Perceived Value of Information Sharing in Online Environments: User Engagement and Social Reputation

Dongho Choi, Chirag Shah
School of Communication & Information (SC&I), Rutgers, The State University of New Jersey
4 Huntington St, New Brunswick, NJ 08901
dongho.j.choi@rutgers.edu, chirags@rutgers.edu

ABSTRACT
Consumer reviews have received much attention both in academia and industry, since it has been found that they have significant effects on people's decision-making behaviors relating to online shopping or choosing services. The readers/visitors on various online communities where such reviews are posted evaluate the helpfulness of a review based on the extent to which the review is helpful in their information seeking and decision-making tasks. However, it is often not clear what makes a review useful to a reader. Several previous works have analyzed textual features relating to reviews to determine their usefulness, but given that most of these reviews are generated and shared through community-based or social media sites, the features that incorporate social features and social engagement could have an important role to play in making a review useful. The work described in this paper uses data available from Yelp, a social review and recommendation site, to build models that examine the impact of various features, including basic, reviewer's engagement, social reputation, and business type, based on the number of votes for helpfulness a review receives. Our findings suggest that reviewer's social contextual information (engagement and reputation) is influential in affecting perceived helpfulness of a review and improves the accuracy of prediction model. The findings also suggest that business type (restaurants vs. transportations) affects the ways in which consumers consider a review.

Keywords
Information sharing, consumer review, helpfulness.

INTRODUCTION
In order to reduce the amount of information one needs to consult, a person evaluates and relies on the credibility of that information in order to select more useful, accurate, current, objective, complete, and reliable information (Hilligoss & Rieh, 2008). With the emergence of Web 2.0 and social media platforms, however, information created and shared by individuals is rapidly increasing, regardless of the information's credibility. Among the shared information, consumer reviews that convey information about products and/or services have become an increasingly important subject for both academics and industry. Since it has been found that reviews have a significant effect on the decision-making of a consumer, understanding the quality and helpfulness of review is important to participants in the information sharing community.

In order to provide consumers helpful reviews, major websites such as Amazon.com and Yelp.com have a feature which sorts and presents consumer reviews with regard to the extent to which readers have thought the review was helpful ie; the "Most Helpful first" option. In response to a question about a review, such as "Was this review useful?" other readers can give a vote to the review. The reviews are then ranked based on the number of votes for 'usefulness' or 'helpfulness'.

While most review studies have concentrated on the features of review content itself (Chen & Tseng, 2011; Ghose & Ipeirotis, 2007; Ghose & Ipeirotis, 2011; Liu et al., 2007), reviewer's information, including individual characteristics and social interaction, has been given little attention. However, most consumer reviews are posted on online social media platforms, and it has been found that the author's social-related features makes a difference in the credibility of the information (Morris et al., 2012); these reviewer characteristics need to be considered in review helpfulness studies.

This paper will examine what features contribute to understanding and explaining how consumers or readers, within the review-sharing platform Yelp.com, perceive a review as helpful. Specifically, the paper will examine how a reviewer's engagement features and social reputation contribute to determining review helpfulness, as well as basic features related to textual information. In addition, the paper will compare the way in which these features affect

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perceived helpfulness of reviews for different business types, restaurants and transportation services. By taking this approach, this study will derive results that could begin to inform the improvement of a prediction model for review helpfulness that can explain the extent to which a reviewer's social contextual background affects the shared information's quality.

This paper will proceed as follows. First, the paper will outline previous research done on consumer reviews. Then, it will discuss the research framework in which textual features, a reviewer's information, and business type are included in prediction models. Next, the paper will present experiment results, findings and analysis, followed by discussion of implications and conclusion.

BACKGROUND

Buying products is one of the most information-demanding situations (Case, 2012, p. 20): especially, consumers look for more reliable cues to determinethe quality of products/services prior to making a purchase. However, in a traditional society, where production and consumption of products is strictly divided, only the manufacturer and producer of the product, or marketer, generally provide a limited amount of information relevant to decision-making for a product. Consumers only passively receive information from them, and have to make a decision based on the limited and biased information.

With the emergence of Web 2.0, however, Web content and applications are no longer created and provided by a small number of people or organizations. Instead they are more easily created and continuously modified by all users of the Web. As social media integrates Internet-based applications and communities built on the philosophical and technical foundations of Web 2.0, social media have contributed to the proliferation of the information produced by individuals both in quantity and quality. As e-commerce sites, such as Amazon, become more and more popular, the number of consumer reviews for a product grows rapidly, and more people utilize reviews as reliable standard for judgment before the decision-making.

Some research related to consumer reviews has focused on the relation between reviews and business outcome. Several studies revealed that the quantity and the quality of the reviews affect consumer purchasing intention and decision (Dewan & Ramaprasad, 2012; Godes & Mayzlin, 2004; Gopinath, Chintagunta, & Venkataraman, 2013; Y Liu, 2006; Onishi & Manchanda, 2012; Stephen & Galak, 2012). Contrary to the brisk research on review from the information consumption perspective, there is not enough research studying the behavior of the people producing the information. As for the general information and experience sharing, Wasko and Faraj (2005) empirically tested a model of knowledge contribution within electronic network of practice and categorize the motivations of knowledge sharing into three cases: when they earn professional reputation from the knowledge contribution, when they have proper experience to share, and when they have a strong commitment to the community. As for the motivation of general user generated content (UGC), Stöckl et al. (2008) find four main reasons for generating content: fun, information dissemination, contacts, and personal documentation. Their findings, however, only cover general-purpose content, and explains a global perspective of users without analysis about "top performers" who might give different implications.

However, regardless of purpose and/or motivation for knowledge contribution, perceived helpfulness of the shared information is a different matter. Previous works examined a variety of features surrounding review in order to understand what factors determine the perceived helpfulness, such as syntactic and semantic features, objectivity and subjectivity of the narrative.

Subjectivity has been investigated as one of the important determinants of review helpfulness. Chen & Tseng (2011) employ an information quality framework to extract representative review features, finding that high quality reviews tend to be subjective and provide in-depth comments on a product's features. Ghose & Ipeirotis (2007) find that reviews that include a mixture of objective and subjective elements are considered helpful.

Readability and writing style have also been examined to determine their impact on the quality of review; while Liu et al. (2007) find that readability has a marginal effect of quality prediction, Ghose and Ipeirotis (2011) articulate that readability in reviews matter in influencing perceived usefulness, as well as subjectivity and informativeness. A reviewer's writing style is found to be important to helpfulness vote ratio, along with a reviewer's expertise and timeliness of the review (Yang Liu, Huang, An, & Yu, 2008a, 2008b).

The reviews written by customers who had experienced the product and/or service have rich and useful information for other consumers' decision making. Also, expressed evaluations, both through ratings and narrative, are useful feedback used by businesses to improve the quality of a product/service. For the sites/services that have publicized reviews, the quantity and quality of reviews are an important measure of information leverage. As social media evolves to meet a variety of demands of different users, specialized types of social media that focus on user-generated reviews of products and services have emerged. While general portals or blogs, such as Google Places[a] and Yahoo Local[b], have been extending their features so that they can include consumer review data within their geographical services, business review sites, such as Yelp

[a] This feature is embedded in Google+, Google Maps, and other Google services.
[b] http://local.yahoo.com

and Judy's Book[c], have strengthened features related to social media.

In addition, a reviewer's contextual information, including individual characteristics and social interaction, has garnered attention as a sophisticated feature that predicts the review helpfulness. Agichtein et al. (2008) use a graph-based model of content generator relationships to predict the quality of content within a web-based social Q&A portal. Lu et al. (2010) exploit contextual information of reviewer identities and social networks to find that understanding the helpfulness of a review is affected by a reviewer's social context. Also, O'Mahony and Smyth (2009) find that reviewer reputation is significant to the helpfulness of a review, and the mean helpfulness of a reviewer's reviews is the strongest predictor of classification accuracy. Ngo-Ye and Sinha (2014) apply reviewers' overall engagement to text mining experiments and find that both review text and reviewer engagement characteristics help predict review helpfulness.

In addition, product type affects the review quality and perceived helpfulness of reviews. Mudambi and Schuff (2010) analyze reviews across six products and found that product type affected the perceived helpfulness of the review, as well as review extremity and review depth. Reviews of experience goods are considered helpful with moderate ratings rather than extreme ratings.

RESEARCH FRAEMWORK

We categorize the elements engaged in the information-sharing system into five groups, in order to find out the primary factors and determinants in information sharing practices in online environments. Schematic diagram of the systematic structures related to information managing and sharing is presented in Figure 1.

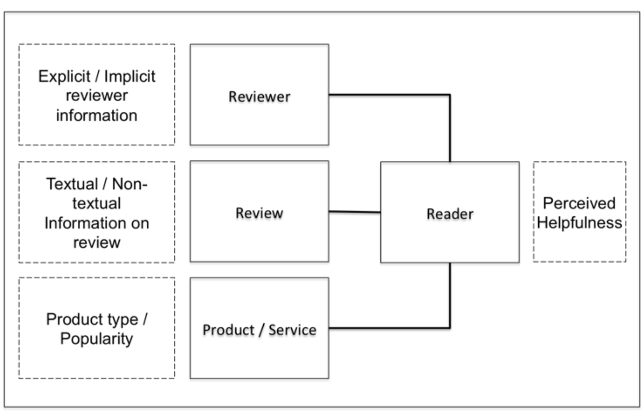

Figure 1: Elements related to review in information sharing structure.

1) *Product/service*: In the context of purchasing, information carried to consumers needs to be sufficiently relevant to a product or service they are considering consuming. Depending on the particular type of product/service, different features have different informational influence on the final decision-making process.

2) *Review*: A review delivers an objective explanation about the product/service and a subjective experience and evaluation of it. A review might have a variety of features, including length in terms of characters and/or words, number of meaningful terms, subjectivity and objectivity, and syntactical and semantic characteristics.

3) *Reviewer*: Since a review is a form of document written by author, characteristics of the author necessarily are embedded in the narrative. In addition, the reviewer's engagement in the community and their social reputation affect the probability of being read by more readers.

4) *Reader*: Reading reviews is one type of information seeking behavior, which has different patterns and processes depending on the context in which a reader seeks information.

5) *Information sharing community*: Every community, a group of society, has different social norms and practices between members. Characteristics of information shared in a community are affected by different expectations, and different social interactions within the community. Systematic infrastructure also affects on the way in which information is represented and shared.

In this study, we explore three elements, product/service, review, and reviewer, in order to determine what factors influence the perceived helpfulness of a review.

Research questions

To study what factors affect the perceived value of shared information and how many people agree with the helpfulness of information, we examine four types of determinants of perceived helpfulness, including the review characteristics (RQ1), reviewer's engagement (RQ2), reviewer's social reputation (RQ3), and business type (RQ4).

RQ1: What characteristics of a review affect the perceived helpfulness of a review?

A review, as an independent type of document, can have multiple dimensions of features, depending on the perspective. From the perspective of "information-as-thing (Buckland, 1991)", tangible features, such as number of characters and words, number of bytes for storage, and physical appearance, explain the characteristics of a review. Likewise, intangible features of review also account for other aspects of a review from the perspectives of "information-as-process" or "information-as-knowledge (Buckland, 1991)": syntactic and semantic features, readability, subjectivity and objectivity, informativeness, linguistic correctness, and so on.

RQ2: To what extent does a reviewer's engagement affect perceived helpfulness of a review?

[c] http://www.judysbook.com

Marcus uses RFM analysis to sort consumers' transaction records and segment consumers (Marcus, 1998). RFM refers to *Recency, Frequency*, and *Monetary Value* of consumer's transactional history: *Recency* is measured by how long ago the consumer made the last purchase; *Frequency*, the frequency or total number of purchases by the consumer; and *Monetary Value*, the average amount of money the consumer spent per transaction. These variables represent the extent to which a consumer contributes to monetary flow in the product market.

In a similar context, we define variables, *Recency*, *Frequency*, and *Knowledge Contribution*, which mean the extent to which a reviewer contributes to the community with helpful knowledge and/or information. Since the number of votes for helpfulness measures the helpfulness of a review, *Knowledge Contribution* is measured by the average number of votes for helpfulness the reviewer received for his/her previous posted reviews.

RQ3. To what extent do a reviewer's social reputation affect perceived helpfulness of a review?

Social reputation, in this study, refers to the extent to which a review is known in the information sharing community. Morris et al. (2012) explain that author credibility and twee credibility have high correlation and both direct and indirect social relationships between reader and author have an effect on the perceived credibility.

RQ4: Do features investigated in this study show different result from different business type (restaurants vs. transportations)?

It has been found that different kinds of products have different types of judgments. For utilitarian products and experiential products, while Strahilevitz and Myers (1998) articulate that consumer judgments to utilitarian products tend to be cognitively driven and goal-oriented, Hirschman and Holbrook (1982) explain that experiential products are characterized by affective experiences, including aesthetic and sensual pleasure, fantasy, and fun. Considering these findings, Pan and Zhang (2011) examine the revealed differences in review helpfulness for different product types, experiential and utilitarian products.

In a broad sense, the products for which reviews are written in the data we use are almost all experiential products. Still, we found that some different subcategories exist, which might have different characteristics: restaurants and transportation services.

The assumption for these two business types is related to the number of alternative options for business and primary purpose of using the business. For restaurants, one of the main reasons one visits restaurants and looks for information and reviews of restaurants is because one wants to taste good food and to experience good atmosphere and mood. Since there are so many restaurants, and one of which is potential alternative option, we tend to be pickier when choosing a restaurant, and sensitive to the content of review. Ultimately we want more features to be expressed in a review and their experience to be delivered properly.

On the other hand, one may not have many options for transportation. Other contexts, such as location, destination, available time, and expense, would dictate which transportation we need to use. In addition, the general purpose of using transportation is not related to good moods or the atmosphere; we tend to consider the efficiency and/or economical benefit when deciding transportation. Based on these assumptions, we tend to have lower expectation for transportation.

Data

Yelp.com is one of the most popular sources where consumers are sharing their experiences and generating reviews about services, mostly about restaurants. Thus, it is an appropriate source to look into for our study. As one of the largest service-related information sharing platforms, Yelp.com has a huge number of reviews generated by users. A reviewer who has experienced the service of a particular business gives stars to evaluate the overall experienced service assessment, from one star to five stars, which means the worst and the best, respectively. The textual content in the review also explains how the reviewer felt about the service along with the reason for the assigned stars. For the posted review, other readers who visit the website can rate the perceived value of the review in response to the question: "Was this review…? Useful, Funny, or Cool." Unlike other online retailing sites and review sharing sites, interestingly, Yelp.com tries to get more precise feedback about the perceived helpfulness of reviews.

Variables	Values
# of total reviews	255,327
Average stars	3.808 (1.203)[d]
# of votes per review	151.1 (185.86)
Number of words per review	125 (112.08)
Average age of a review (in days)	845.5 (590.28)
Total number of votes in our data	721,201
% of reviews with one star	7.13%
% of reviews with two stars	8.72%
% of reviews with three stars	14.98%
% of reviews with four stars	34.63%
% of reviews with five stars	34.55%

Table 1: Summary statistics of data.

This study uses dataset from the recently publicized *Yelp Data Challenge*[e]. We selected reviews that are generated by

[d] Standard deviations are reported in parentheses.

reviewers who had written more than one review in order to measure the user's engagement based on recent posting activities. Also, we excluded the reviews written within 60 days from the date of data collection, because the recently posted reviews may not have sufficient time to get votes and feedbacks from other readers. The summary statistics of the data are presented in Table 1.

Independent variables

There are four groups of independent variables here.

1) Basic information for review:

From each review in the selected sample, we derived the following variables that convey the basic information. (1) *The number of reviews of a business:* the number of reviews a particular business has gathered by 60 days before the time of data collection. (2) *Age of review:* time elapsed since a review was posted. (3) *Stars:* the number of stars a reviewer gives as the overall evaluation of a business. (4) *Review length:* the number of words in textual content in a review.

2) Reviewer's engagement:

In order to present a reviewer's engagement to the information sharing community, three variables examined in Marcus (1998) are derived. (1) *Recency*: how long ago the reviewer wrote a review, measured by the number of days between the posting date of the latest review and that of most recent review prior to the latest one. (2) *Frequency*: the number of previous reviews written by a reviewer before the latest preview. (3) *Knowledge contribution*: how much a reviewer contributes to the stock of knowledge, measured by the average number of votes for helpfulness received over all reviews. We removed the latest review from the calculation, with an assumption that the latest review does not have sufficient time for readers to read it.

3) Reviewer's social reputation:

Social reputation refers to the extent to which a person is known among members in a society or community. In the data for this study, provided by Yelp.com, each user has a variable *the number of fans*; which refers to the number of people who like a reviewer and follow a reviewer's newly posted reviews.

4) Business type:

A business can have multiple tags related to business type, such as restaurants, shopping, and transportation, which makes difficult assign a specific business type to an establishment. In this study, we collected data only from two business types, restaurants and transportation services, in order to isolate distinct characteristics for different business types.

Dependent variable

As a proxy variable for perceived helpfulness, we use *the number of total votes the review receives from readers*. Note that we use the total number of votes for useful, funny, and cool altogether. Here are two primary reasons for choosing this variable as a proxy. First, though there might be some differences in the meaning of useful, funny, and cool, the main motivation for a reader to vote for one of these features is because he/she finds something in the review and feels supported and helped by the expressed information. Second, some might argue the use of the ratio between 'yes' votes and for 'no' votes to measure helpfulness, as previous works did using Amazon.com data. Some might also argue that the accumulated number of votes is dependent on the time a review has been exposed to public. However, the ratio is still missing some meaning in the sense that not all readers respond to the question that asks about helpfulness. Therefore, helpfulness measured by the ratio is overestimated.

EXPERIMENT 1

The experiment 1 empirically tests our propositions regarding the effects of a user's social engagement, implicitly and explicitly presented, to the review generating and sharing communities, where the information and experience are shared as social knowledge.

The models

We designed four models according to the categories to explain and predict the outcome of the total number of votes for helpfulness.

As we described in the section on research framework, we expected that content-related features, reviewer's engagement, and social reputation would affect the total number of votes for helpfulness. Therefore, we wanted to investigate effects of those components on the predictive power of the perceived helpfulness.

Model 1:

$$\textit{Total Votes} = \beta_{11} * \textit{number of reviews of a business} + \beta_{12} * \textit{age} + \beta_{13} * \textit{age}^2 + \beta_{14} * \textit{consumer rating} + \beta_{15} * \textit{review length} + \varepsilon_1$$

We want to explore the effect on the model fit when reviewer's engagement features are added. Therefore we considered:

Model 2:

$$\textit{Total Votes} = \beta_{21} * \textit{number of reviews of a business} + \beta_{22} * \textit{age} + \beta_{23} * \textit{age}^2 + \beta_{24} * \textit{consumer rating} + \beta_{25} * \textit{review length} + \beta_{26} * \textit{recency} + \beta_{27} * \textit{frequency} + \beta_{28} * \textit{knowledge contribution} + \varepsilon_2$$

In order to investigate the effect of the social reputation, we considered:

Model 3:

[e] http://www.yelp.com/dataset_challenge

Total Votes = β_{31} * *number of reviews of a business* + β_{32} * *age* + β_{33} * *age*^{2} + β_{34} * *consumer rating* + β_{35} * *review length* + β_{36} * *number of fans of reviewer* + β_{37} * *(number of fans of reviewer)*^{2} + ε_3

Lastly, integrating all features we already explored in a model:

Model 4:

Total Votes = β_{41} * *number of reviews of a business* + β_{42} * *age* + β_{43} * *age*^{2} + β_{44} * *consumer rating* + β_{45} * *review length* + β_{46} * *recency* + β_{47} * *frequency* + β_{48} * *knowledge contribution* + β_{49} * *number of fans of reviewer* + β_{410} * *(number of fans of reviewer)*^{2} + ε_4

Results

Table 2 presents the results of experiment 1. According to Model 1, the positive coefficient estimate of Consumer rating ($\beta = 0.18$, $p < 0.01$) indicates that positive reviews have a greater probability of being evaluated as helpful than negative ones. We also find that the estimate for Review length ($\beta = 5.342e\text{-}3$, $p < 0.01$) indicates that longer reviews are considered to be more helpful than shorter one. Additionally, the number of reviews of a business ($\beta = 1.23e\text{-}4$, $p < 0.1$) and Age of review ($\beta = 2.35e\text{-}4$, $p < 0.01$) also suggest that they have effects on the perceived review helpfulness, but the coefficients are not so significant.

According to Model 2, the estimates of *Recency* ($\beta = -7.782e\text{-}5$, $p < 0.1$), *Frequency* ($\beta = 2.136e\text{-}4$, $p < 0.05$), and *Knowledge contribution* ($\beta = 0.967$, $p < 0.01$), indicate that the reviewer's engagement in the community has an affect on the total number of votes the review receives.

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-0.29***[g] (4.37e-2)[h]	-0.7037*** (3.02e-2)	-0.1463*** (3.85e-2)	-0.6898*** (3.03e-2)
# of reviews of a business	1.23e-4* (5.52e-5)	7.57e-4*** (3.81e-5)	4.35e-4***	7.51e-4*** (3.81e-5)
Age of review (in days)	2.35e-4*** (5.68e-5)	-9.20e-5* (3.93e-5)	1.34e-5 (5.00e-5)	-8.97e-5* (3.93e-5)
Age of review^2	7.21e-7*** (2.53e-8)	7.44e-9 (1.75e-8)	5.49e-7*** (2.25e-8)	8.63e-9 (1.75e-8)
Consumer rating (in stars)	0.18*** (8.57e-3)	0.0257*** (5.91e-3)	0.05234*** (7.55e-3)	0.02502*** (5.90e-3)
Review length (in # of words)	0.0135*** (9.24e-5)	5.342e-3*** (6.55e-5)	9.855e-3*** (8.242e-5)	5.34e-3*** (6.55e-5)
Recency		-7.782e-5* (3.78e-5)		-8.16e-5* (3.78e-5)
Frequency		2.136e-4** (3.76e-5)		-3.597e-5 (8.87e-5)
Knowledge contribution		0.967*** (2.05e-3)		0.9598*** (2.40e-3)
# of fans of reviewer			0.115*** (4.80e-4)	2.766e-3*** (5.50e-4)
(# of fans of reviewer)^2			-1.275e-4*** (1.01e-6)	-3.10e-6*** (9.26e-7)
R^2	0.1274	0.5866	0.3241	0.5867
AIC	1559552	1368815	1494351	1368790
BIC	1559625	1368920	1494445	1368915

Table 2: Results of Experiment 1.

[g] *Significant at 10% level; **significant at 5% level; ***significant at 1% level.
[h] Standard deviations are reported in parentheses.

From the results of Model 3, which includes reviewer's social reputation to the base model, the coefficient estimates for *the number of fans of the reviewer* and (*the number of fans of the reviewer*)^2 are statistically significant and suggest that a review that is written by a reviewer who has more fans has a higher probability of being considered helpful. According to the parameter estimates (β = 0.115 for *the number of fans of reviewer*, and β = -1.275e-4 for (*the number of fans of the reviewer*)^2), there appears to be an inverted U-shaped relationship between the number of fans of the reviewer and the perceived review helpfulness, which suggests that the least and the most popular reviewers are less influential than the moderately popular reviewers in helpfulness.

Lastly, when we include both reviewer's engagement and social reputation together in Model 4, the coefficient estimates for *the number of fans of reviewer* and (*the number of fans of reviewer*)^2 are statistically significant and suggest that a review that is written by a reviewer who has more fans has higher probability of being considered helpful.

When it comes to the effect of the age of the review, the results show that the statistical significance of age becomes smaller with other factors included. This means that perceived helpfulness of a review is not affected by the age of it. This justifies the selection of the dependent variable, the number of total votes for helpfulness, rather than ratio of helpfulness, as appropriate for this study.

In terms of the fitness of models, we use AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) as goodness-of-fit statistics. Both AIC and BIC statistics overcome the problem of over-fitting, which refers to the phenomenon that increasing the number of variables in the model always improves the goodness of the fit. Considering the fact that a smaller number of AIC and BIC of a model means higher fitness, the Model 4 is the best model, followed by Model 2, Model 3, and Model 1. Though the effect of adding the reviewer's social reputation to the goodness-of-fit is not as strong as expected, we still see that Model 4 is most exhaustive model among them.

Since, the differences of goodness-of-fit between two models, Model 2 and Model 4, are not sufficiently large, we compare two models with ANOVA. The *p-value* of the result is less than 0.01, which means highly significant. Model 4 is also significantly better than Model 2. Overall, though the effect of social reputation and the number of fans of a reviewer looks relatively smaller than we expected, the feature still improves the prediction model.

EXPERIMENT 2

This experiment tests the effect of business type on perceived helpfulness of a review with the following model.

Total Votes = β_1 * *number of reviews of a business* + β_2 * *consumer rating* + β_3 * *review length* + β_4 * *knowledge contribution* + β_5 * *number of fans of reviewer* + β_6 * (*number of fans of reviewer*)^2 + β_7 * *business type* + β_8 * *business type* * *consumer rating* + β_9 * *business type* * *review length* + β_{10} * *business type* * *knowledge contribution* + β_{11} * *business type* * *number of fans of reviewer* + ε

Variables	Restaurants	Transportations
# of total reviews	3,858	1,154
Average stars	4.21 (1.00)[i]	3.29 (1.18)
# of votes per review	4.59 (6.33)	4.378 (7.59)
Number of words per review	129.3 (118.47)	131.52 (122.66)
Average age of a review (in days)	996.1 (651.68)	931.1 (626.60)
Total number of votes in our data	17,687	6,190
% of reviews with one star	2.05%	10.40%
% of reviews with two stars	5.13%	14.12%
% of reviews with three stars	10.73%	25.22%
% of reviews with four stars	34.11%	36.31%
% of reviews with five stars	47.98%	13.95%

Table 3: Summary statistics of data for Experiment 2.

Data

This experiment tests the effect of business type on perceived helpfulness of a review with the following model. From the same dataset we used in the Experiment 1, we collected reviews of two types of businesses to examine differences in expected and perceived value of reviews over businesses. We first identified the top 5 restaurants and the 5 transportation services based on the number of reviews available for the businesses. The selected restaurants includes Italian restaurants and bars. The transportation services here include airports, airlines, and railways. Note that we used a limited sample of popular individual businesses, rather than random sampling. Because consumer reviews tend to concentrate

[i] Standard deviations are reported in parentheses.

on a small number of popular products/services (Chevalier & Mayzlin, 2006), randomly selected businesses likely are to have few reviews and thus fewer votes. Also, randomly selected services represent general features of overall services in the data. However, they do not have sufficient information to represent features of general reviews. In order to keep balance between the number of reviews of restaurants and transportation, we collected five popular businesses.

Collected data for Experiment 2 includes 5,012 reviews: 3,858 reviews for restaurants and 1,154 reviews for transportation services. Table 3 presents the summary statistics. While for restaurants, consumer ratings are distributed more toward the positive end with average stars of 4.21/5.00, transportation services, consumer ratings skewed much lower with an average rating of 3.29/5.00. On average, a restaurant receives 771.6 reviews, whereas a transportation service receives 230.8 reviews.

Results

As shown in Table 4, most factors, such as *Consumer rating, Review length, Knowledge contribution*, and *the number of fans*, show consistent effects with those in Experiment 1. Note that the number of reviews of a business in this study does not present a significant effect on the total number of votes, since we selected limited number of business, which does not have enough variance.

The focus of Experiment 2 is on the business type effect on the total number of votes. Given the dummy coding (1 for restaurants and 0 for transportation services), the negative estimates for *Business type* indicate that reviews for restaurants, on average, received less votes for helpfulness than those for transportation services. This phenomenon is consistent with our assumption about business type effects on expectation and perception of reviews.

One of interesting findings in this dataset is a negative relationship between consumer ratings and total number of votes. Considering the fact that we selected a very limited number of reviews from the most popular business, we conclude that for well-known popular businesses, people consider more critical, even negative, reviews as helpful. Still, the non-zero and positive coefficient estimates for the interaction term (*Business type × Consumer rating*) indicate that business type moderates the relationship between review rating and the votes of helpfulness.

Our results also suggest that the business type moderates the effects of review length and knowledge contribution on the total number of votes. Though longer reviews tend to receive more votes for helpfulness, a length increase in review text has more influence for transportation services, rather than restaurants.

In terms of knowledge contribution, our results indicate that helpfulness of a review for restaurants is more affected by knowledge contribution of the reviewer.

Variables	Estimates
Intercept	2.8944· (1.5714)^{m}
# of reviews of a business	-8.7e-4 (1.57e-3)
Consumer rating (in stars)	-0.4065***^{n} (2.62e-2)
Review length (in # of words)	7.988e-3*** (1.70e-4)
Knowledge contribution	1.09*** (2.94e-3)
# of fans of reviewer	5.026e-3*** (9.68e-4)
(# of fans of reviewer)^2	-1.39e-5*** (3.06e-6)
Business type	-1.448*** (0.195)
Business type × Consumer rating	0.338*** (5.81e-2)
Business type × Review length	-2.92e-3* (1.31e-3)
Business type × Knowledge contribution	-5.313e-3 (1.95e-2)
Business type × (# of fans of reviewer)	5.2e-3 (2.69e-3)

Table 4: Results of Experiment 2

DISCUSSION

The findings from the study indicate the relationship between perceived helpfulness with reviewer's engagement and social reputation. As independent variables, a reviewer's features are able to explain the extent to which the review he/she posted is perceived as helpful. Comparing the goodness-to-fit of models, the significant effects of reviewer's features would suggest a profound model that predicts perceived helpfulness of a review more accurately. This indicates the potential for further study that explores other individual characteristics and social relations relevant to the perception of a review.

The finding that the number of fans significantly affects perceived helpfulness provides managerial implications for an information sharing community and/or information management systems: reviewers, or participants, who have many fans are important social features in terms of helpful information as a whole. This implication also means that in order to improve the total quality of information shared in a community, it is much more effective to promote and support reviewers who already have many fans, rather than to expect a novice's extraordinary review. Along with significant importance of reviewer's knowledge contribution, this implication has the potential for community and/or system manager or designer. Rieh et al. (2014) also finds that interaction with audience establishes and enhances the credibility of content posted on weblogs.

The effect of business type, restaurants or transportation services in this study, indicates different types of business have different characteristics in terms of expectations about service quality, thus trends in consumer rating are significantly different. Also, the way in which people perceive a review as helpful depends on business type. For restaurants, readers tend to see more critical reviews with fewer stars as helpful. This is not the case for reviews of transportation. Different business expectations explain this finding. People usually have more alternative options for choosing restaurants and they have more diverse tastes for good restaurants, which make them more sensitive to other's individual experiences and subject explanation. For transportation services, people do not have as many options and do not expect extraordinary service quality, which makes reviews more generous than ones for restaurants.

Although these findings are encouraging, there still remains work to be done. Previous works utilized several text-related features of review content to predict perceived helpfulness of a review to find out that those features are significant predictors. Based on this consideration, the results of our study can be improved in terms of model fitness and predictability by including other textual measures in the model.

In addition, the results estimate diminished effects of a reviewer's social reputation on perceived helpfulness. The primary reason for underestimated prediction is high correlation between knowledge contribution and social reputation. Knowledge contribution, measured by average number of votes for helpfulness among previous reviews of a reviewer, is necessarily related to the number of fans, regarding our assumption. In other words, the number of fans cannot help connecting to the helpfulness of reviews the author posted before. However, a study with cross-sectional analysis cannot tell the dynamics and/or the mechanism between them precisely. In order to find out the interaction between personal features, panel data is needed: number of fans of reviewer when his/her review receives a vote for helpfulness.

In terms of social reputation of a reviewer, we only use the number of fans. Though the number of fans can represent a person's reputation and awareness within community, we have other social interactions between members in a community, such as friendship that composes social network. As more online communities and/or web services accommodate social network features, several characteristics derived from the social network of a reviewer might contribute to the perceived helpfulness of posted reviews written by the reviewer. Understanding sophisticated social networking features within the community would also help examine how knowledge contribution, one of the primary factors used to predict review helpfulness, interacts with other features.

CONCLUSION

Consumer reviews are getting more attention from academia and industry, because of not only the increasing volume of information, but also the significant importance to consumer's purchasing and decision-making. Because of the trend of consumer reviews increasingly being incorporated into social media platforms, this study explored the relationship between predicting determinants of perceived helpfulness of review as provided by review content (basic textual features), reviewer's characteristics (engagement to knowledge sharing and social reputation), and product type (business type in this study).

The findings indicate that reviewer characteristics make a significant contribution to the perceived helpfulness of a review, showing a significant portion of the suggested model is explained by these features. This study suggests that in order to understand the quality and helpfulness of review, a reviewer's explicit and implicit features need to be considered in the prediction model. The study also articulates different patterns in review generation and perception, which has interesting implications for information sharing system design and management.

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