Chapter 8
The Impact of Customer Reviews on Product Innovation: Empirical Evidence in Mobile Apps

Zhilei Qiao, G. Alan Wang, Mi Zhou, and Weiguo Fan

Abstract Product innovation is important for firms to gain competitive advantages in a dynamic business environment. Traditionally, customers are not very much involved in product innovation processes. With the technology of Web 2.0, online users are enabled and motivated to provide reviews and discussions about product features and use experiences. User generated product reviews have been found to have a word-of-mouth effect as a new element of marketing communication. However, their implication on improving product innovation cycles have not been studied before. Guided by a persuasion theory, we extracted the central and peripheral persuasion cues from user generated reviews and examined their impact on mobile app developers' product innovation decisions. Using data collected from the Google App store, our empirical study shows that long and easy-to-read user reviews with mildly negative reviews can increase the likelihood of a future mobile app update. Our findings highlight the need for researchers to explore user generated reviews in the context of customer-centered product innovation.

Keywords Product innovation • Text mining • Mobile apps • Survival analysis • Persuasion

8.1 Introduction

A product innovation strategy is critical for firms to survive and prosper in a dynamic business environment (Alegre and Chiva 2008; Holahan et al. 2014; Wales et al. 2013). Dunk (2011) defines product innovation as an innovation process that

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Z. Qiao (✉) • G.A. Wang
Department of Business Information Technology, Pamplin College of Business, Virginia Tech 1007, Blacksburg, VA 24061, USA
e-mail: qzhilei@vt.edu

M. Zhou • W. Fan
Department of Accounting and Information Systems, Pamplin College of Business, Virginia Tech 1007, Blacksburg, VA 24061, USA

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conceives new and better products, which are unique or different in some ways from existing products (Nakata and Sivakumar 1996). The ability of firms to develop innovative products is key to their competitive advantages (Cankurtaran et al. 2013; Jayaram et al. 2014). Evidence suggests that product innovation can assist firms to enter an emerging industry and strengthen their competitiveness in the corresponding market (Keupp et al. 2012; Kotabe et al. 2011). Therefore, product innovation is critically important to a firm's performance (Prajogo and Ahmed 2006; Yao et al. 2013).

Existing innovation literature suggests several different channels of information acquisition for the product innovation process (von Hippel 1998; O'Hern and Rindfleisch 2008; Ramaswamy and Prahalad 2004). The traditional perspective suggests that firms dominate the product innovation decisions (Porter 1980). It views product innovation as a firm-centric activity, with most information flowing one way from the firm to its customers (Ramaswamy and Prahalad 2004). While customers are considered as the passive recipients of product innovation, firms have very limited understanding of customers' perception and opinions before the release of a new product. Firms only target the "right" customers and cannot accurately capture their customers' needs. Recent studies show that customers have been more involved in product co-creation processes. For example, the 3M company took advantage of identifying lead users before creating breakthrough products in order to avoid a market decline (Von Hippel et al. 1999). In addition, Cohen et al. (2002) show evidence that customers can offer useful ideas for new R&D projects and contribute substantially to the improvement of existing R&D projects. However, firms, still taking a dominant position in the innovation process, present their ideas to customers and gather customers' needs and feedback from only a small fraction of customers (Di Gangi and Wasko 2009; von Hippel and Katz 2002). Firms tend to be biased towards listening to their current customers, and even among these, to their most important customers or those who speak the most (Sawhney et al. 2005).

Recent literature shows that the product innovation process is shifting from a firm-centric view to customer-driven perspective. While customers are considered as the passive recipients, firms have very limited understanding of customers' perception and opinions before the release of a new product. Due to the limitations of developing new knowledge internally, integrating and using external knowledge is critical. While most existing literature searches external knowledge from other companies and alliances and finds evidence that sourcing this knowledge is beneficial to the firm's product innovation decisions, some other scholars identify customers as the most important source of information for new product development. Also, customer oriented innovation literature illuminates why and how external knowledge is significant and potentially valuable. O'Hern and Rindfleisch (2008) consider users as being central and vital participants in the product innovation process. Particularly, with the fast development and proliferation of online customer review communities, customers today willingly contribute and share their thoughts and opinions online. Zhang et al. (2013) show that innovative users share common interests and ideas in online communities. Since product innovation aims to provide higher quality products and give higher benefit to users. Therefore, customer-driven product innovation, enabled by the Web 2.0 technologies, is getting more and more attention from researchers and practitioners.

Online customer reviews have become an important new channel to acquire customers' feedback about product features and potential product defects (Abrahams et al. 2013; Lee and Seo 2013; Mudambi and Schuff 2010). Existing studies show that online customer reviews have a significant impact on other customers' adoption decision and firms' sales performance due to the word-of-mouth (WOM) effect (Chen and Xie 2008; Duan et al. 2008; Ghose and Ipeirotis 2011). In addition to being useful for customers and marketing purposes, online customer reviews also contain useful information for product development and improvement. Jin et al. (2015) find that online customer reviews are an important information source for collecting customer feedback and new requirements for product developers or designers. Some researchers have developed text analysis methods in order to extract and measure aggregated customers' preferences and feedback on product features (Decker and Trusov 2010; Xiao et al. 2015). However, to the best of our knowledge, we have not found any literature that show empirical evidence about the impact of online customer reviews on product innovation decisions. Our study aims to find empirical evidence that online product reviews can affect product developers' innovation decisions.

The mobile app industry provides a perfect research context for our research question. First, unlike physical products or enterprise software products, mobile apps are updated much more frequently (Syer et al. 2013). It provides more observation instances for product innovation activities than traditionally developed products that usually have a much longer development cycle. Second, mobile apps have a large user base through which a large number of user reviews have been generated through online app stores. Our research can potentially help improve the communication between app users and developers. Knowing the impact of user reviews on developers, the app users will be more motivated to contribute reviews. App developers can quickly identify those reviews that have high impact on their innovation decisions. Our study can also benefit app store providers such as the Google Play Store by making a better ecosystem in support of product innovation for mobile apps.

This study contributes to literature in several ways. First, our research enriches existing customer-driven product innovation literature. Prior studies suggest that firms have to design the right toolkits in order to get users involved in the product innovation process. Our study shows that product developers can learn from the widely available online customer reviews without developing specialized tools. Specifically, we reveal how online customer reviews can affect the product innovation cycles. By analyzing online customer reviews, product developers can learn customer feedback and feature requests in their complete view compared to traditional ways of collecting customer feedback such as surveys. The second contribution of our study is to complement the online customer reviews literature, which mainly show the impact of online customer reviews on the perception and purchasing decisions of future customers (Chen and Xie 2008; Duan et al. 2008; Ghose and Ipeirotis 2011). Our study will be the first to empirically show the impact of online customer reviews on product developers and designers. The third major contribution lies in a deeper understanding in how innovation works in the emerging mobile apps industry. According to the Silvias (2014), the global mobile app market will reach \$187 billion in 2017. Examining the innovation activities in this emerging industry will be economically significant.

From a managerial perspective, our study underscores the business strategy value of online customer reviews that executives struggle to quantify. Our results indicate that investment made on analyzing online customer reviews would pay off over time in terms of better product quality and a higher customer retention rate. In addition, based on marketing literature, it is important to understand customers' needs so that product managers can allocate resources to more productive and promising product innovation activities.

The rest of the chapter is organized as follows. We first review the Elaboration Likelihood Model, a persuasion theory that we use to guide our research design. We then develop our research hypotheses followed by our empirical study. We provide conclusions, discussions, and future directions at the end.

8.2 A Persuasion Theory—Elaboration Likelihood Model

Existing literature indicates that online customer reviews provide important external knowledge for product developers to identify new user requirements, detect product defects, and incorporate user solutions (Abrahams et al. 2013; Lee and Seo 2013; Mudambi and Schuff 2010). Therefore, online customer reviews have not only a word-of-mouth (WOM) effect for fellow customers, but also an implicit persuasion effect on product designers and developers.

The Elaboration Likelihood Model (ELM) has been commonly used to explain how a message can possibly change the perception of the message recipient. The theory suggests that a message recipient has a continuum of elaboration methods to deal with persuasive messages (Tam and Ho 2005). The essence of elaboration processing goes beyond simply focusing on comprehending the arguments embedded in the text content of the received message. When a message recipient does not have the motivation or ability to read and understand the arguments in a received message, persuasion is made through the peripheral route rather than the central route or argument quality, according to the ELM model. However, in most cases, both central and peripheral routes work collectively in persuading message recipients' decisions.

The central route of persuasion requires a message recipient to carefully scrutinize the arguments in a received message, thus the recipient's cognitive efforts on argument processing determines its influence (Zhang 1996). Existing studies have found that argument quality, such as information completeness and accuracy, has a significant impact on the message recipient's perception on information usefulness and willingness to adopt the message (Sussman and Siegal 2003).

The peripheral route relies on simple cues that are content-irrelevant indicators reflecting a recipient's perception of the credibility of the message source (Chaiken 1980). ELM researchers find that source credibility becomes an important predictor of the recipient's attitude change especially when the recipient cannot comprehend the arguments embedded in the received message (Petty et al. 1981). When a message recipient cannot or is not willing to scrutinize the message arguments, he or she will access the expertise, knowledgeability, reliability, and trustworthiness of the message source (Wu and Shaffer 1987). In addition, mood reflected from message content is also considered as a peripheral route that can affect message recipients' decisions (Batra and Stayman 1990; Payne-James and Khawaja 1993).

In our research context, we consider mobile app reviews generated by app users as persuasion messages, with which app users try to influence app developers in their product design and improvement. App users may provide arguments promoting certain features or demoting features to be improved or abandoned. App developers, as message recipients, are likely to scrutinize the arguments in each review and assess the peripheral cues about the reviewer in order to prioritize feature requests and make product release decisions. Guided by the ELM theory, we develop our research hypotheses about the impact of central and peripheral routes on app developers' product innovation decisions.

8.3 Research Hypotheses

Our research model, as depicted in Fig. 8.1, illustrates how we hypothesize central route and peripheral route would affect app developers' product innovation decisions. The central route constructs include the amount of information and readability, reflecting the argument quality of each app review. Both have been used to assess the argument quality of text messages (Zhou et al. 2015). The peripheral route constructs include review sentiment and sentiment strength. They reflect nothing about the arguments but the general mood of the reviewer. Classic peripheral cues such as expertise and trustworthiness do not apply in our research context

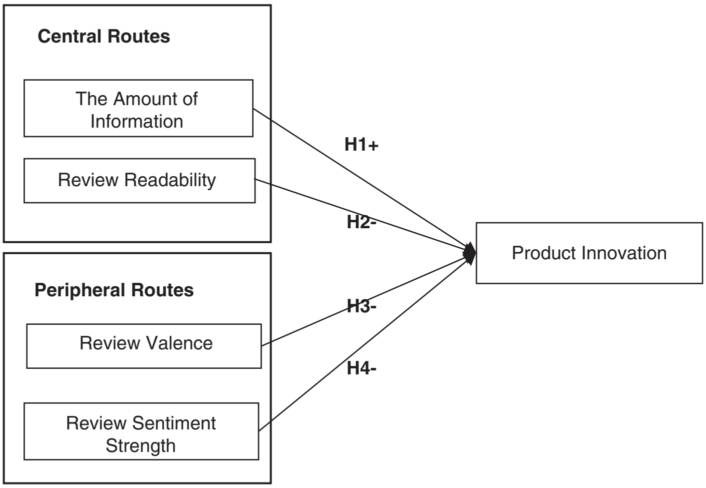

Fig. 8.1 Research model

because many user reviews are anonymous. As we discussed earlier, positive sentiment or mood conveyed through messages may positively influence the attitude of message recipients (Petty et al. 1993), i.e., the app developers in our context. In the rest of this section, we describe our research hypotheses in details.

8.3.1 The Amount of Information

The amount of information directly influences the capability of the message recipient to scrutinize the arguments embedded in a message. When the amount of information in a message is low, the recipient has few opportunities to elaborate because the motivation to elaborate is low (Palmer and Griffith 1998). Previous literature shows that the amount of information in product reviews, which is measured by the review length, has a positive influence on customers' adoption decisions due to the WOM effect (Chen and Turut 2013; Duan et al. 2008). Mudambi and Schuff (2010) also suggest that long reviews are perceived as being more useful than short ones because readers consider the word count as the depth of information usefulness and comprehensiveness.

A greater amount of information in app reviews presumably has more value to app developers. Lee (2007) suggests that customer reviews reflect customer needs. Some studies show that customer reviews contain critique about existing product features and suggestions about new product features (Mudambi and Schuff 2010; Troy et al. 2001). Customer feedback and suggestions on product features can help app developers reduce the uncertainty in customers' perception on new products, increase their confidence in product innovation decisions, and increase the frequency of product innovation (Dougherty and Dunne 2011; Zirger and Maidique 1990). Therefore, we propose:

Hypothesis 1: Mobile apps that have received a higher amount of information in its user reviews are more likely to have a new product release.

8.3.2 Review Readability

In addition to the amount of information, the persuasion effect of argument quality is also related to the willingness of message recipients exerting their mental efforts. Obscure words will inhibit the message recipient's willingness to make sense of the message content. Readability measures the effort it takes for a message recipient to comprehend a text message. It relates to the linguistic complexity of the text, in particular to the semantic and syntactic dimensions of the text. Text readability affects the message recipient's ability to cognitively process the arguments in a message (Lehavy et al. 2011). Bloomfield (2002) shows that less readable text requires investors to devote more time and effort to identify and extract relevant information. By contrast, easy-to-read text improves the message recipient's reading speed, comprehension, and memory retention (Ghose and Ipeirotis 2011). Existing studies have shown that the readability of product reviews can be used to predict the usefulness and impact of the reviews (Ghose and Ipeirotis 2011). Similarly, we propose:

Hypothesis 2: *Mobile apps that have received reviews with higher readability are more likely to have a new product release.*

8.3.3 Review Sentiment

Review sentiment, that includes both sentiment valence and extremity, reflects the subjectivity of the reviewers. Although it is derived from the message content, sentiment is often considered as a peripheral cue because it reveals the mood or affection status of the author (Bardzil and Rosenberger 1996). Past research shows that review sentiment can affect the perceived value or usefulness of product reviews. For example, Schindler and Bickart (2012) find that a moderate proportion of positive evaluative statements in product reviews positively relates to consumers' perceived helpfulness. Sen and Lerman (2007) find that review readers are more likely to consider negative opinions as being helpful for utilitarian products. Cheung et al. (2012) concludes that fair reviews are perceived more favorably when they cover both positive and negative aspects of the reviewed product. Existing studies do not provide consistent conclusions for the impact of review sentiment because of the moderation effects of product category and different message recipients. In our research, we aim to study the effect of review sentiment on the perceived usefulness of product reviews for app developers, not for fellow consumers. We use the SentiStrength method proposed by Thelwall et al. (2010) to automatically identify and classify the emotional information of customers. SentiStrength estimates the strength of positive and negative sentiment in informal short text messages using sentiment word dictionaries. We consider negative app reviews to be the major concerns for app developers due to the negative word-of-mouth (nWOM) effect, which has shown to have both short-term and long-term effects on firms' financial performance (Luo 2009). Moreover, Schindler and Bickart (2012) find that a product review with more descriptive statements is considered as being more helpful. Reviews with extreme sentiment do not have increased value and may decrease the readers' perceptions about its helpfulness. According to review sentiment strength in the text, this will make reviews lean toward neutral polarity. Therefore, we hypothesize the following:

Hypothesis 3: *Mobile apps that show negative sentiment in their reviews are more likely to have a new product release.*

Hypothesis 4: Mobile apps with a lower review sentiment strength are more likely to have a new product release.

8.4 Research Methodology

8.4.1 *The Stratified Cox Proportional Hazard Model*

Our primary interest is to study the impact of app user reviews on product innovation, i.e., the probability of having a new product release. More specifically, we would like to know if app reviews might shorten the time to the next product release. If we define an app update to be an event, we can use survival analysis to model this "time to event" data. On the other hand, survival analysis is capable of incorporating time-independent explanatory variables, which fits our scenario since our hypothesized explanatory variables are time invariant. Moreover, mobile apps usually have several updates over time. Therefore, events are recurrent and event time order matters (i.e., for each mobile app, an update at time t1 is different from that at time t2). We choose the Stratified Cox Proportional Hazard (SCPH) model (Cox 1972) for our empirical analysis, which makes no assumption about the form of the baseline hazard function. The SCPH model does not depend on distributional assumptions of survival time and defines the hazard ratio as the relative risk based on comparison of event rates. Thus, we employ the SCPH model to examine the relative association between the effects of independent variables (i.e., amount of information, review readability and review sentiment) and a subsequent product release event.

The hazard function, $h(t)$, represents the occurrence rate of a product per unit time (t). We use T to denote the time to event. The hazard function has the following form:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\left(t \le T < t + \Delta t \mid T \ge t\right)}{\Delta t} \tag{8.1}$$

The SCPH model assumes that the elapsed time to event T is conditional on the independent variables ($X_1, X_2, \ldots, X_j$). In our study, T measures the time between the product launch date or the previous product update date and the date of the event of interest—a new product release—or the end of the observation period. Thus, our hazard ratio represents the "risk" of having a new product release within a time unit (where the time is measured in days). The SCPH model is expressed as:

$$h_g(t, X) = h_{0g}(t) \times e^{\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_j X_j} \tag{8.2}$$

where $\beta_1, \beta_2, \cdots, \beta_j$ is a vector of regression parameters to be estimated. The baseline hazard function $h_{0g}(t)$ corresponds to the case where $x_j = 0$, involving time but not independent variables at each stratum with $g = 1, \cdots, k^*$. The second component is the exponential functions with the sum of $\beta_j X_j$, which involves independent variables' effects but not time.

$$\frac{h_g\left(t, X_i + 1, |X_{j(J \neq i)}\right)}{h_g\left(t, X_i, |X_{j(J \neq i)}\right)} = e^{\beta_i} \tag{8.3}$$

8.4.2 Data

As of Q1 of 2015, Google Play store was the largest mobile app provider in terms of number of app downloads, surpassing the first mobile app store-the Apple App store. We have collected data for 1215 mobile apps from the Google Play store between April 8, 2014 and April 5, 2015. All apps have appeared at least once in the top charts of new game apps. Because our study is focused on text analysis, we dropped 63 apps that did not receive any user review or have empty reviews during the data collection period. The final dataset contains 281,202 customer reviews for 1152 mobile apps. Data collected include basic app attributes, the business model (free or paid apps), app release/update dates, user ratings, user reviews, and developer information. Table 8.1 shows the basic summary statistics for collected data.

8.4.3 Variables

The dependent variable. We retrieved and analyzed the reviews that app users posted for each mobile app before the app's next update. We used the variable *Hazard Rate* to represent whether the app update event happened and how long the update interval (i.e., time between the previous update or the initial release date and its next update date). If a mobile app has not been updated, *Hazard Rate* represents the (instantaneous) rate of update for the apps to some time point during the next instant of time. Some mobile apps were not updated at all during the observation period. Therefore, the right censoring problem occurs in our data set. To solve the problem, we used an *event* variable to indicate whether an observation is censored (i.e., event is 1 for a complete observation and 0 for a censored one).

Table 8.1 The summary statistics of collected data

Measure	Value
Time period	April 8, 2014–April 5, 2015
Number of mobile apps	1152 (171 paid apps; 981 free apps)
Number of app reviews	281,202
Number of app updates	3307

Independent variables. *Amount of Information.* As suggested by Mudambi and Schuff (2010), we used review length to measure the amount of information in user reviews. We calculated the average review length and the total number of words for the reviews that we collected during each app update cycle.

Review Readability. The Fog index is commonly used to computationally measure text readability (Li 2008). It estimates the number of years of formal education that a reader of average intelligence would need to understand the text. It is built on the premise that complex words and long sentences are difficult to understand. A word is considered as a complex word if it contains three or more syllables. The larger the Fog index, the more difficult it is to understand the text. The Fog index is calculated as follows:

$$Fog = \left(Words\_Per\_Sentence + Percent\_of\_complex\_words\right) \times 0.4 \tag{8.4}$$

Review Sentiment Strength. SentiStrength is a lexicon-based classifier that uses supplementary (non-lexical) linguistic information and rules to identify sentiment strength in short informal English text, which is perfect for analyzing text in user generated app reviews. For each text message, SentiStrength generates two integer values ranging from 1 to 5, one being the positive sentiment strength and the other the negative sentiment strength (Thelwall et al. 2010). The average review sentiment strength or extremity was calculated over all the reviews collected for each app update cycle.

Review Valence. Review valence indicates whether a positive or negative sentiment stands out in a text message. We used the difference between positive and negative sentiment strength values calculated by SentiStrength to measure review valence. If the difference is less than 0, the review valence is negative. When it is greater than 0, it is positive. The average review sentiment valence was calculated over all the reviews collected for each app update cycle.

Control Variables. We considered the mobile app business model (free 0 or paid 1) and competition intensity (strong or weak) to be important control variables in our study. Existing literature find that both can affect product innovation decisions (Goettler and Gordon 2011; Greenstein and Ramey 1998; Stewart and Zhao 2000). Casual, arcade, puzzle, and action game categories have the strongest competition among all game categories because each of those game app categories has at least 100 games.

8.4.4 Results

8.4.4.1 Descriptive Statistics

Table 8.2 shows the descriptive statistics and pairwise correlations of our variables. In our dataset, 97% mobile apps had released at least one update during the observation period. For those mobile apps where at least one update occurred, the average

Table 8.2 Descriptive statistics

	Min.	Max	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Avg. review length	0.00	184.00	7.46	10.03	–	–	–	–	–	–	–
(2) Total no. of words	1	62,136	53.67	21.76	0.1	–	–	–	–	–	–
(3) Review readability	0.00	40.4	4.25	4.73	0.08	0.24	–	–	–	–	–
(4) Review sentiment strength	−3.00	4.00	0.63	0.63	0.04	0.27	0.38	–	–	–	–
(5) Review valence	0.00	4.00	0.48	0.76	0.02	0.15	0.27	0.68	–	–	–
(6) Business model	0.00	1.00	0.14	0.35	−0.08	0.11	−0.04	0.05	0.05	–	–
(7) Competition intensity	0.00	1.00	0.58	0.49	−0.02	−0.07	0.01	−0.04	−0.06	−0.14	–

Time to Update is 39.3 days. Fifty percent mobile app update cycles received user reviews before an update occurred. All pairwise correlations between independent variables are below 0.5 except the correlation between review valence and review sentiment strength. We also checked the variance inflation factor (VIF) values for all independent variables in our model. The result indicated that multicollinearity was not a concern (Zhang et al. 2013).

8.4.4.2 Hypotheses Testing Results

Table 8.3 presents the estimates of our research model. Review length was found to positively influence the likelihood that a future mobile app update would occur (β = 0.0083, $p < 0.01$). This suggests that mobile apps receiving longer user reviews on average are more likely to receive a new update. However, we found that the total number of words was negatively related to the possibility of having a future mobile app update. The hypothesis 1 is only partially supported. We need to conduct further analysis on this hypothesis in the future.

The Fog index, used to indicate review readability, was found to be negatively associated with a future app update ($\beta = -0.038$, $p < 0.01$). Mobile apps that receive user reviews with a high Fog index (i.e., more difficult to read) are less likely to receive a new update. The observation supports Hypothesis 2.

As predicted by Hypothesis 3, mobile apps that had received positive user reviews were less likely to receive a new update ($\beta = -0.10$, $p < 0.1$). Mobile apps that have received user reviews with extreme sentiment were less likely to receive a future update ($\beta = -0.084$, $p < 0.05$). Therefore, Hypothesis 4 is also supported.

Table 8.3 Results of hypothesis testing

	Coefficients	Hazard ratios
Central routes		
1. The amount of information (avg. review length)	0.0083***	1.0083***
2. The amount of information (total no. of words)	−1.1e-05***	1.0***
3. Review readability	−0.038***	0.96***
Periphera routes		
4. Sentiment strength	−0.084*	0.92*
5. Review valence	−0.10**	0.90**
Control variables		
6. Business model	−0.48***	0.62***
7. Competition intensity	−0.046	0.95
Wald χ^2	165.5	
Likelihood ratio test	197.3	

*Note. Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01*

8.5 Discussion and Conclusions

User generated product reviews have been found to have a word-of-mouth effect as a new element of marketing communication. However, their implication on improving product innovation cycles have not been studied before. Guided by the ELM persuasion theory, we examined the central and peripheral cues of online mobile app reviews and their impact on app developers' product innovation decisions. Our empirical study shows that easy-to-ready user reviews with high average review length and mildly negative reviews can increase the likelihood of a future app update. Our findings highlight the need for researchers to explore user generated reviews in the context of customer-centered product innovation.

Our work has theoretical and practical implications. First, our research enriches customer-centered product innovation literature and is the first paper to empirically examine the impact of online product reviews on product innovation in the mobile app industry. Second, our research can benefit different stakeholders in the mobile app industry. For customers, our research encourages them to continue contributing reviews because those reviews do matter in getting better products in return. Moreover, our study provides specific guidelines for writing online product reviews that can be better perceived by app developers. For app developers, our study can be used to automatically process user reviews and extract useful information content in their product innovation processes. Lastly, our study can also benefit mobile app platform providers such as the Google Play Store and Apple App Store by promoting useful user reviews and making a better ecosystem for product innovation.

Our work has also several limitations. First, our data set may contain mobile apps that was only updated once during our observation period. That will introduce anomalies in our analysis. Second, our model can be improved by including important control variables such as mobile app rank, app category, and app tenure. Third, our findings can only be applied to the data set that we collected. Additional analysis is necessary to improve the generalizability of our findings. We acknowledge that predictive analytics could be used to generalize our conclusions to other mobile app platforms such as Apple's App Store and Windows App Store.

Biographies

Zhilei Qiao is a third year Ph.D. student in Business Information Technology at Virginia Tech. He received Master degree in Computer Science from Tianjin Polytechnic University, P.R. China, in 2007, and a Bachelor degree in Computer Science and Technology from Shandong University of Science and Technology, P.R. China, in 2004. He has more than 6 years' work experience in IT companies (Infosys and DNV) as Software Engineer/Senior Software Engineer. His research interests include social media analysis, text mining, product innovation and decision support systems. He has published papers in a variety of conferences.

G. Alan Wang is an Associate Professor in the Department of Business Information Technology, Pamplin College of Business, at Virginia Tech. He received a Ph.D. in Management Information Systems from the University of Arizona. His research interests include heterogeneous data management, data mining and knowledge discovery, and decision support systems. He has published in Production and Operations Management, Decision Support Systems, Communications of the ACM, IEEE Transactions of Systems, Man and Cybernetics (Part A), IEEE Computer, Group Decision and Negotiation, Journal of the American Society for Information Science and Technology, and Journal of Intelligence Community Research and Development.

Mi Zhou is a Ph.D. student in Accounting and Information Systems at Virginia Tech. His research interests include Big Data Analytics, Corporate Disclosures, and Capital Markets. He has published papers in a variety of journals and conferences. Jamie earned his master degrees concurrently in Accounting and Computer Science from UNC Charlotte. He started his career with IBM and AmerisourceBergen Corporation as a software engineer. He then worked as a consultant/Senior Consultant at Deloitte for 3 years.

Weiguo Fan is a Full Professor of Accounting and Information Systems and Full Professor of Computer Science (courtesy) at Virginia Tech. He is also a L. Mahlon Harrell Research Fellow. He received his Ph.D. in Business Administration from the Ross School of Business, University of Michigan, Ann Arbor, in 2002, a M.Sc. in Computer Science from the National University of Singapore in 1997, and a B. E. in Information and Control Engineering from the Xi'an Jiaotong University, P.R. China, in 1995. His research interests focus on the design and development of novel information technologies—information retrieval, data mining, text/web mining, business intelligence techniques—to support better business information management and decision making. He has published more than 140 refereed journal and conference papers. His research has appeared in journals such as Information Systems Research, Journal of Management Information Systems, Production and Operations Management, IEEE Transactions on Knowledge and Data Engineering, Information Systems, Communications of the ACM, Journal of the American Society on Information Science and Technology, Information Processing and Management, Decision Support Systems, ACM Transactions on Internet Technology, Pattern Recognition, IEEE Intelligent Systems, Pattern Recognition Letters, International Journal of e-Collaboration, and International Journal of Electronic Business. His research has been cited more than 3600 times (h-index:33, i10-index:72) Google Scholar. His research has been funded by five NSF grants, one PWC grant, and one KPMG grant.

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