Depth = High	NA Breadth = Low	212	0.63	P4
	NA Breadth = High	130	0.50	

To test the propositions, we performed a difference of proportion test to confirm that the difference of posterior probabilities for the sibling nodes are statistically significant. Our test statistic is given by

$$Z = \frac{\hat{P}_1 - \hat{P}_2}{\sqrt{\frac{\hat{P}_1(1-\hat{P}_1)}{n_1} + \frac{\hat{P}_2(1-\hat{P}_2)}{n_2}}}$$

Where p_1 and p_2 are the sample proportions of two independent samples of size n_1 and n_2 respectively. This approach has been used in prior IS research in internet security breaches announcement (Andoh-Baidoo & Osei-Bryson, 2007), user performance (Osei-Bryson and Ngwenyama 2011), and ecommerce initiatives announcements (Andoh-Baidoo et al., 2012). Table 3 presents the results of the empirical validation of the propositions developed from the DT induction. The results reveal that all the four propositions are statistically significant suggesting that they can be subjected to empirical validation using other data from the similar or different contexts.

Table 3. Propositions test results

Proposition	**Z Score**	**P(Z)**	**Supported/Not Supported**
P1	4.215	0.00001	Supported
Surrogate Hypotheses			
P2	3.036	0.00119	Supported
P3	3.358	0.00039	Supported
P4	2.364	0.00902	Supported

7. Discussion

The statistical significance of the four propositions in Table 3 convey various insights on authenticity and its dimensional impact on online review helpfulness. First, EA breadth which is located at the root of the tree is the most significant predictor of online review helpfulness and the rest of the variables vary based on EA breadth levels. A review with low EA breadth (in this case <= 5.43) makes a review more likely to be helpful and can be classified as helpful whereas those >5.43 can be classified as unhelpful. Thus, reviews that possess minimal expressions will be received as helpful to the readers.

However, when EA breadth is high, then EA depth can be used to discriminate a review where EA depth is high i.e., for reviews with higher EA breadth (>5.43), greater EA depth (>51.31) is necessary to be classified as helpful. The results suggest that the readers tend to perceive a high EA breadth review as helpful only when the reviewers provide sufficient explanation behind those expressions. These results are consistent with prior studies in which extreme positive or negative valence reviews tend to be more narrative (Jurafsky et al., 2014) and negative reviews tend to be more helpful (Yin et al., 2014). When EA breadth is higher (>5.43) and EA depth is high (>51.31), relatively low NA breadth (<8.18966) is preferred for helpful reviews. This finding depicts the dominance of EA breadth and EA depth and is supported by the literature where expressions or emotions in a review are found to be more persuasive (Yin et al., 2014).

8. Implications

Although prior research has examined the impact of such review characteristics as honesty, trust, and appeal on online review helpfulness, few studies have examined the influence of authenticity as a key indicator of review veracity or credibility on online review helpfulness. Additionally, prior studies conceptualize authenticity of reviews as a unidimensional construct. The exploration and confirmation of the two authenticity dimensions emerging from online reviews highlights the nuanced roles which the granular level of authenticity dimensions can play in influencing reader inference and attitude formation about online reviews. Our research also supplements literature on the representation of verification concepts. The current study plays an important role in establishing a more nuanced understanding of authenticity in the context of online reviews, where authenticity is usually perceived from the eye of the customers rather than 'verified facts' of objects. The study discussed the interplay between two dimensions of authenticity and online review helpfulness, that provide insights for collaborative consumption. Further, the study tested for the differences in sibling rules that foster recommending of personalized services. The ability to use DT induction to derive propositions that can be further be subjected to empirical statistical analysis demonstrates the importance of the approach used in this study to lead to inductive theory building and testing of authenticity and online review helpfulness.

The two dimensions explored in this paper have important implications not only from the reader perspective but also for the third-party online review platforms and business owners. Specifically, online review platforms can identify and segment reviews based on the authenticity, to reduce information overload to the readers. Also, businesses could identify and segment their customers based on their assessments and expectations of authenticity. By doing this, they can target and cater to specific expectations of authenticity for each customer segment, which in turn increases their customers' satisfaction and loyalty. The results can aid service providers with appropriate digital and mobile technologies to enhance verification of various dimensions of authenticity of online reviews.

9. Conclusion and Future Research

The results from the current study suggest that prospective consumers or review readers perceive an online review to be helpful when the review contains minimal expressions. Also, when a review contains extreme emotions or expressions the readers tend to depend on root cause of the emotions in evaluating the helpfulness. The limitations of our prior investigation are as follows. We have a limited sample size, so expanding the dataset will enhance the robustness of the current findings. Also, our content analysis is constrained by the amount of time and effort required by our manual classification technique. Using the proposed theoretical framework, we intend to develop models that would be able to detect authenticity of an online review and categorize it into different dimensions which will allow us to automate the manual process. This will help us to examine the effect of authenticity dimensions in a large dataset, thus facilitating a wider range of application in other contexts. In the future work, we will also check for inter-reliability validity benefiting the operationalization of the two dimensions of authenticity. The propositions advanced in this preliminary study are not causal. Future studies would test these propositions in an experimental setting to refine the theory developed and provide fine-grained insights for managers. Overall, the two-dimensional authenticity confirmed in this research warrants further examination to establish their casual effect. However, the two-dimensional framework can be further expanded given more granular understanding to influence of authenticity to online review helpfulness.

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