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The Value of Incorporating Review Tags into an Online Review System for User Review Generation

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Short Paper

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Abstract

Online review mining has become an important way for businesses to understand consumer preferences and product characteristics. Many online review platforms have started to incorporate the extracted information as review tags to guide future reviews. In this study, we leverage a quasi-experiment from an online health service platform to investigate the value of incorporating the review tags (extracted from prior reviews) into the online review system in user review generation. Our preliminary results show that after the provision of review tags, more reviews are provided for doctors but the length of those reviews is shorter. Notably, we also find a decrease in sentiment and an increase in novel reviews. Our findings provide actionable managerial insights for platform managers to design online review systems.

Keywords: Design of online review systems, review tags, user generation review, construal level theory

Introduction

Online user-generated reviews have become an important information source for businesses and consumers to make decisions (Chen et al. 2021). With an increasing number of online reviews, researchers have proposed a series of review mining techniques to extract valuable information from these massive online reviews (Hu and Liu 2004; Jin et al. 2009) and find that the extracted information can provide business insights, such as sale prediction and consumers' need identification (Archak et al. 2011; Timoshenko and Hauser 2019). In recent years, platforms and practitioners have also started to leverage the extracted information for new designs of website features. One of such applications is the review tags function in online review systems, which is increasingly adopted by online platforms (Bao et al. 2018). Specifically, the online review system can generate product feature-related and consumer sentiment-related tags by extracting key topics from existing user reviews (Tsai et al. 2020). For example, platforms like TripAdvisor.com and Tmall.com, present the most frequently mentioned review content in the form of review tags in prominent places of the reviews section of the website. These review tags can effectively assist consumers in understanding different aspects of the products and may reduce the cognitive load for users to write the reviews.

In this study, we focus on the role of providing review tags in the generation of user reviews. Typically, the review tags provided in the process of review generation are usually generated via a combination of automated text mining and human selection by the managers of review systems, providing an option for users to post reviews (Bao et al. 2018). In practice, this new feature typically allows users to select one or more related review tags according to their product experiences, in addition to writing specific textual reviews in detail. Thus, the review tags feature endows the platform operators with additional controls regarding user review generation (Deng et al. 2021). While ample literature has documented the value and methods of extracting product-related features from online reviews (Archak et al. 2011; Hu and Liu 2004; Timoshenko and Hauser 2019), the impact of a key application of this literature -- incorporating the extracted features as review tags into online review system -- on user reviews generation is not well studied. In addition, an emerging stream of literature has investigated the impacts of different review system designs, such as the multidimensional rating system (Chen et al. 2018), management responses system (Kumar et al. 2018), social network integration system (Huang et al. 2017), but those findings in existing literature may not be directly applicable to examining the implication of review tags function because their roles in the process of user review generation are obviously different. Thus, the objective of this study is to investigate how the review tags provision influences subsequent user review generation in both quantitative and qualitative aspects.

At first glance, the review tags provision may trigger substitution effects. More specifically, users can now select the review tags with minimal effort instead of writing textual reviews, which reduces the barriers for users to post reviews, thereby leading to more, yet shorter reviews. The increase in the volume of reviews may come at the cost of a decline in the quality of online reviews, as textual reviews usually include more personalized experiences compared to structured review tags. Moreover, review tags may prime users to recall more details of product experience because they contain different dimensional information about product features (Chen et al. 2018). This may lower users' construal level of product experience, and thus influence their evaluation sentiment in textual reviews (Aerts et al. 2017). More importantly, users may use the review tags function in different ways. For example, users can refer to several review tags as discussion titles and then further elaborate on the tags in the textual reviews. In addition, they may also choose some tags as a supplement to replace a part of textual content but talk about other personalized things in the remaining textual reviews. In this regard, given that users' product experience and language expression might be significantly different, the content similarity of users' textual reviews may change after the review tags function is provided. Previous research has suggested that the similarity of user-generated content is an important aspect of content quality (Burtch et al. 2021; Deng et al. 2021). In this study, we seek to understand these questions by empirically examining the implication of incorporating review tags into the online review system. And bearing the above discussion in mind, we propose the following research question:

How does incorporating review tags into the online review system affect subsequent user-generated reviews?

We examine our research questions with a unique data set of online patient reviews from a leading online health service platform in China, Haodf.com. The platform launched the review tags feature in June 2020. This provides us with an opportunity to conduct a quasi-experiment analysis. We first examine the effects of review tag provision on basic characteristics of user-generated reviews, such as volume and length. We then combine natural language processing techniques and econometric approaches to quantify its effects on the textual content of user-generated reviews, including sentiment and content similarity. As expected, our preliminary analysis shows that after review tags provision, there is an increase in the number of patient reviews and a little decrease in the length of textual reviews. The preliminary results also uncovered several interesting findings on the effects of review tags provision on textual characteristics of user-generated reviews: there was a significant decrease in both the sentiment scores and the content similarity of user reviews. It appears that review tags provision is beneficial to the online platforms as a number of studies have suggested that consumers usually perceive relatively negative reviews to be more helpful (Hong et al. 2016; Yin et al. 2014), and the content dissimilarity among user reviews makes them provide more additional information of products (Ke et al. 2020).

Related literature and Theoretical Prediction

First, this study is related to the literature on review mining and review tags. Extant work in this area mainly focuses on (a) text mining of the content characteristics of user reviews and (b) how the content characteristics provide decision support for consumers and businesses (Archak et al. 2011; Timoshenko and Hauser 2019). Using a data set from Amazon, Archak et al. (2011) use text mining techniques to extract product features and consumer sentiment from online reviews. They find that these extracted review characteristics can be used to predict future sales. Timoshenko and Hauser (2019) propose a deep learning approach to identify consumer needs from user reviews, which can inform marketing strategy and product development. Based on the above extant research, this study aims at addressing an underexplored implication of user reviews mining -- review tags function in online review systems. To the best of our knowledge, only one work by Bao et al. (2018) examines the role of review tags in consumers' product evaluation. However, our study is different from their work because our study mainly focuses on the effects of review tags in the stage of user review generation, whereas Bao et al. (2018) concerned its role in the process of product search. Our study is among the first to examine the effects of review tags provision in the review system on user-generated reviews and contributes to the literature on the implication of review mining in the online review system.

Second, we draw on and contribute to an emerging research topic on online review system design, which can be broadly classified into three sub-streams of literature. The first sub-stream focuses on the design of the interaction between businesses and consumers in the online review system, such as the simultaneous review system (Mousavi and Zhao 2022) and management responses system (Chen et al. 2019). The second sub-stream concerns the design of integrating social factors into the review systems, which focuses on the interaction design between users and their peers. For example, a number of studies have investigated how showing or highlighting information about crowd', friends' and experts' reviews influence online review generation (Deng et al. 2021; Huang et al. 2017; Lee et al. 2015). The third sub-stream focuses on the designs of the interaction between users and the review system. Specifically, such design concerns the functions, policies, and guidelines of requiring users how to post their reviews in the online review system. For instance, Chen et al. (2018) and Schneider et al. (2021) examine the impacts of adopting a multidimensional rating system (vs. a single-dimensional rating system) on consumer ratings. Our study is most relevant to the third sub-stream of literature because review tags are also a kind of function that helps and guides users to post reviews. With the continuous iterations of the online review systems, Gutt et al. (2019) call for more research on the design of online review systems. Given the strong research interest in using machine learning or hybrid approaches to extract topics; sentiments and features from review texts; and a lack of research on the effects of summarizing the extracted information (e.g., review tags) in the online review system, we seek to contribute to this stream of literature by examining the impacts of providing review tags on subsequent user-generated reviews.

In the specific context of review tags provision, we argue that the existence of review tags can improve users' perceived ease of use of the review system and thus, stimulate user participation to submit online reviews. Specifically, the review tags function often involves the evaluation of multiple attributes of the product consumption (e.g., good quality, fast logistics, and good service attitude), so users can directly select the one or more corresponding review tags according to their actual consumption experiences, so as to decrease the workload of writing textual reviews. In our context, we also propose that the provision of review tags leads to the shortening of textual review length in addition to the benefits of increasing the volume of reviews. This is because there is a substitution relationship between review tags and textual reviews.

Also, grounded in construal level theory, a recent work by Aerts et al. (2017) suggests that the design characteristics of online review systems might influence users' construal level by changing users' psychological distance of product experiences, and then influence users' review rating (i.e., individuals' evaluation). Similarly, we also assume that the provision of review tags in the online review system may influence users' construal level by changing their psychological distance of product experience. In particular, review tags can be considered an important information resource with high informativeness because they include a set of specific information on products' multiple dimensions. As a result, the existence of review tags might trigger a "priming effect" and prime users to recall more product experiences and contextual details, which make users user feel as if the product experience was a recent event. Thus, we argue that this might shorten users' psychological distance of product experience, and thereby lead to a decrease in users' construal level. Generally, the construal level theory states that the pro is more likely to have a high level of construal, while the con is more likely to have a low level of construal (Eyal et al. 2004; Trope and Liberman 2003). We thus expect that the sentiment in users' reviews would be less positive (i.e., more negative) after the review tags function is provided.

Review similarity reflects the novelty of online reviews, which is also an important measurement of review quality. Research suggested that if the review content among user reviews is significantly overlapped, these reviews do not offer additional information for subsequent users and thus, are regarded as low quality (Ke et al. 2020). We argue that users may respond to review tags in two different ways when they use review tags to post their reviews, which might influence review similarity. In particular, we refer to the concept of exploitation-exploration proposed in organization learning literature (March 1991) to theorize these two behaviors. On the one hand, users may show an exploitation-exploration response. Specifically, users might refer to the dimensional information in review tags as their discussion topics in their reviews (i.e., exploitation behavior to review tags), and then further expand these topics according to their own experiences (i.e., exploration behavior to review tags). In this case, the significant differences in users' experiences and their language expressions may thus lead to a decrease in review similarity with the increasing number of discussion topics. On the other hand, users may simply show an exploitation response to review tags. Specifically, users might only select some tags as a supplement to replace a part of user-written textual content and mainly talk about their personalized experiences that are not involved in review tags in their textual reviews (i.e., only a simple exploitation behavior to review tags). These personalized experiences for each user may be significantly different and thus, also decrease the review similarity. In sum, we assume that the provision of review tags may decrease the review similarity (i.e., an increase in review novelty).

Empirical Methodology

Research Context

The context of this study is Haodf.com, one of the leading online health service platforms in China. On this platform, doctors can provide online health consultation services for patients. Each doctor has a personal homepage that includes detailed information about the doctor (e.g., gender, title, hospital, specialty) and services (e.g., types and prices).

Figure 1. Screenshot of the Review Tags Function

After receiving doctors' healthcare services, patients can submit ratings and textual reviews to the corresponding doctors, which are also presented on doctors' homepages. In June 2020, this platform added a new feature to its online review system to provide the review tags option (see the red content in Figure 1).

This new review system requires patients to select at least one review tag when they evaluate doctors' services. Given the nature of healthcare services as typical credence good, patients often do not know how to evaluate the quality of a doctor's service even after receiving the doctor's service. Therefore, compared with consumers in common e-commerce platforms, the patients need more guidance on review tags to post reviews. On the platform, the selected review tags by each patient are appended to the textual content of each review and are publicly visible, but only when subsequent review readers choose to browse the details of a review can they see the selected review tags in this review. This review tags feature serves as an exogenous shock for patients who subsequently write the reviews, which provides us with an opportunity to conduct an analysis based on a quasi-experiment design.

Data Description and Variable Measures

We collected 488,845 user reviews for a random set of 6,953 doctors. The observational period is between June 2019 and June 2021 (i.e., one year before and after the review tags provision). Further, we collect other information about doctors, e.g., the title, hospital level, specialty, and service-related information. We construct our data set as panel data at the doctor-month level. We first measure two basic characteristics of user reviews: $Volume_{it}$and $Length_{it}$. Specifically, $Volume_{it}$ refers to the number of user reviews doctor i received in month t. $Length_{it}$ represents the average number of characters of the user reviews doctor i received in month t.

Second, we measure the two key textual characteristics of user reviews, including $Sentiment_{it}$ and $Similarity_{it}$. $Sentiment_{it}$ is the average sentiment score of user reviews doctor i received in month t. Specifically, the sentiment of a review reflects the perception of the reviewer regarding the doctor's services. In terms of sentiment analysis methods, we employed SnowNLP, which is often used to implement sentiment analysis of textual documents in the Chinese language. It is a Naïve Bayes algorithm-based tool, which measures sentiment for each piece of each review in terms of the probability of positive emotion. Specifically, the more positive the expression of one review is, the closer the value is to 1. $Similarity_{it}$ represents the average content similarity among user reviews doctor i received in month t. For these measures, we employ the cosine similarity between numeric representations of textual reviews in vector spaces. Before calculating the cosine similarity, we first construct vector representations of each review within some embedding space. Specifically, we use GloVe, which is an unsupervised learning algorithm for obtaining vector representations for textual documents and it has excellent performance on text mining-related tasks (Pennington et al. 2014). We first trained the GloVe model based on the broad corpus of our collected reviews. Then, we employ the trained GloVe model to vectorize each review. After that, we construct a vector representation for a virtual reference review by averaging each dimension among the review vectors at each doctor-month level. Finally, we calculate the review content similarity score of each doctor-month level by averaging the pairwise cosine similarity between each review vector and the vector of the virtual reference review.

The primary independent variable of interest is $Postlaunch_t$, which indicates whether the review tags function is provided in the online review system at month t. We also control for a series of observable time-variant variables for each corresponding dependent variable. For instance, regarding $Volume_{it}$, we control the cumulative number of user reviews and the cumulative average rating for doctor i by month t. Regarding $Length_{it}$, we control the cumulative average length, the cumulative number, and the cumulative average rating of user reviews for doctor i by month t. Regarding $Sentiment_{it}$, we control for the average rating and the average length of user reviews for doctor i at month t. Regarding $Similarity_{it}$, we control for the average length and average sentiment scores of user reviews for doctor i at month t.

Model-Free Evidence

Table 1 shows the average value of main dependent variables at the doctor level before and after the review tags provision in the online review system, and we also report the comparations with t-tests. Overall, we observe that the average number of user reviews increased after the review tags provision. However, the average length, sentiment scores, and content similarity of user reviews after the review tags provision significantly decreased. These differences are statistically significant at the conventional significance level.

Next, to visualize the effects, we also plot the changing trend of the average value of each dependent variable based on doctor-month data in Figure 2. The y-axis and the x-axis represent the average value of each dependent variable and the month index, respectively. The dotted line points out the value of each dependent variable at the 12th month (i.e., May 2020, the month before review tags are incorporated into the system). Figure 2(a) demonstrates that the average number of user reviews has a noticeable upward trend after the review tags provision. In contrast, Figure 2(b) indicates that there is a discontinuous, downward trend in the average length of user reviews after the review tags provision. According to Figure 2(c)-(d), both sentiment scores and content similarity of user reviews have a significant and discontinuous decrease after the review tags provision, and the level of these variables seems to stabilize after a discontinuous drop when the new feature was released. These descriptive results suggest that review tags provision can stimulate users, in general, to produce a higher volume of reviews that are shorter, more negative, and less similar. The model-free evidence serves as a basis for our subsequent econometric analysis.

Variables	Before June 2020	After June 2020	Difference
Average number of user reviews	2.230	3.354	1.124***
Average length of user reviews	38.198	35.023	-3.175***
Average sentiment scores of user reviews	0.907	0.882	-0.025***
Average content similarity among user reviews	0.895	0.872	-0.023***

Table 1. Statistics of Main Dependent Variables at Doctor-Month Level, *** $p < 0.01$

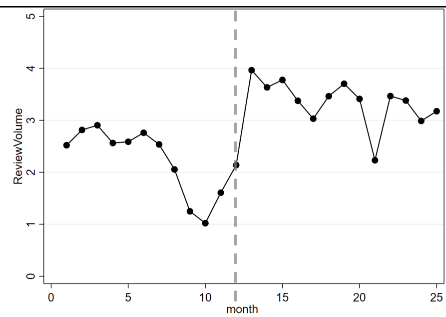

Figure 2(a). Review Volume

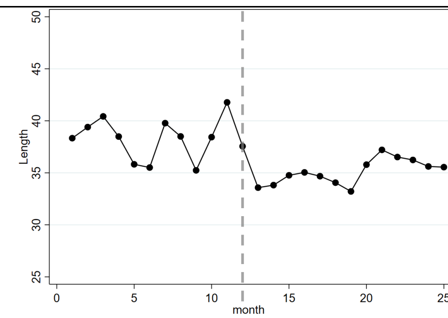

Figure 2(b). Review Length

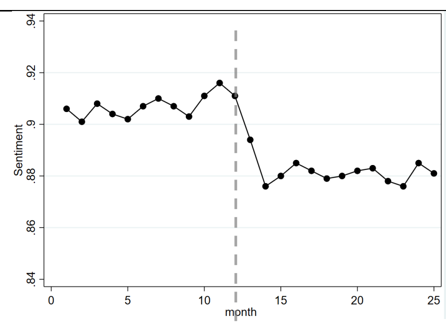

Figure 2(c). Review Sentiment

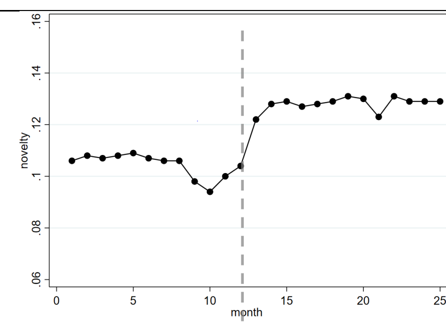

Figure 2(d). Content Similarity

Main Analysis

Next, we leverage the quasi-experiment to quantify the impacts of the review tags provision in the online review system, on user-generated reviews. Based on the model-free graphs, we observe discontinuous effects by contrasting the key dependent variables at the pre and post-system change periods. Based on prior studies that tackle a similar empirical setup (Gonzalez-Navarro 2013; Pu et al. 2020; Zhang and Zhu 2011), our goal is to estimate the change in the key DVs after controlling for the general trends at the month level. We, therefore, estimate Equation (1), which is similar to the construction of an interrupted time-series design (Pu et al. 2020):

$$Y_{it} = \beta_0 + Month_t + \beta_1 Postlaunch_t + Month_t * Postlaunch_t + Control_{it} + \sum_{m=2}^{12} MonthDummy_m + \delta_i + \varepsilon_{it}$$

Where Y_{it} includes the aforementioned dependent variables. $Postlaunch_t$ is the main independent variable of interest, suggesting whether the review tags function is provided in the online review system, and it equals one if the observation month is on or after June 2020 (i.e., the month of review tags provision) and zero otherwise. The corresponding coefficient β_1 is the regression estimator of our main interest, which quantifies the effects of the review tags provision on user-generated reviews. $Control_{it}$ includes some observed time-variant factors for each corresponding dependent variable. Moreover, a doctor-level fixed effects term δ_i is included to control for time-invariant unobserved doctor factors; we also incorporate calendar-month dummies, $MonthDummy_m$, to capture the unobservable trends that are common to both pre-and post-periods. Meanwhile, we report clustered-robust standard errors at the doctor level to account for the potential existence of heteroskedasticity and within-doctor correlation. Finally, β_0 is the intercept, and ε_{it} is the error term.

In Table 2, we first report the preliminary estimate results when the dependent variables are the basic characteristics of user-generated reviews. When the dependent variable is $Volume_{it}$, column (1) shows that the estimated coefficient of $Postlaunch_t$ is positive and statistically significant, indicating that after the review tags provision, there is a significant increase in the number of patient reviews. However, when the dependent variable is $Length_{it}$, the results in column (2) show that the estimated coefficient of $Postlaunch_t$ is significantly negative, which suggests that the provision of review tags decreases the length of user-written textual reviews. The above two results support the evidence that there may be a substitution effect of review tags on user-written reviews. In other words, the results show that patients generate a larger review volume but afford less effort per review after the review tags provision. These results are consistent with the model-free evidence reported.

Variables	(1) log(*Volume*)	(2) log(*Length*)	(3) *Sentiment*	(4) *Similarity*
PostLaunch	0.105*** (0.010)	-0.057***(0.007)	-0.024***(0.001)	-0.019*** (0.000)
Control	Yes	Yes	Yes	Yes
Constant	-10.449*** (0.950)	4.441** (0.213)	0.734*** (0.006)	0.769*** (0.003)
Observations	173,825	90,146	90,146	63,151
R-squared	0.283	0.005	0.033	0.123
Doctor FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Table 2. Estimated Results for Basic and Textual Characteristics of User Reviews

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Next, we report the preliminary estimation results when the dependent variables are the textual characteristics of user-generated reviews (i.e., review sentiment and content similarity). In column (3), we observe a negative and significant coefficient of $Postlaunch_t$ when the dependent variable is $Sentiment_{it}$. This result indicates that review tags provision leads to a decrease in the sentiment scores of patient reviews. According to the descriptive statistics in Table 1, we observe that before review tags provision, the content of patient reviews is almost positive as the average sentiment score nearly equals 0.9. After review tags provision, because there involves more informativeness about various dimensions of doctor services within review tags, patients sometimes are likely to recall one or more negative dimensions about doctor services with the introduction of review tags. Thus, the sentiment scores of patient reviews may experience a decrease after the review tags are provided. Meanwhile, regarding the content similarity of patient reviews, we again find that there is a significant and negative coefficient of $Postlaunch_t$ reported in column (4), indicating that after the review tags provision, the content similarity among patient reviews decreases. That is, patients react to the review tags, on average, with an exploration response rather than an exploitation response, thus reducing the content similarity of their reviews. The reported results are quite consistent with the model-free evidence.

Discussion

The online review system has become an integral part of many digital platforms. In this short paper, we focus on an under-explored design of the review system, namely review tags provision at the stage of user reviews generation. This study provides an initial effort to examine the effects of review tags provision on subsequent user-generated reviews via a quasi-experiment research design. The preliminary results suggest that the provision of a review tags function significantly influences both quantitative and qualitative aspects of users' review provision.

Therefore, this work has an important contribution to the literature on review mining, user-generated reviews, and the design of the online review system (Archak et al. 2011; Chen et al. 2018). Specifically, we observe that after the provision of review tags the number of reviews significantly increases, and the average length of reviews decreases. We attribute the changes in review volume and length to the substitution effects. That is, review tags can to some extent reduce the need for textual reviews posted by users. Moreover, it appears that the provision of review tags leads to a decrease in review sentiment. We attribute this change to the priming effect of review tags that can primes users to recall more information about product experience and thus decrease users' psychological distance and construal level. Interestingly, we also find that the content similarity among user reviews decreased after the review tags provision. We surmise that because of the individuals' heterogeneity in product experience and language expression, users' exploitation-exploration behaviors or only exploitation behaviors to the review tags might decrease the review similarity.

As this study is still in progress, we are working on the following several aspects. First, since the training data of the sentiment analysis model in the SnowNLP tool is mainly based on online product reviews, which are significantly different from online reviews about doctor services, it would be useful to train the sentiment analysis model using our review data. And we will also use other sentiment analysis methods, such as Linguistic Inquiry and Word Count (LIWC), to evaluate the robustness of the findings. Second, our measurement of content similarity derives from GloVe to perform word vector representations of user reviews. We thus also plan to use prediction-based methods, such as Word2Vec, and other attention-based models, such as BERT, to construct the content similarity measure. Third, although the results from both model-free analysis and the quasi-experiment design provide significant support for the effects of review tags provision on user-generated reviews, we plan to further our analyses by adopting the Regression Discontinuity in Time (RDiT) framework (Hausman and Rapson 2018), ruling out possible alternative explanations and conducting a series of randomized experiments to improve our causal identification. Fourth, we plan to further enhance our theoretical framework and theoretical contribution to this study by enhancing the hypotheses section. More importantly, we will further perform a series of mechanism analyses to understand how and why the review tags provision influences user-generated reviews.

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