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Wenqi Zhou
The George Washington University, wenqi@gwmail.gwu.edu

Wenjing Duan
The George Washington University, wduan@gwu.edu

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Wenqi Zhou **Wenjing Duan**

Department of Information Systems and Technology Management

School of Business

The George Washington University

Funger Hall, Suite 515, 2201 G Street, NW Washington, DC

wenqi@gwmail.gwu.edu wduan@gwu.edu

Abstract

We propose a Bayesian analysis of mediation and moderation effects embedded within a hierarchical structure to examine the impacts of two sources of WOM information — online user reviews and professional reviews in the context of software download. Our empirical results indicate that the impact of user reviews on software download varies over time and such variation is moderated by product variety. The increase in product variety strengthens the impact of positive user reviews, while weakening the impact of negative user reviews. Furthermore, professional reviews influence software download both directly and indirectly, partially mediated by volume of online user reviews. Receiving positive professional reviews leads to more software download, yet receiving very negative professional reviews has a negative impact on the number of download. The increase in professional ratings not only directly promotes software download but also leads to more active user WOM interactions, which in turn leads to more download.

Keywords: Online user reviews, professional reviews, hierarchical model, moderation effect, mediation analysis

Introduction

Consumers are facilitated by Internet technology to expediently exchange their experiences and learn from others' recommendations about product information, which significantly influences their decision-making in online markets (Godes and Mayzlin 2004). This digital Word-of-Mouth (WOM) effect is particularly important for experience goods whose attributes are hard to evaluate before consumptions. The two most prominent and commonly discussed sources of online WOM are online user reviews and professional reviews. User reviews are believed to reflect prior users' experiences and preferences, whose two most important attributes are valence and volume (Neelamegham and Chintagunta 1999). The former often refers to the average numerical ratings (i.e., whether they are positive, neutral or negative) and the latter usually denotes the total number of user reviews. Professional reviews are shown to build up product reputations and be a better signal of product quality information (Hann et al. 2005). There is an extensive body of research on the impact of either online user reviews or professional reviews on user choices (Basuroy et al. 2003; Duan et al. 2008, 2009).

There is, however, lack of attention on how these two sources of WOM information work together to influence consumers' decision-making. Because of the broad reach of Internet, nowadays consumers can easily have access to these two sources of WOM information. For example, many popular websites, such as CNETD (www.download.com) and Amazon readily provide both user reviews and editorial reviews for their products. Consumers are also shown to search for multiple WOM information sources across websites (Park et al. 2009). Nevertheless, it is unclear from literature how consumers analyze and integrate user reviews and professional reviews to formulate their evaluations and make decisions, if at all. Being an attempt to answer this important question, Amblee and Bui (2007) find that user reviews and professional reviews influence freeware download equally by modeling these two impacts independently. However, this conclusion could be misleading due to ignoring the interrelationship between user reviews and professional reviews.

The major objective of this paper, therefore, is to open the "black box" of the process through which user reviews and professional reviews jointly influence user choices. Specifically, we investigate two related issues by conducting a Bayesian analysis of mediation and moderation effects embedded within a hierarchical structure on a panel data set of software download in CNETD. One issue is that how volume of user reviews mediates the impact of professional reviews on user choices. Reinstein and Snyder (2005) find the surprisingly large influence of professional reviews on box office revenue could be partly due to the indirect impact of professional reviews through user-generated WOM in addition to their direct impact. This finding suggests a mediation mechanism wherein professional reviews–>volume of user reviews–>user choices. The relationship between professional reviews and volume of user reviews is in essence related with the motivation behind consumers' sharing experiences with others. Consumers are motivated to engage in both offline and online WOM activities partly to enhance their own self-worth (Dicher 1966; Hennig-Thurau et al. 2004). Professional reviews, unlike the abundant user-generated WOM information, are only provided by a small group of specialized professionals on a very limited number of products. As a result, consumers are more willing to write reviews on products receiving professional reviews, especially on those obtaining higher evaluations, for a greater potential to attract other consumers' attentions and then show their connoisseurship. More WOM activities could lead to more user choices (Duan et al 2008; Godes and Mayzlin 2004), resulting in the mediated impact of professional reviews on user choices. We find empirical evidences to argue that professional reviews influence software download partially mediated by volume of user reviews. The fact that products are selected to get reviewed by professionals both directly and indirectly influences download via its impact on volume of online user reviews. Overall receiving very negative professional reviews significantly reduces products' download, whereas receiving positive professional reviews contributes to more download. The valence of professional reviews not only directly promotes software download but also leads to more active user WOM interactions, which in turn leads to more software download.

In order to provide a broad picture about how both user-generated and professional WOM information influence user choices, it is also important to correctly interpret the relationship between valence of user reviews, another attribute of user-generated WOM information, and user choices. Therefore, the other issue explored in this study is how the impact of valence of online user reviews varies over time and is moderated by product variety. Zhu and Zhang (2010) find that product popularity information moderates the impact of online user reviews. Zhou and Duan's paper (2009) demonstrates a significant nonlinear interaction effect between product variety and online user reviews, implying a moderation effect of product variety on the impact of user reviews. Yet, they do not go a step further to fully explore the variation of the impact of user reviews caused by the change of identified moderator.

And neither of those two studies considers the existence of other moderators, which is sufficiently addressed by a hierarchical structure embed in the empirical model in this study. We find that the impact of online user reviews varies over time, which is mainly caused by the moderation effect of product variety. The increase in product variety strengthens the impact of positive user reviews, while suppressing the impact of negative user reviews.

Our study makes significant contributions to Information System (IS) and Marketing literature. First, to our best knowledge, our paper is the first study that identifies the mediation role of volume of online user reviews on the link from online professional reviews to user choices. This is partly attributed to the methodological advantage of Bayesian framework adopted in our empirical work. Mediation analysis conducted in a Bayesian framework overcomes the limitation of its application in the alternative frequency framework, which has been criticized in literature for the difficulty of obtaining a robust estimation of standard deviation for a mediation test (MacKinnon et al. 2007). The Markov Chain Monte Carlo (MCMC) sampling method, which naturally comes with the Bayesian approach, could easily solve this difficulty. Second, this paper is also the first to hierarchically model the nonlinear moderation role of product variety on the impact of online user reviews. Moreover, this identified moderation effect of product variety makes the impact of online user reviews on software download vary over time. The conventional moderation modeling approach specified by the interaction between product variety and user reviews in explaining user choices is at risk of neglecting other omitted situational moderators (e.g., promotional event). These factors would be left into error term, which leads to the endogeneity problem. Instead, we use a hierarchical structure to first control for those noises and capture the moderation effect of product variety in lower level model, and thus isolate them from modeling the time variant impact of user reviews.

In the next section, we review the extant literature and build up the theoretical foundation for this study. We then describe the data and introduce model development, followed by empirical analyses. Finally, we discuss the results and implications, as well as identifying areas for future research.

Theoretical Background

Online User Reviews and Product Variety

Researchers studying user-generated WOM effects have mainly focused on two attributes of online user reviews: valence and volume (Duan et al. 2008; Liu 2006; Senecal and Nantel 2004). Yet conclusions about the relationship between valence of user reviews and user choices are mixed. Some researchers believe that valence of user reviews has a persuasive effect on a user's attitude (Liu et al. 2006) and thus has a positive impact on user choices (Chevalier and Mayzlin 2006; Zhou and Duan 2009). For example, Chevalier and Mayzlin (2006) find that the increase in valence of user reviews leads to more sales. Yet, there are also different voices from other scholars that online user reviews are not influencers of user choices (Chen et al. 2003; Duan et al. 2008, 2009; Liu 2006).

The psychological choice models proposed by Hansen (1976) seem to shed some lights on reconciling these divergent results from empirical works. He points out that situational variables would interact with predispositional variables, which leads to external responses (i.e., user choices) at the end. In an e-commerce context, online user reviews falls into the territory of predispositional variables. Thus the moderation effect of situational variables should not be neglected while examining the impact of user reviews on user choices. Studies conducted in different contexts involve distinct situational variables. Without controlling for the moderation effects of these situational variables, it would be hard to make consistent conclusions beyond data sets with a different mix of situational variables. In line with this reasoning, Zhu and Zhang (2010) empirically identify product popularity information as a moderator for the impact of valence of online user reviews on video game sales.

In this paper, we are interested in examining the moderation effect of product variety on user reviews in influencing user choices. Product variety changes over time due to many reasons. Suppliers may have their own schedules to promote new products or withdraw unsuccessful products; online platforms also have their own criteria to select listing products. In this sense, product variety is actually a final supply-side representation of all these potential multiple factors. Hence, product variety, which information almost every user would easily obtain in all online stores and is also easily observed by researchers and practitioners, captures those unobserved or uneasily measured yet important variations on supply side. The implications from the moderation effect of product variety would be thus more comprehensive in academics and more insightful in practice. Recent long tail related studies also demonstrate the interaction effect between online user reviews and product variety on product sales. Brynjolfsson et al. (2007) briefly discuss that product variety, as a supply side factor, and online recommendation system, as a demand side factor, may influence the consumption pattern concurrently. Zhou and Duan (2009) find a significant nonlinear interaction impact between valence of online user reviews and product variety on online software download. However, we do realize that there may exist other moderators for online user reviews out of all situational variables in addition to product variety. Unfortunately we are short of knowledge from literature that in what context which situational variable significantly moderates the impact of online user reviews. As a result, a more advanced methodology is required to take these potential moderators into account in order to generate robust estimates, which is introduced in the model development section.

Volume of Online User Reviews Mediates the Impact of Professional Reviews

Professional reviews are provided by experienced experts to build up reputation, provide advertisement and product information (Cameron 1995). Most extant researches agree on the significant relationship between professional reviews and consumer decisions (Amblee and Bui 2007; Basuroy et al. 2003; Boatwright et al. 2007; Liman 1983; Reddy et al. 1998; Reinstein and Snyder 2005). Liman's (1983) study shows that professional reviews are significant factors in predicting the cumulative box office revenue. Surprisingly, Reinstein and Snyder (2005) find a larger impact of positive professional reviews than expected. They argue that one of the reasons could be the indirect impact of professional reviews on box office revenue through user-generated WOM in addition to its direct impact widely tested in extant studies. Thus, ignoring this indirect impact would cause an inaccurate estimated impact of professional reviews.

This finding motivates us to look into the mediation mechanism through which online user reviews transmits the impact of professional reviews on user choices. Following Baron and Kenny's (1986)'s suggestions on mediation analysis, the choice of mediator in context of online WOM activities should satisfy the following two conditions: 1) professional reviews can influence this mediator but not vice versa; 2) this mediator influences user choices. Empirically, Holbrook (2005) finds a positive correlation between professional reviews and the volume of IMDB (www.imdb.com) user reviews in movie industry. Yet, this study is not able to investigate the causal inference between professional reviews and volume of online user review due to its data and methodology limitations. Hinging on this empirical work, we argue that volume of user reviews is the mediator on the impact of professional reviews for several reasons. First, users feel more likely to enhance their own self-worth by writing reviews on products with professional reviews of higher evaluations. Self-involvement, which refers to users' emotional needs to gain attentions and enhance images among other users, is shown as one of four motives for incidences of offline WOM (Dichter 1966; Engel et al. 1993; Sundaram et al. 1998). Recently, Hennig-Thurau et al. (2004) extend and validate it in online context as well. Since not all products on the market are reviewed by professionals, products received higher professional evaluations have a better chance to stand out.

Second, professional reviews usually precede user reviews and are available at the early stages of products' life cycles. For example, in movie industry, professionals are invited to view the film and publish their reviews before the film is open to public. This time lag between these two reviews rules out the possibility that professionals favor products with more user reviews. Also professional reviews are expected to be more objective and unbiased as a better proxy of product quality than user reviews (Hann et al. 2005). Therefore, user reviews are more likely influenced by professional opinions from experts that are posted earlier, which renders the support for the first condition of volume of user reviews to be the mediator.

Third, volume of user reviews has been widely shown to improve market outcome (Dellarocas et al. 2007; Duan et al. 2008; Liu 2006). The rational is that consumers are more likely to get informed about products with more reviews, which in turn promotes sales (Godes and Mayzlin 2004). The second condition of being a mediator is thus satisfied too. Based on aforementioned discussion, we propose volume of user reviews as the mediator of the impact of professional reviews in our empirical model.

Data

We conduct this study in the context of online software download at CNETD, which is a leading and representative online platform for software download. CNETD is a library of over 30,000 free or free-to-try software programs for four different platforms including Windows, Mac, mobile device and webware. For each platform on CNETD, there are more than 10 groups of software programs with approximately 5~20 categories in each group. CNETD lists detailed product descriptions as well as weekly and cumulative download counts for each software program. Users can post their reviews by detailed comments and an overall rating on a scale of one to five, with one being the worst and five the best. CNETD also provides editorial reviews for selected software programs in a similar manner by a five-star rating system (usually popular products). For each category, CNETD lists the number of software programs available for download by license type and operation system, which makes the information of product variety readily available for consumers.

Providing both user reviews and professional reviews for selected programs on CNETD is the main reason that we choose this context. This makes our study feasible to examine the impacts of these two sources of online WOM information simultaneously without the need to link two independent platforms providing them separately. Specifically, we use cumulative average user ratings (on a scale of one to five) as a measure for valence of online user reviews and cumulative number of online user reviews as a measure for volume of online user reviews. Reviews whose average ratings are above/equal/below 3 are defined as positive/neutral/negative reviews, regardless whether they are created by users or professionals. Most information on CNETD is updated on a daily basis. Though professional reviews written by CNETD are usually posted at the early stages of selected software programs' life cycles, once a reviewed product has a substantially update, CNETD editor would update their reviews within two business days. Therefore, we can comprise a longitudinal data set of those two sources of online WOM information to analyze the dynamics of software download.

Our data was collected weekly for four categories between Aug. 2007 and Feb. 2008. These four categories are: Digital Media Player, Download Manager, File Compression and MP3 Finder, which includes popular downloaded categories and also categories with different application purposes. We extract the following information on every software program listed in each category on a weekly basis: software name, date added, software characteristics, total download, last week download, average user ratings, number of user reviews and CNET ratings. Since every category represents a unique group of software with similar functions, we define each category as a single market.

Bayesian Model Development

We employ a Bayesian framework in this study mainly for its more feasible and efficient implementation to conduct a mediation analysis. It is always a challenge to conduct a mediation analysis in a traditional frequency framework in order to obtain the robust estimation of standard error. Its asymptotic estimation results in a poor power of the mediation test for small samples (MacKinnon et al. 2007), such as our case in category of MP3 Finder, which only has less than 100 products weekly. Nevertheless, Bayesian approach could easily estimate standard error of a mediation effect in a more straightforward and less restricted manner by using the MCMC method. More generally, Bayesian framework works better in finite sample context, while most widely used techniques of frequency statistics are built upon the asymptotical assumption that requires a large sample size of data, i.e., long time series dimension for a panel data set. Most data sets explored in previous studies, however, do not meet such requirements. The Bayesian framework has been widely implemented in fields such as Marketing and Finance, yet seldom discussed in IS research. Therefore, we choose to apply the Bayesian technique instead of the often used probability models aiming to provide a new perspective to explain digital WOM effect, given its advantage in modeling mediation effect in finite sample.

In this section, we introduce a series of models. We first focus on the valence of online user reviews to model the moderation effect of product variety on its impact on software download. We use a single equation model including interaction terms between product variety and user ratings as a benchmark, which is the conventional way to capture moderation effect. We then introduce a hierarchical structure as a more robust method to test the moderation effect of product variety and control for other omitted moderators. We do not include volume of online user reviews into these two models in order to narrow down the variation sources from independent variables and thus clearly demonstrate the advantage of hierarchical structure. We then proceed to present a Bayesian version of a standard mediation analysis with volume of online user reviews as the mediator for professional reviews, which leads to our final empirical model.

To facilitate our introduction of models, we illustrate the notation as following,

$i=1,\ldots,I$ software programs,

$t=1,\ldots 26$ the week when software i is posted,

Y_{it}= number of weekly download of software i at week t,

X_{it}= control variables: X_{it1} =$LOGTOTALDOWNLOAD_{it}$ (log transformation of cumulative number of download of software *i* at week *t*), X_{it2} =$WEEKLYRANK_{it}$ (weekly download rank of software *i* at week *t*), X_{it3} =$FREEPRICED_{it}$ (a dummy variable measures if software *i* is free-to-try at week *t*), X_{it4} =AGE_{it} (Days since software *i* has been posted), X_{it5} =$AGESQ_{it}$ (square term of AGE_{it}),

$WEEKLYVARIETY_t$ = total number of software programs listed in the category at week *t*.

$USERVAL_{it}$ = average user rating for software *i* at week *t* (one to five scale with half points),

$USERVAL^R_{it} = USERVAL_{it} - 3$,

$USERVAL^RSQ_{it}$ = square term of $USERVAL^R_{it}$,

$USERVOL_{it}$ = number of user reviews software *i* has received by week *t*,

$PROD_{it}$ = a dummy variable measures if software *i* receives CNET editorial review at week *t*,

$PROVAL_{it}$ = CNET editorial rating software *i* receives at week *t* (one to five scale with half points).

Baseline Model

To model the moderation effect of a moderator (*Mo*) on the outcome (*Y*) impact of an independent variable (*X*), the conventional approach is to test the significance of a product term *X*Mo* in explaining *Y* (Kenny et al. 1998). In our study, *Mo* is product variety, *X* are user ratings and *Y* is software download. We use this model as a benchmark to compare with the following hierarchical moderation model, which would be shown as theoretically superior.

Previous literature suggest that the impact of user reviews with different valence level is nonlinear (Chevalier and Mayzlin 2006; Clemons et al. 2006; Zhao et al. 2008; Zhou and Duan 2009). We apply a simple linear transformation on $USERVAL_{it}$ to help differentiate the impacts of different levels of user ratings. Since 3 is the middle point of the rating scale, we use $USERVAL_{it} -3$ instead of $USERVAL_{it}$, which is named as $USERVAL^R_{it}$ for parsimony. Built upon this, we then include both $USERVAL^R_{it}$ and the quadratic term of $USERVAL^R_{it}$, denoted by $USERVAL^RSQ_{it}$. As a result, neutral user reviews have zero values of $USERVAL^R_{it}$ and any deviation from 3 point leads to extreme user reviews with non-zero values of $USERVAL^R_{it}$ and $USERVAL^RSQ_{it}$. Zhou and Duan (2009) empirically demonstrate that the interaction effect between product variety and user ratings is nonlinear. Therefore, to capture the moderation effect of product variety on user reviews, we include the interaction term indicated as $USERVAL^RSQ_{it}*WEEKLYVARIETY_t$. Moreover, we include all control variables, X_{it}, into the equation as explained beforehand. We also include the software fixed effects (ε_i) in the model to control for any unobserved intrinsic individual software characteristic. Hence, the model can be expressed as below:

$$LOG(Y_{it}) = \gamma_1 + \gamma_2 * USERVAL^R_{it} + \gamma_4 * WEEKLYVARIETY_t + \gamma_5 * USERVAL^R SQ_{it} + \gamma_6 * USERVAL^R SQ_{it} * WEEKLYVARIETY_t + \gamma_x * X_{it} + \varepsilon_i + \varepsilon_{it}$$
$$\varepsilon_i \sim N(0, tau.e),\ \varepsilon_{it} \sim N(0, tau.y) \text{ i=1,...,I; t=1,...,26.}$$

where γ_x is a coefficient matrix on control variables with a dimension of 1 by 5. The impact of valence of user reviews is measured by $\gamma_2*USERVAL^R_{it}+(\gamma_5+\gamma_6*WEEKLYVARIETY_t)*USERVAL^RSQ_{it}$. Negative user reviews have opposite signs of $USERVAL^R_{it}$ and $USERVAL^RSQ_{it}$. Therefore, $\gamma_5+\gamma_6*WEEKLYVARIETY_t$ denotes the significance of difference between the impacts of 5-star and 1-star reviews in magnitude, which differentiates between positive and negative WOM effects.

Hierarchical Moderation Model

The baseline model aims to model the moderation effect of product variety on the impact of user reviews on software download. However, if there is any other factor that also moderates user reviews, the estimation could be seriously biased due to the endogeneity problem. Hansen (1976) summarizes four categories of situational variables, which interact with predispositional variables (online user reviews in this context). Product variety may be after all only one situational variable captured in our context, which moderates the impact of online user reviews. For example, Zhu and Zhang (2010) find product popularity information to be the moderator in the video game context. Therefore, the likelihood that there are always some moderators omitted to enter the interaction term in baseline model due to the lack of knowledge or unavailability of data should be nontrivial. This raises the endogeneity problem, which brings biases into parameter estimations. Let us hypothetically assume an omitted moderator denoted by *Moo*. The error term ε_{it} in our baseline model now actually contains two extra components in addition to the standard normally distributed noise: *Moo* and $Moo*USERVAL^{R}SQ_{it}$, the latter of which makes ε_{it} correlate with $USERVAL^{R}_{it}$, $USERVAL^{R}SQ_{it}$ and the interaction term in the baseline model. Therefore, we propose a hierarchical model to separate those omitted potential moderators from estimating the impact of online user reviews.

We build up a hierarchical structure on the coefficients on $USERVAL^{R}SQ_{it}$ to capture the moderation effect of product variety on the impact of valence of user reviews. We allow the coefficients on $USERVAL^{R}SQ_{it}$ (β_3^t) random over study period, which vary along weekly product variety with an error term δ_3^t. To avoid confusion, in this paper we name the equation to explain random coefficients as lower level model. This error term δ_3^t is indispensable in the sense that it can control for all omitted moderators other than product variety. This is the key to free this hierarchical moderation model from the endogeneity problem that our baseline model suffers from. In addition, we follow the suggested way of setting up a hierarchical model to completely separate the lower level dimension (time dimension) from the estimation of software download model (Rossi et al. 1995). As a result, the intercept term (β_1^t) in software download model is also allowed to vary along weekly product variety with an error δ_1^t. The following is our hierarchical moderation model setup:

$$LOG(Y_{it}) = \beta_1^t + \beta_2 * USERVAL_{it}^{R} + \beta_3^t * USERVAL^{R}SQ_{it} + \beta_x * X_{it} + \varepsilon_i + \varepsilon_{it}$$

$$\beta_j^t = \alpha_1^j + \alpha_2^j * WEEKLYVARETY_t + \delta_j^t,\ \text{j=1,3}$$

$$\varepsilon_i \sim N(0, tau.e),\ \varepsilon_{it} \sim N(0, tau.y), \delta_j^t \sim N(0, tau.\delta),\ \text{i=1,...,I; j=1,3; t=1,...,26.}$$

where β_x is a coefficient matrix on control variables with a dimension of 1 by 5. Similarly, β_3^t denotes the significance of difference in magnitude between the impacts of positive and negative user reviews with the same valence deviation from neutral user reviews. In addition to its robustness in estimation by counting all omitted potential moderators into the error term of the lower-level equation (δ_3^t), this hierarchical structure has another advantage of examining whether the impact of valence of user reviews on software download varies over time. The impact of valence of user reviews is measured by $\beta_2*USERVAL^{R}_{it}+\beta_3^t*USERVAL^{R}SQ_{it}$. If β_3^t is significant over time, the impact of valence of user reviews is shown to be time variant. Compared with the baseline model, this model is also more flexible to extend to other contexts, where there emerge or exist other interesting moderators besides product variety. Those factors can be simply added into the lower level model as independent variables to take their moderation roles into account.

Bayesian Mediation Analysis

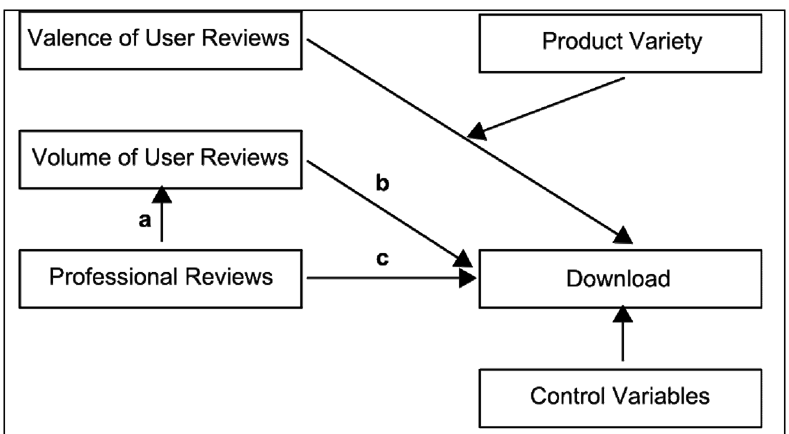

Figure 1. Model of Mediation and Moderation Effects

We now go one step further to examine how volume of user reviews transmits the impact of professional reviews on software download. As discussed in theoretical background section, we here propose a partial mediation model in a Bayesian framework based on the previous hierarchical moderation model. Figure 1 depicts the overall empirical model we would like to examine. Volume of user reviews ($USERVOL_{it}$) is the mediator and software download (Y_{it}) is the outcome variable. If path *c* is missing, indicating a complete mediation, this means the association between professional reviews and software download is completely accounted by volume of user reviews. However, Judd and Kenny (1981) point out that it is unrealistic to expect a complete mediation for psychological behaviors, which are influenced by various causes. We, hence, believe it is more rigorous to examine a partial mediation model at the first place and determine whether professional reviews is irrelevant to software download after volume of user reviews has been controlled by testing the significance of path *c*. We intentionally differentiate between valence and existence of professional reviews. Unlike user reviews, professionals, in a much smaller community than ordinary consumers, would only have limited time and efforts to review a fairly small portion of products available on the market. For example, CNET editorial team only reviews less than 20% of products posted in CNETD. As a result, it is important to understand the impact of whether receiving professional reviews on a product's performance in addition to the impact of the valence of professional reviews. Accordingly, we include two terms, $PROD_{it}$ and $PROD_{it}*PROVAL_{it}$, to both capture the impact of the valence of professional reviews and differentiate products with professional reviews from those without. As for products without CNET reviews, their $PROVAL_{it}$ values are irrelevant to model estimation and thus specified as zero for simplicity. According to the procedure suggested by Baron and Kenny (1986), the first step of a standard mediation analysis is to examine the relationship between professional reviews and software download without considering the mediator, which leads to the following first-step model setup:

$$LOG(Y_{it}) = \beta_1^t + \beta_2 * USERVAL_{it}^R + \beta_3^t * USERVAL^R SQ_{it} + \beta_4 * PROD_{it} + \beta_5 * PROD_{it} * PROVAL_{it} + \beta_x * X_{it} + \varepsilon_i + \varepsilon_{it}$$
$$\beta_j^t = \alpha_1^j + \alpha_2^j * WEEKLYVARETY_t + \delta_j^t, \text{ j=1,3}$$
$$\varepsilon_i \sim N(0, tau.e), \varepsilon_{it} \sim N(0, tau.y), \delta_j^t \sim N(0, tau.\delta), \text{ i=1,...,I; j=1,3; t=1,...,26.}$$

The impact of valence of professional reviews is measured by β_5 and the impact of whether receiving professional reviews is captured by $\beta_4+\beta_5*PROVAL_{it}$. If these two estimators are significant, the relationship between professional reviews and software download is established. We can then proceed to estimate our final model. As suggested by the standard mediation test procedures (Baron and Kenny 1986; Judd and Kenny 1981), the model of volume of user reviews is designed to capture the path *a* by including variables mediated by volume of user reviews, i.e., professional reviews in this case. We then add the volume of user reviews into software download model to measure the additional impact of volume of user reviews on software download (path *b*) besides the direct impact of professional reviews (path *c*), which is described as following:

$$LOG(Y_{it}) = \beta_1^t + \beta_2 * USERVAL_{it}^R + \beta_3^t * USERVAL^R SQ_{it} + \beta_4 * PROD_{it} + \beta_5 * PROD_{it} * PROVAL_{it} + \beta_6 * USERVOL_{it} + \beta_x * X_{it} + \varepsilon_i + \varepsilon_{it}$$
$$\beta_j^t = \alpha_1^j + \alpha_2^j * WEEKLYVARETY_t + \delta_j^t, \text{ j=1,3}$$
$$USERVOL_{it} = \lambda_1 + \lambda_2 * PROD_{it} + \lambda_3 * PROVAL_{it} + \sigma_{it}$$
$$\varepsilon_i \sim N(0, tau.e), \varepsilon_{it} \sim N(0, tau.y), \delta_j^t \sim N(0, tau.\delta), \sigma_{it} \sim N(0, tau.\sigma) \text{ i=1,...,I; j=1,3; t=1,...,26.}$$

We recognize that other possible explanations to influence volume of user reviews may exist. For instance, recently there have been some studies that argue retailing sales and the valence of user reviews would also influence volume of user reviews that a product attracts (Duan et al. 2008). Accordingly, the error term in the model of volume of user review (σ_{it}) may include these influencers. To obtain an unbiased estimated mediation effect, we need to make sure that σ_{it} does not correlate with professional reviews. Valence of user reviews and past download can be interpreted as indicators of ordinary users' tastes while professional reviews represent experts' tastes. Holbrook (1999) shows that ordinary user and experts have different criteria in their tastes. Hence, valence of user reviews and past download left in σ_{it} would not correlate with professional reviews and the model of volume of user reviews is free from endogeneity problem. λ_2 and λ_3 can then properly estimate the impact of professional reviews on volume of user reviews, which represents the path *a* in Figure 1. β_6 captures the impact of volume of user reviews on software download, which represents the path *b* in Figure 1 In addition, β_4 and β_5 in software download model capture the direct impact of professional reviews on software download, which represents the path *c* in Figure1.

Empirical Analyses

For all the models estimated in this study, we specify very vague priors for all unknown parameters. Given the mixed findings about digital WOM effect in literature, it is more rigorous not to adopt any extant research conclusions as prior information. We assume normal $N(0,10^3)$ prior distributions for all regression coefficients and inverse gamma $IG(10^{-3},10^{-3})$ prior distributions for the variance parameters. We then estimate all models using MCMC method for each category. We discard the first 15,000 draws with 10 thins for burn-in and use additional 15,000 draws with 10 thins to characterize the posterior distributions of parameters. We also conduct a convergence diagnostic to ensure the "true" parameters are recovered and thus the estimates are reliable. For all parameters, the visual check based on the history plots and autocorrelation plots show that convergence has been reached well before the end of the burn-in period. We also assess convergence by inspecting Gelman-Rubin diagnostic (BGR), which confirms the validity of estimate results as well. The estimations of key covariates for the following three models in each category are reported in Tables 1-4 through the posterior means and standard deviations.

Baseline Model

Table 1 shows the empirical results of our baseline model in each category. The coefficients on the interaction term $USERVAL^{R}SQ_{it}*WEEKLYVARIETY_{t}$ (γ_6) in all categories are significantly positive, which implies a significant interaction effect between valence of user reviews and product variety. However, when we look into the coefficient on $USERVAL^{R}_{it}$ (γ_2), except in category of Download Managers, all other three categories have insignificant estimates. The discussion in model development section has pointed out that other omitted moderators could confound this estimation, which would be addressed in the following hierarchical moderation model. As a result, the online WOM effect is improperly estimated as $(\gamma_5+\gamma_6*WEEKLYVARIETY_t)*USERVAL^{R}SQ_{it}$. The impact of 1-star user reviews is not only of the same magnitude but also of the same sign as the impact of 5-star reviews in these three categories. It is obviously misleading to infer based on the insignificance of γ_2 that negative user reviews benefit download as much as positive user reviews do.

Table 1. Estimation Results of Baseline Model

	M	SD	M	SD	M	SD	M	SD
	Digital Media Player		Download Manager		File Compression		MP3 Finder	
Software Download Model								
$USERVAL^{R}_{it}$ (γ_2)	-0.0104	0.019	**0.143**	0.023	0.005	0.027	0.046	0.049
$WEEKLYVARIETY_t$ (γ_4)	**0.003**	0.0001	**0.006**	0.0002	**0.006**	0.0004	**0.023**	0.001
$USERVAL\ ^{R}SQ_{it}$ (γ_5)	**-0.273**	0.011	**-0.150**	0.012	**-0.286**	0.016	**-0.262**	0.025
INTERACTION TERM (γ_6)	**0.001**	0.0001	**0.001**	0.00003	**0.002**	0.0001	**0.004**	0.0002
DIC	-774.094		1443.640		334.578		1357.110	

Note that for all estimation results listed in Tables 1~4, boldface type indicates the significance of estimators, namely the 95% posterior credible interval does not cover zero.

Hierarchical Moderation Model

We report the empirical results from our hierarchical moderation model in Table 2. The most obvious difference between the results of baseline model and hierarchical moderation model is that the coefficients on $USERVAL^{R}_{it}$ (β_2) in hierarchical moderation model become significant in all categories, which are insignificant in most categories in baseline model. The impacts of positive and negative user reviews on software download are thus shown to be significantly distinct in both magnitude and sign. We also compare the frequency estimations between baseline model and hierarchical moderation model. It is not surprising to see the similar difference for coefficients on $USERVAL^{R}_{it}$ from the frequency results comparison, given the uninformative priors used in the original Bayesian estimations. This change in significance confirms our concern about the existence of omitted moderators other than product variety, which would result in the endogeneity problem if tested by a conventional moderation modeling approach, no matter either of Bayesian or frequency framework is applied. Hence, this result empirically demonstrates the advantage of employing a hierarchical structure to model the moderation effect over the conventional approach, together with its theoretical superiority we have argued in model development section. Additionally, we also try to allow β_2 also random over time and regress it on product variety in a similar way as we deal with β_3^{t}. Yet the coefficients on its lower level model are both insignificant in all categories, which suggests that the moderation effect of product variety is nonlinear, being consistent with Zhou and Duan's finding (2009). Therefore, it is reasonable to only allow coefficients on $USERVAL^{R}SQ_{it}$ (β_3^{t}) random over weeks in our hierarchical moderation model in order to capture the nonlinear moderation effect of product variety on the impact of user reviews. We find that β_3^{t} are mostly significant over 26 weeks[1]. Thus the impact of user reviews on software download is significant and time-variant, measured by $\beta_2*USERVAL^{R}_{it}+\beta_3^{t}*USERVAL^{R}SQ_{it}$. Results from lower

[1] The plot of β_3^{t} over weeks in each category for hierarchical moderation model is available upon request.

level equation suggest that this variation over time is mainly caused by product variety. α_2^3, the coefficient on product variety in lower level model to explain β_3^1, is significantly positive, which implies the nonlinear moderation effect of product variety on the impact of user reviews on software download.

Table 2. Estimation Results of Hierarchical Moderation Model

		M	SD	M	SD	M	SD	M	SD
		Digital Media Player		Download Manager		File Compression		MP3 Finder	
Software Download Model									
$USERVAL^R_{it}$ (β_2)		**0.237**	0.015	**0.078**	0.014	**0.236**	0.017	**0.095**	0.023
Lower Level Model									
INTERCEPT	α_1^1	**2.141**	0.256	**4.224**	0.153	**2.828**	0.215	**3.404**	0.264
	α_1^3	**-0.127**	0.059	**-0.194**	0.044	**-0.151**	0.061	**-0.219**	0.064
$WEEKLYVARIETY_t$	α_2^1	**0.004**	0.001	**0.006**	0.001	**0.006**	0.001	**0.023**	0.003
	α_2^3	**0.0005**	0.0001	**0.001**	0.0002	**0.001**	0.0003	**0.003**	0.001
DIC		20420.800		7983.740		7391.270		4103.110	

Bayesian Mediation Analysis

Given the satisfactory performance of the above hierarchical moderation model to test the moderation effect of product variety, we further investigate the mediation process from professional review to software download through volume of user reviews.

For the sake of limited space, we do not report the estimation results of our first-step model, which are available upon request. We observe that the coefficient on $PROD_{it}*PROVAL_{it}$ (β_5) is significant in each category, indicating a significant impact of valence of professional reviews on software download. The coefficient on $PROD_{it}$ (β_4) is also significant in each category. The impact of whether the product receives professional reviews is then measured by $\beta_4+\beta_5*PROVAL_{it}$. We conduct a series of estimations for this term at each possible value of $PROVAL_{it}$, i.e. 0.5, 1,…, 4.5, 5. Most of them are shown significant with negative/positive values, implying the negative/positive impact of receiving very negative/positive professional reviews on download. These tests establish a significant relationship between professional reviews and software download. We thus are able to step forward to test our final model, whose results are shown in Table 3.

As we briefly mentioned beforehand, Bayesian framework has an advantage of computing the standard error of a mediation effect through MCMC sampling method. For example, in this model, the indirect impact of valence of professional reviews is measured by $\lambda_3*\beta_6$. In a frequency framework, it is difficult to estimate its standard error in a small sample, as the distribution that a product of two normally distributed statistics follows is unknown. And using the asymptotic estimator of this standard error requires a large sample (MacKinnon et al. 2007). Yet, MCMC method simply calculates a product of λ_3 and β_6 from their each draws, which produces a sample of a new quantity: $\lambda_3*\beta_6$. The standard error of $\lambda_3*\beta_6$ is thus easily computed. MCMC sampling method has no requirement for sample size, which makes Bayesian mediation analysis especially fit small sample size problem, as the case of category of MP3 Finders with less than 100 weekly products in our study. In addition, this MCMC sampling method also facilitates our estimation involved with any combination of estimators, i.e., the way we estimate impact of receiving professional reviews in the above first-step model.

We first check the estimated coefficients related with the mediation process described as three paths in Figure 1. In software download model, the coefficient on $USERVOL_{it}$ (β_6) is significantly positive in each category, indicating the positive impact of volume of online user reviews on software download, which explains path *b* in Figure 1. This result is consistent with previous studies' findings (Duan et al. 2008; Liu 2006). The coefficients on $PROD_{it}$ (β_4) and $PROD_{it}*PROVAL_{it}$ (β_5) are significant for each category, the latter of which denotes a positive direct impact of valence of professional reviews on software download. Similarly as the analysis for first-step model, to infer the direct impact of whether receiving professional reviews on download captured by $\beta_4+\beta_5*PROVAL_{it}$, we present a series of estimations for this term at each possible value of $PROVAL_{it}$, i.e. 0.5, 1,…, 4.5, 5, by a series of box plots shown in Figure 2. In each category, receiving negative professional reviews results in less download directly while receiving very positive professional reviews leads to more download directly. The path *c* in Figure 1 is thus verified.

Table 3. Estimation Results of Final Model

		M	SD	M	SD	M	SD	M	SD
		Digital Media Player		Download Manager		File Compression		MP3 Finder	
Software Download Model									
$USERVAL^{R}_{it}$ (β_2)		**0.181**	0.014	**0.051**	0.012	**0.172**	0.012	**0.066**	0.021
$USERVOL_{it}$ (β_6)		**0.0003**	0.00002	**0.003**	0.0001	**0.004**	0.0001	**0.0002**	0.00001
$PROD_{it}$ (β_4)		**-0.848**	0.074	**-0.227**	0.064	**-0.023**	0.065	**-0.885**	0.145
$PROD_{it}$ * $PRODVAL_{it}$ (β_5)		**0.382**	0.020	**0.052**	0.018	**0.054**	0.018	**0.392**	0.044
Lower Level Model									
INTERCEPT	α_1^1	**2.505**	0.278	**5.001**	0.140	**4.713**	0.153	**4.407**	0.255
	α_1^3	**-0.141**	0.029	**-0.225**	0.021	**-0.239**	0.034	**-0.267**	0.039
$WEEKLYVARIETY_t$	α_2^1	**0.004**	0.001	**0.006**	0.001	**0.006**	0.001	**0.023**	0.003
	α_2^3	**0.0004**	0.0001	**0.001**	0.0001	**0.002**	0.0001	**0.004**	0.0004
Volume of User Reviews Model									
$PROD_{it}$ (λ_2)		**21.550**	9.415	**-25.050**	7.914	**- 89.800**	8.137	18.450	9.805
$PROD_{it}$ * $PRODVAL_{it}$ (λ_3)		**32.560**	3.661	**10.860**	2.289	**42.420**	2.284	**71.280**	8.912
Indirect Impact of Professional Ratings (λ_3*β_6)		**0.009**	0.001	**0.031**	0.007	**0.189**	0.011	**0.016**	0.002
Total Impact of Professional Ratings (β_5+λ_3*β_6)		**0.391**	0.020	**0.083**	0.019	**0.242**	0.020	**0.408**	0.044
DIC		184349.000		72083.400		58031.000		42326.100	

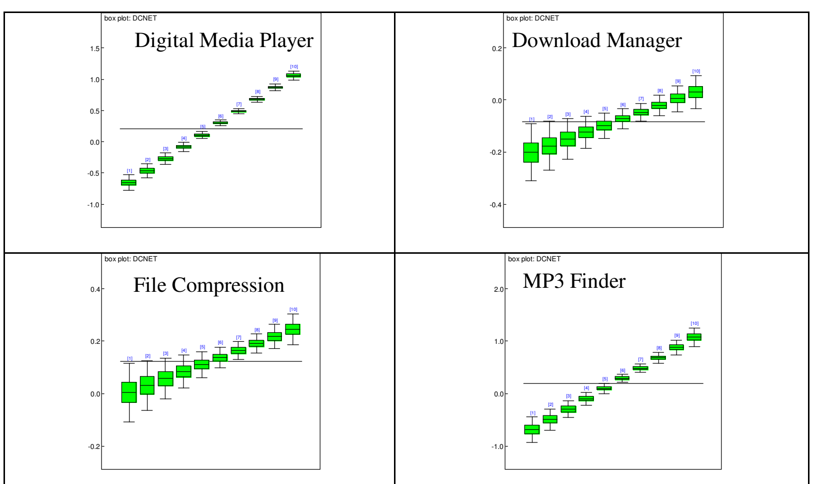

Figure 2. Direct Impact of Receiving Professional Reviews

Note: that for all box plots in Figures 2~5, the middle line denotes the mean. The vertical length denotes the 95% posterior credible interval.

In the model of volume of user reviews, the coefficients on $PROD_{it}*PROVAL_{it}$ (λ_3) are significant for all four categories, which denotes a significantly positive impact of valence of professional reviews on volume of user reviews, indicated by path *a* in Figure 1. Mediated by volume of user reviews through path *b*, the indirect impact of valence of professional reviews on download ($\lambda_3*\beta_6$) is shown to be significantly positive as well. The coefficients on $PROD_{it}$ (λ_2) are significant for all categories other than MP3 Finder. Yet to claim the significance of mediated impact of whether receiving professional reviews on software download, we need to consider this term: $(\lambda_2+\lambda_3*PROVAL_{it})*\beta_6$. Similarly as what we did to show the direct impact, we also present a series of estimations for this term in Figure 3. Being consistent with its direct impact, in categories of Download Manager and File Compression, receiving very negative professional reviews has a negative indirect impact on software download through volume of user reviews while receiving very positive professional reviews has a positive indirect impact. However, in other two categories, we find that receiving professional reviews always indirectly increases software download through its positive impact on volume of user reviews regardless of the level of valence.

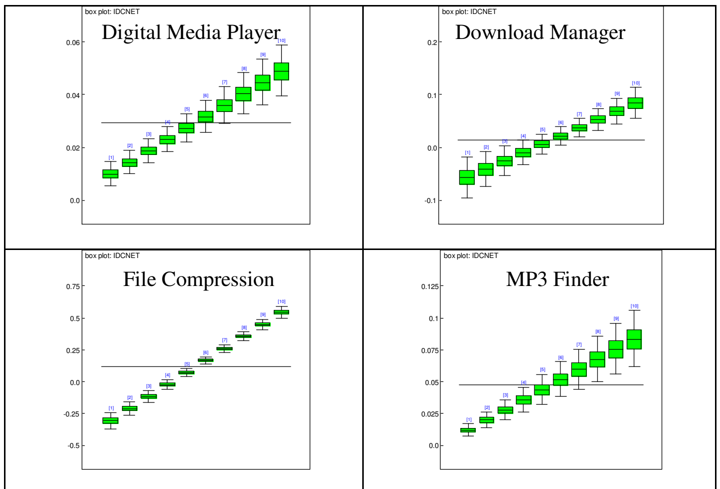

Figure 3. Indirect Impact of Receiving Professional Reviews

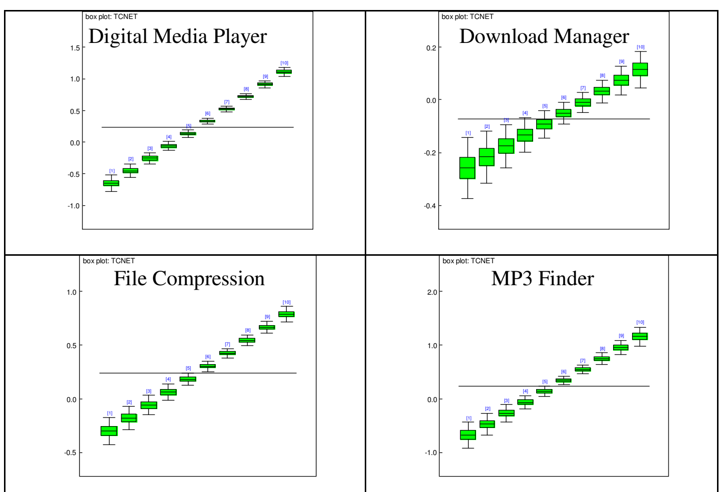

Figure 4. Total Impact of Receiving Professional Reviews

We then investigate the total impacts of both valence of professional reviews and the existence of professional reviews. The former is shown to be significantly positive, indicated by $\beta_5+\lambda_3*\beta_6$. The total impact of whether receiving professional reviews is simply the summation of its direct and indirect impacts, measured by $\beta_4+\beta_5*PROVAL_{it}+(\lambda_2+\lambda_3*PROVAL_{it})*\beta_6$. After a rearrangement, this term becomes $\beta_4+\lambda_2*\beta_6+(\beta_5+\lambda_3*\beta_6)*PROVAL_{it}$. For a better illustration, we report this impact in Figure 4 by a similar manner as we presented its direct/indirect impact. The inference is very similar to that of its direct impact. For example, in category of Digital Media Player, receiving professional reviews with valence lower than 2.5 leads to decreased software download. Only receiving professional reviews with valence higher or equal to 2.5 can result in more download.

The estimations related to valence of online user reviews are similar to those from previous hierarchical moderation model. In each category, the coefficient on $USERVAL^{R}_{it}$ (β_2) is significantly positive, which suggests a difference in sign between the impacts of positive and negative reviews on download. As expected, most of the coefficients on $USERVAL^{R}SQ_{it}$ (β_3^t) are significant over the data collection period as shown in Figure 5, which plots β_3^t by each week. This finding shows that the impact of user reviews denoted by $\beta_2*USERVAL^{R}_{it}+\beta_3^t*USERVAL^{R}SQ_{it}$ varies over weeks. The time variant part of this impact, β_3^t, is explained by our lower level model, $\alpha_1^3+\alpha_2^3*WEEKLYVARIETY_t+\delta_3^t$. We find that in each category α_2^3 is significant, indicating the nonlinear moderation effect of product variety on the impact of user reviews on software download. In other words, the variation of the impact of user reviews is mainly caused by the change in product variety over time. The increase in product variety enforces the impact of positive user reviews on download, while diminishing the impact of negative user reviews. For example, in category of MP3 Finder, the expected value of β_3^t can be explained as $-0.267+0.004*WEEKLYVARIETY_t$, which implies that the addition of one more software program would change the impact of use reviews on software download by $0.004*USERVAL^{R}SQ_{it}$. Thus this change in the impact of user reviews caused by product variety also varies over different valence levels of user reviews. The higher/lower the positive/negative ratings are, the more their impact on software download increases/decreases due to the increase in product variety.

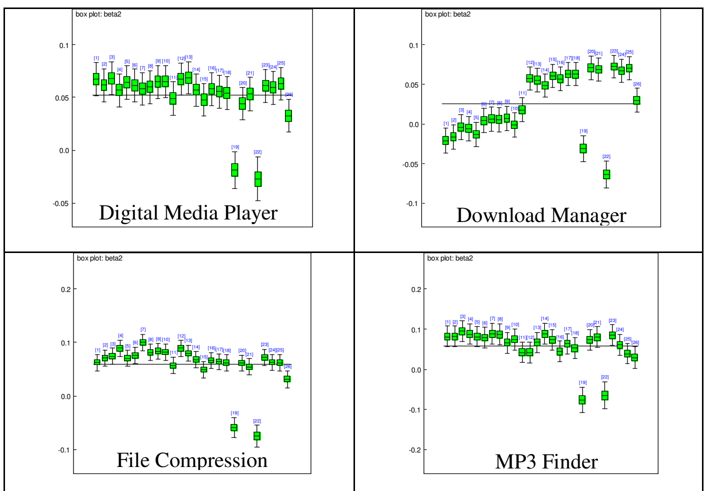

Figure 5. Box Plots for Coefficients on $USERVAL^{R}SQ_{it}$ (β_3^t)

It is also interesting to notice the possible existence of product variety threshold because of the opposite signs of estimated coefficients on $USERVALRSQ_{it}$ (β_3^t) over weeks. Estimated β_3^t are positive over most weeks of our study period but are negative for other weeks as shown in Figure 5 in each category. The lower level model provides a technical explanation that there may exist a switching point of product variety beyond which β_3^t turns positive from negative, given the different signs of α_1^3 and α_2^3. We name this switching point as product variety threshold estimated by $(-1)*(\alpha_1^3/\alpha_2^3)$, which is shown in Table 4. As a result, product variety larger than the threshold would result in positive β_3^t. This suggests that the moderation effect of product variety above threshold strengthens the impact of positive user reviews and weakens the impact of negative user reviews to such a degree that 5-star positive user reviews benefit download more than 1-star negative reviews hurt download. However when product variety is lower than this threshold, β_3^t is expected to turn negative. For example, in category of Digital Media Player, on 19th and 22nd weeks, β_3^t are exceptionally negative due to the much lower product variety during these two weeks than the threshold — 316. In these two weeks, the amount of which 1-star user reviews lead to less software download is significantly larger than the increased number of download by receiving 5-star user review by $8*\beta_3^t$. This is consistent with conclusions from the earlier study conducted by Chevalier and Mayzlin (2006).

Table 4. Estimated Product Variety Threshold								
	M	SD	M	SD	M	SD	M	SD
	Digital Media Player		Download Manager		File Compression		MP3 Finder	
THRESOLD $((-1)*(\alpha_1^3/\alpha_2^3))$	**316**	24.21	**191**	5.117	**139**	5.757	**72**	3.356

We also make a comparison of magnitudes between the impacts of professional reviews and user reviews. We find that valence of professional reviews $((\beta_5+\lambda_3*\beta_6)*PRODVAL_{it})$ is more influential than valence of positive user reviews $(\beta_2*USERVAL^R{}_{it}+\beta_3{}^t*USERVAL^RSQ_{it})$ in each category only when product variety is below threshold to result in negative $\beta_3{}^t$, because of the larger value of $(\beta_5+\lambda_3*\beta_6)$ than β_2. In parallel with this, the valence of professional reviews is more influential than valence of negative user reviews only when product variety is above threshold for positive $\beta_3{}^t$. Yet, since the impact of user reviews is moderated by product variety, the comparison between the impacts of professional reviews and positive/negative user reviews under situations with product variety above/below threshold is indefinite and much more complex. This is in contrast to findings of Amblee and Bui's (2007) study. They regress user choices on both professional reviews and user reviews independently, which only captures the direct impact of professional reviews without investigating the indirect impact of professional reviews on user choices through volume of user reviews. Our results show that total impact of valence of professional reviews $(\beta_5+\lambda_3*\beta_6)$ is larger than its direct impact (β_5) given the positive values of λ_3 and β_6. For example, in category of File Compression, the direct impact only accounts for its total impact by 22.31%. Thus the estimated impact of professional reviews in Amblee and Bui's (2007) study is very likely underestimated.

Conclusions, Discussions and Future Works

We develop a Bayesian analysis of mediation and moderation effects embedded within a hierarchical structure to investigate how online user reviews and professional reviews jointly influence software download. For user-generated online WOM information, we look into two attributes: valence and volume of online user reviews, which are both shown to significantly influence users' decision-making. In terms of valence of online user reviews, we find that product variety moderates the impact of online user reviews on software download, which results in the time variation of this impact. The way consumers react to user ratings depends on how many product choices are available at some time. The increase in product variety enhances the impact of positive user reviews while reducing that of negative user reviews. Consumers tend to get persuaded easier/harder by the positive/negative user reviews as a response to a surge in product variety. In addition, the moderation effect of product variety also infers a possible existence of product variety threshold, which is specific to product category, being consistent with Zhou and Duan's finding (2009). In a market with product variety below threshold, the impact of 1-star user reviews is more significant than the impact of 5-star reviews, which echoes the findings of Chevalier and Mayzlin (2006). On the contrary, in a given product category, 5-star user reviews would benefit download more than 1-star reviews hurt download in a market with abundant products more than threshold level, all else being equal.

In terms of volume of user reviews, consumers prefer products with more user reviews, which is also consistent with results from previous studies (Duan et al. 2008; Liu 2006). This finding reinforces the emphases that volume of online user reviews has received in academic research regarding consumer decision-making of online shopping and supports the practice of encouraging active online user-generated WOM interactions.

Yet, we find that volume of online user reviews also mediates the impact of professional reviews on software download. As a mediator, volume of user reviews magnifies the impacts of both whether receiving professional reviews and valence of professional reviews, via its positive impact on software download. The results from our mediation analysis indicate that consumers do care about whether professionals pick the product to review and the evaluations from them. Consumers are more interested in writing reviews for products with more positive professional reviews, which then leads to more download indirectly. The direct impact of valence of professional reviews on software download is also positive. Thus, overall higher valence of professional reviews is always helpful in promoting download among products reviewed by professionals. However, compared with products not reviewed by professionals, those with very negative professional reviews are receiving less download. Although receiving negative professional reviews may still attract more consumers to write their own reviews, its total impact on software download is negative due to the strong adverse direct impact.

This identified mediation process, through which user reviews and professional reviews influence user choices, is an important finding for practitioners. Professional reviews and user reviews are shown to influence users' decisions in different manners, which makes consumers get more informed by learning from and integrating these two distinct sources of WOM information. Hence our findings recommend that both user-generated and professional reviews should be provided on a single e-commerce platform. Being forced to seek across websites for these two kinds of reviews would inevitably increase consumer search costs and discourage their purchases. Moreover, marketers are suggested to utilize both user and professional reviews for predicting a product's performance. It is sometimes difficult to obtain actual sale and transaction data. Accurate predictions of user choices then become important for firms' marketing and R&D strategies. Since volume of user review only partially mediates the impact of professional reviews, the information of online user reviews alone is not sufficient to obtain an accurate prediction of a product's performance.

Our paper also generates new insights on reconciling the divergent findings of digital WOM effect in literature. First, one possible source for the mixed conclusions regarding the impact of valence of online user reviews could be the omission of the moderation effect of situational variables, which may vary across contexts. The conventional moderation modeling approach is to include interaction terms between user reviews and identified moderators in explaining user choices. However, our empirical comparison between the baseline model and hierarchical moderation model shows a nontrivial likelihood that other omitted moderators exist in addition to product variety, the identified moderator in our study. Therefore, the estimation could still be biased even after modeling the moderation effects of interested factors through the conventional moderation modeling approach, which may infer misleading conclusions about impact of valence of online user reviews.

Second, our results contribute to the understanding of the explanatory power of the impact of online user reviews and professional reviews. Amblee and Bui (2007) find that impact of user reviews and professional reviews are at the same magnitude level by modeling them independently. Our study demonstrates the potentially underestimated impact of professional reviews due to lack of recognizing the mediation process. The direct impact of professional reviews, which is mistakenly treated as the total impact in their study, is shown to be smaller than the actual total impact for all categories in our study. The results from our Bayesian mediation analysis imply that overall the impact of valence of professional reviews is more significant than the impact of valence of positive/negative user reviews for sure only when product variety is below/above threshold.

Third, our findings also contribute to the debate about whether professional reviews are predictors or influencers of user choices. Eliashberg and Shugan (1997) find that professional reviews are predictors instead of influencers. Yet Basuroy et al. (2003) argue that professional reviews are both predictors and influencers of box office revenue. In support of their finding, our results imply that product category could be the reason to cause the disagreement in this debate. Professional reviews function as opinion leaders in terms of their direct impact on user choices and as predictors in terms of their indirect impact on user choices through volume of user reviews. We find that the comparison result between these two influence and prediction effects is indefinite, depending on product category. In other words, in some category, the prediction effect dominates influence effect, which could be the case as Eliashberg and Shugan's study (1997), or vice versa for other categories.

This study can be extended in several directions. We empirically find that for some categories receiving professional reviews always attracts more user reviews while for other categories receiving very negative professional reviews decreases the volume of user reviews. It would be interesting to take a deeper look at the role product category plays in the relationship between receiving professional reviews and volume of user reviews. Our results also imply that the impact of online user reviews could be moderated by situational variables other than product variety. Future research could thus test whether this claim is empirically supported in a specific context with other interesting moderators available. Finally, recent studies point out that the impact of online user reviews on sales diminishes over time because of the early reviews' positive self-selected bias (Li and Hitt 2008). It is thus interesting to examine whether this self-selected bias of user reviews is still significantly positive after controlling for the fluctuation of product variety or other moderators over time.

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