# Do Professional Reviews Affect Online User Choices through User Reviews?: An Empirical Study

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# Do Professional Reviews Affect Online User Choices through User Reviews?: An Empirical Study


### Abstract

With the broad reach of the Internet, online users frequently resort to various word-of-mouth (WOM) sources, such as online user reviews and professional reviews, during online decision making. Although prior studies generally agree on the importance of online WOM, we have little knowledge of the interplay between online user reviews and professional reviews. This paper empirically investigates a mediation model in which online user reviews mediate the impact of professional reviews on online user decisions. Using software download data, we show that a higher professional rating not only directly promotes software download but also results in more active user-generated WOM interactions, which indirectly lead to more downloads. The indirect impact of professional reviews can be as large as 20% of the corresponding total impact. These findings deepen our understanding of online WOM effect, and provide managerial suggestions about WOM marketing and the prediction of online user choices.



**Keywords:** Online user reviews, professional reviews, word-of-mouth, mediation model, online software market, Bayesian modeling


## 1 Introduction

Word-of-mouth (WOM) information has been growing substantially on the Internet, especially in the industries of experience goods, whose attributes are hard to evaluate before consumption. Because of the broad reach of the Internet, consumers can easily access and utilize various types of online WOM information at their fingertips. Nearly 9 out of 10 consumers who read online reviews agree that they are influenced by online reviews before making purchasing decisions [17]. Accordingly, websites and vendors actively solicit WOM information, hoping to promote products and improve products from feedback [53]. For example, many popular websites, such as CNETD (CNET download.com) and Amazon (amazon.com), provide both user reviews and professional reviews for listed products. Online user reviews are generated by online users to share their experience, such as book reviews on Amazon, movie reviews on IMDB (Imdb.com), software reviews on CNETD, and so forth. Professional reviews, on the other hand, are provided by well-trained experts to demonstrate product quality, such as critiques that movies have often received before release, and professional reviews for some selected products on Amazon and CNETD [27].

Spending on online WOM marketing has already exceeded that for offline WOM marketing. Most marketers believe their companies should further increase spending on online WOM [52]. Academic research on the online WOM effect also generally supports the practice of providing online user reviews as well as professional reviews [2, 5, 7, 13, 18, 22, 24, 29, 33, 37, 41, 46, 47, 55 ]. Consumers find online user reviews helpful mainly from two aspects: a large *volume* of user reviews (total number of user reviews) makes the corresponding product stand out from the crowd and thus brings it to consumers' attention [40]; the *valence* of user reviews (average numerical rating) provides consumers information about product quality and influences their attitudes on the expected uncertainty and utility of choosing the product [13, 15, 22, 55]. Professional reviews, however, provide more trustworthy and authoritative judgments by precluding personal biases to some degree [1].

Despite the prevalence of the online WOM marketing strategy in the industry, we lack in-depth understanding of how online user reviews and professional reviews interplay with each other to affect online users' decisions. The common underlying assumption of previous studies is that the way professional reviews influence user choices is independent of the way user reviews affect user choices [1]. Nevertheless, a few empirical investigations have implicitly inferred that professional reviews may indirectly influence user choices through user-generated WOM. Reinstein and Snyder [48] believed that this can explain the surprisingly large impact of professional reviews for dramas and narrowly-released movies found in their study. Although they did not further empirically test it, this argument is also supported by theories on why consumers contribute to online user-generated WOM. A product's professional review is part of the review environment and influences the motivation for which an individual user would choose to write reviews on this product [16, 28, 45, 46]. Built upon this line of research and the already documented causality between volume of online user reviews and user choices [18, 24], we propose that professional reviews influence online user choices indirectly through the volume of online user reviews, in addition to their direct impact. Therefore, this study examines how online user reviews and professional reviews simultaneously influence online user choices by focusing on the mediation relationship.

To do so, we construct a model system in the Bayesian framework, using a panel data set of software downloads and online WOM on CNETD. We find empirical evidence that professional reviews influence software downloads, being partially mediated by the volume of user reviews. In particular, online users are more willing to write reviews on products with higher professional ratings, and this leads indirectly to more download. More interestingly, we find that although the direct impact is generally larger than the indirect impact, the latter is still too significant to be neglected. The indirect impact of professional rating can be as large as one fourth of the direct impact. In addition, receiving a professional review matters a lot, compared to not being reviewed by experts at all. Receiving a 1-star professional review can overall reduce the number of software downloads by up to 40%, compared to not receiving a professional review, all else being equal. On the contrary, receiving a 5-star professional rating can even double the download of not being selected by experts for a professional review. Those findings strongly suggest that firms should proactively solicit positive professional reviews. The managerial implications are discussed in more details at the end of the paper.

Our work expects to contribute to the literature mainly in two ways. First, this research adds to the literature that examines multiple WOM sources by identifying the mediation model for the effect of online user reviews and professional reviews. To our best knowledge, this work is the first to study the mediation role of volume of online user reviews on the relationship between professional reviews and user choices. Second, this research applies and expands two theories of the generation of online user reviews. We find that professional reviews affect users' decisions on whether to post feedback online. Those contributions are discussed in detail in the next section.

## 2 Related Literature

In this study, we mainly draw on two streams of research in Information Systems and Marketing: (1) the impact of online user reviews and professional reviews, and (2) the generation of online user reviews. Built upon those related studies, we propose our research model at the end of this section.

### 2.1 The impact of online user reviews and professional reviews

Two measures of online user reviews have been widely discussed: volume and valence. Volume of user reviews has been found to significantly improve market outcome [15, 18, 40, 47]. A larger volume of user reviews can better attract users' attention to the product and accordingly results in a higher chance of choosing it [24, 40]. Unlike the consistent opinion about volume of online user reviews, opinions about the relationship between valence of online user reviews and user choices have been mixed. Some researchers believe that valence of user reviews can have a persuasive effect on user attitudes and thus has a positive impact on user choices [13, 15, 22, 55]. However, other scholars have concluded that valence of online user reviews do not influence user choices [6, 12, 40]. Recently, some scholars have proposed a potential explanation to reconcile those divergent conclusions by examining the moderation effects of contextual factors. Factors such as product popularity information and product variety, which characterize the context where online WOM and user choices occur, are believed to moderate the impact of the valence of online user reviews [56, 42, 55, 56]. In other words, online users' reliance on online user ratings depends on the level of contextual moderators. We adopt this finding in our modeling of valence of online user reviews.

As another WOM source, professional reviews are provided by experts to build up the product reputation, offer product information, and serve as advertisements [27]. Extant studies have agreed on the significant relationship between professional reviews and user decisions [1, 5, 8, 11, 35, 38, 48]. For instance, professional reviews function as opinions leaders and thus play the role of influencer in affecting online users' decisions [39, 48]. Reinstein and Snyder [48] found the influence impact of professional reviews on opening weekend box office revenue is surprisingly large for dramas and narrowly-released movies. They suspected the underlying reason is this impact includes the direct impact, and also the indirect impact through user feedback. Our work provides evidence for Reinstein and Snyder's inference by validating the mediation role of online user reviews on the influence impact of professional reviews.

However, most of those studies either examine a single WOM source, for example, online user reviews or professional reviews, or investigate them together but independently (see Table 1 for a summary of some representative WOM studies). The only two exceptions are studies conducted by Chakravarty et al. [10] and Liu [40]. Chakravarty et al. [10] found that consumer's reliance on the valence of online user reviews depends on the presence of conflicting professional reviews, through lab experiments. In essence, Chakravarty et al. [10] conceptualized professional ratings as contextual moderators for the valence of online user reviews. Different from their focus, we do not aim to show how another WOM source affects online user's reliance on online user ratings. Instead, we investigate whether the WOM generated by experts, that is, professional reviews, affects the generation of online user reviews, and how such impact transmits the impact of professional reviews to online user choices. We recognize the mediation role of volume of online user reviews by which professional reviews can influence online users' willingness to participate in online WOM. Therefore, professional reviews can influence user decisions through user reviews, a mechanism which has not been fully considered in the WOM literature.

Insert Table 1 about here

The study conducted by Liu [40] directly tests the impact of professional reviews on volume of online user reviews, although its main focus is the dynamics of online user reviews and their impact on sales. Liu's underlying argument is that professional reviews can affect online users' expectations of a film and hence influence the generation of online user reviews on this film. However, this impact can be insignificant if online users do not actually read professional reviews. Liu's empirical findings support the latter. Professional reviews from *Variety* magazine were not found to influence the volume of user-generated messages on Yahoo Movies. Unlike Liu's study [40], which used professional reviews from offline media, we aim to investigate professional reviews hosted by websites. Various studies have shown that online users now widely resort to WOM information across websites due to the low cost of online searching [26].

Many websites, such as Amazon and CNETD, readily display both online user reviews and professional reviews on the product page. Therefore, in terms of professional reviews distributed by websites, we expect a different result from Liu's findings [40] about the relationship between professional reviews and online user reviews.

This study also adds to the understanding of the impact of professional reviews in the literature by indicating that the impact of professional reviews is possibly underestimated in extant studies. Prior work, which investigated online user reviews and professional reviews simultaneously, did not realize the mediation role of user reviews and thus only took into account the direct impact of professional reviews. The indirect impact professional reviews on user choices through user-generated WOM was omitted. Our study explicitly models both direct and indirect impacts and compares their magnitude, to quantify the underestimation that results from omitting the indirect effect. In fact, our empirical results show that the indirect impact of professional reviews accounts for up to one fifth of the total impact of professional reviews.

### 2.2 Why do people write reviews online

The second stream of relevant literature concerns effects on users' decisions to share feedback online. There are two main theories: psychological motivation theory and review environment theory. We apply both theories to propose that professional reviews can affect the volume of online user reviews. This argument helps to propose our mediation model in the next sub-section.

The first theory looks into the psychological motivation behind users' sharing behavior. Users are shown to share their experiences online for self-enhancement [16, 28]. Self-enhancement is defined as users' emotional desires to gain attention and enhance their images among others [16, 28, 50]. Hennig-Thurau et al. [28] empirically verified that self-enhancement has a significant impact on the number of comments in online opinion platforms. Therefore, psychological motivation theory implies that users are willing to write reviews to different extents towards products with and without professional reviews. One the one hand, professional reviews can be perceived by online users as a popularity or eye-catching indicator of the corresponding product, because professional reviews, unlike abundant user-generated WOM, are normally only offered on a limited number of products by a small group of specialized experts. In other words, products that are reviewed by experts are more visible, compared to those without professional reviews. By writing reviews on those highlighted products that receive professional reviews, users may perceive a greater potential to get others to read their feedback and thus be more likely to project themselves as intelligent shoppers. On the other hand, online users may foresee a greater value of their reviews perceived by the readers in absence of professional reviews, and thus are more motivated to write reviews on those products. Both two competing arguments can occur. Therefore, we would expect to see a significant relationship between professional reviews and volume of online user reviews. However, we would leave the question of which argument is more significant to our empirical analysis.

Review environment theory also supports this relationship between professional reviews and volume of online user reviews. In essence, it argues that users' decisions to post reviews are subject to environmental factors, such as others' opinions [25, 44, 45]. For example, ratings previously posted by early users can influence the feedback posted afterwards [45]. Online user interactions can also increase the number of product reviews [25]. Following this theory, we also argue that professional reviews, when they are normally offered either earlier than or concurrently with online user reviews, contribute to characterize users' review environment. As a result, what experts have said about an individual product can influence users' decisions on whether to write reviews on this product. Our study empirically validates professional reviews as an environmental factor that affects users' decisions of whether to post feedback online.

The above theoretical inference is also echoed by a significant positive correlation between professional ratings and the volume of online user reviews found in an earlier work [31]. However, this previous study did not look into the causality nor the impact of professional reviews on the final user choices. Instead, it perceived volume of online user reviews as an indicator of the ordinary users' taste and compared it with experts' evaluations. Being different from this work, our study adopts various statistical techniques to test the causal impact of professional reviews on volume of online user reviews. Moreover, we also take a step further to investigate the indirect impact of professional reviews on online user choices through influencing the volume of online user reviews.

### 2.3 Mediation Model

Based on the above literature review and discussion, we propose our research model by following mediation literature. Mediation literature theorizes two conditions for specifying a mediation model: (1) the initial variable can influence the mediator but not vice versa; (2) the mediator is an influencer of the outcome [4]. We apply these two mediation criteria to theoretically propose the mediation role of volume of online user reviews (the mediator) on the relationship between professional reviews (the initial variable) and user choices (the outcome). We do not propose valence of online user reviews as the mediator, mainly because ordinary users and experts have been shown to have different criteria in their evaluations [30]. The first condition of valence being a mediator would thus lack theoretical support.

First of all, we argue that professional reviews influence the amount of online user-generated WOM, which is commonly measured by the volume of online user reviews [18, 40]. As discussed beforehand, we argue that what experts have said may affect an individual user's decision of whether to write a review by applying two theories regarding the generation of online user reviews. However, both theories imply two competing arguments on whether favorable professional reviews outperform negative professional reviews in motivating users to post. Psychological motivation theory focuses on the perspective of user's self-enhancement. Users can perceive more positive professional reviews as a signal of higher popularity and are more willing to share their comments on the corresponding product. This argument is also supported by an empirical finding of a positive correlation between professional rating and the volume of IMDB user reviews in the movie industry [31]. However, because experts normally choose to review popular products, whose qualities are generally decent, most professional reviews lean toward non-negative opinions. Therefore, users can more easily differentiate their reviews from other abundant user-generated WOM information by posting on a very small number of products that receive unexpected negative professional reviews. Meanwhile, the review environment theory also debates over the "bandwagon" effect versus the "underdog" effect [44, 45]. On one hand, users may favor products for posting feedback that were winners in the opinion poll, but on the other hand they can certainly prefer to review products that were behind by others' opinions. Therefore, our study leaves the direction of the impact of professional rating on volume of online user reviews to empirical examination and offers subsequent justification.

In addition, volume of online user reviews should not have a causal impact on professional reviews. There are two main reasons. First, the time lag of the availability between professional reviews and online user reviews helps rule out the possibility that experts simply favor or dislike products with more user reviews. Professional reviews usually precede user reviews and become available at the early stages of products' life cycles, before users have extensively spread the word online. For example, in the movie industry, critics are often invited to view the film and publish their reviews even before the film is open to the public. In addition, the nature of professional reviews also determines that professional evaluations should not be determined by how many users have participated in WOM activities. Professional reviews are expected to be more objective and unbiased, as a proxy of product quality [33, 38]. Therefore, the extent to which users participate in online WOM activities can be influenced by professional reviews posted earlier, but not the vice versa, which meets the first mediation criterion.

Second, volume of user reviews has been widely shown to improve market outcome [15, 18, 22, 40]. The underlying rationale is that online users are more likely to get informed about products with a larger volume of user reviews, which in turn promotes online user choices [24]. As a result, the second condition of volume of user reviews being a mediator is valid as well. Based on the aforementioned discussion, we propose volume of user reviews as the mediator on the impact of professional reviews, depicted by Figure 1. We include both the indirect impact of professional reviews via volume of user reviews (path *a*->*b*) and the direct impact (path *c*), indicating a partial mediation [32].

Insert Figure 1 about here

# 3 Data

## 3.1 Research Context

We conducted this study in the online software market. As a typical type of experience goods, the quality of a software program is difficult to evaluate before adoption. In the meantime, the product variety of software programs offered through online channels has been increasing tremendously in recent years [55]. Hence, in the current online software market, it is challenging for online users to locate matched products out of the abundant product selection. This motivates them to extensively resort to various WOM sources, hoping to make well-informed decisions

[26, 41, 54]. Online users with intentions to purchase software programs also have the knowledge and Internet experience to explore online review communities and utilize WOM. Therefore, the nature of software programs, abundant product choices, and online users' IT knowledge determine that users in the online software market have the need and capability to search for and use both professional reviews and user reviews, which are the two most common sources of online WOM information. This makes the online software market an appropriate context to study the mediation mechanism under which professional reviews and online user reviews influence user choices.

In particular, we empirically examine our mediation model by using the data collected on CNETD. User reviews and professional reviews both are available on CNETD. Specifically, for each software program, users can post reviews by detailed textual comments and an overall rating on a scale of 1 to 5, with 1 being the worst and 5 being the best. CNETD summarizes user feedback by highlighting the total number of reviews and providing an average rating based on all user reviews the product has received. As a result, we can easily access the information regarding volume and valence of online user reviews. CNETD also provides professional reviews for some selected software programs by a similar five-star rating system. CNETD editors pick popular products to review by scouring and scrutinizing "*blogs, sites, aggregators, RSS feeds, and any other available resources*" to monitor the review coverage. A selected product will receive one professional review from a CNETD editor in the format of a rating and a detailed comment, normally as soon as the product is first announced. This allows our study to examine the impacts of the aforementioned two sources of online WOM information simultaneously, and avoid linking two independent websites providing those two WOM sources individually.

In addition, CNETD has already been adopted in the literature as an appropriate context in the online software market to examine the online WOM effect [19, 41, 55]. CNETD is a leading and representative online platform for software downloads free of charge. It provides over 30,000 software programs for four operation systems, including Windows, Mac, mobile devices, and webware. Software programs hosted by CNETD have two free trial licenses: free for the lifetime (free) and free to try for limited time (free-to-try). For each operation system, there are more than 10 groups of software programs with approximately 5 to 20 categories in each group. For each software program, it also lists detailed product descriptions as well as weekly and cumulative download counts.

We collected weekly data from August 2007 to February 2008 in four categories over 26 weeks. These four categories are: Digital Media Player, Download Manager, File Compression, and MP3 Finder. They include popular categories and also categories with different application purposes, which are good representations of the online software market. Thus, the data provides us a diversified coverage to explore a large number of user decisions on choosing software and sharing experience. In particular, we extracted the following information on every software program listed in each category on a weekly basis: software name, date first posted on CNETD, software characteristics, total downloads, last week downloads, average user ratings, number of cumulative user reviews, whether the product was reviewed by a CNETD editor, and the CNETD rating, if any. Since every category represents a unique group of software programs with similar functions, we defined each category as a single market, following previous studies [19]. We also followed the literature to define product variety by using the total number of available software programs in each category [55]. The following Table 2 and Table 3 provide the detailed explanations of all the variables used in this study and summary statistics of some key variables respectively.

Insert Tables 2 and 3 about here

### 3.2 Key Variables

Following the literature [19, 55], we used software download ($WEEKLYDOWNLOAD_{i,t}$) to capture online user choices of software programs. We applied a natural log transformation on the weekly software download ($LOG(WEEKLYDOWNLOAD_{i,t})$) to reduce the nonconstant variance. In terms of online user reviews, similarly, we followed the literature to use the weekly number of online user reviews as a measure of review volume ($WEEKLYUSERVOL_{i,t}$) [18, 40]. CNETD posts cumulative number of reviews for each software program, therefore, $WEEKLYUSERVOL_{i,t}$ is calculated as the difference in the number of cumulative user reviews between week $t$ and week $t-1$. This requires us to use software programs that existed in two consecutive weeks in the data. Following extant research, we applied a natural log transformation on $WEEKLYUSERVOL_{i,t}$ as $LOG(WEEKLYUSERVOL_{i,t})$ to have a log-linear relationship with $LOG(WEEKLYDOWNLOAD_{i,t})$ [18, 40]. In addition, we used cumulative average user rating (on a scale of 1 to 5) as a measure of review valence ($USERVAL_{i,t}$), which is readily posted on CNETD for each software program. Reviews of valence above/equal/below 3 were defined as positive/neutral/negative user reviews. We also defined positive/neutral/negative professional reviews in a similar way. As suggested by the literature, we made a simple linear transformation on $USERVAL_{i,t}$. The impact of user reviews on user choices has been shown to be nonlinear with respect to valence level [13, 14, 55]. To help differentiate the impacts of user reviews with different valence levels, we used $USERVAL_{i,t} - 3$ instead of $USERVAL_{i,t}$, which is named as $USERVAL^{R}_{i,t}$ for parsimony, since 3 is the middle point of the rating scale. Built upon this, we then included both $USERVAL^{R}_{i,t}$ and its quadratic term of $USERVAL^{R}_{i,t}$, denoted by

$USERVAL^{R}SQ_{i,t}$, model weekly downloads. As a result, neutral user reviews have zero values of $USERVAL^{R}_{i,t}$, and positive and negative reviews have nonzero values of $USERVAL^{R}_{i,t}$ and $USERVAL^{R}SQ_{i,t}$. To account for the case where the product doesn't receive any user reviews, we also used a dummy variable, $USERD_{i,t}$. If the product has not received one single user review by week $t$, $USERD_{i,t}$ is zero, otherwise its value is 1.

In terms of professional review, we also intentionally differentiated between review rating and review existence. Unlike user reviews, experts, in a much smaller community than ordinary users, only have limited time to review a fairly small portion of products available on the market. For example, as shown in Table 3, in the category of Digital Media Play, CNETD editors only review approximately 10% of posted products. As a result, it is important to understand whether receiving the professional review matters to a product's performance, in addition to the impact of the professional rating [1]. Accordingly, we included two terms, a dummy variable $PROD_{i,t}$ and professional rating $PROD_{i,t}*PROVAL_{i,t}$, to differentiate products with professional reviews from those without, and to capture the impact of professional rating respectively. We used a dummy variable $PROD_{i,t}$ to capture whether the software program was reviewed by a CNETD editor. And if so, $PROVAL_{i,t}$ captures the professional rating. As for products without CNETD professional reviews, their $PROVAL_{i,t}$ values are irrelevant to model estimation and thus they were specified as zero for simplicity. Because each selected program will only have one professional review from a CNETD editor, we did not consider the volume of professional reviews in this context.

We argue that CNETD editors are very unlikely to give professional evaluations based on CNETD users' download choices and reviews. This supports the first condition of specifying a mediation model that the mediator (volume of online user reviews) doesn't affect the initial variable (professional reviews) [4]. CNET claims their professional ratings being "*fair and useful*", as CNETD editors have their own set of standards to select and rate products, being independent of market responses. As a result, CNETD professional ratings have been used as an objective measure of product quality [38]. Empirical evidence also indicates that they are exogenous with respect to online user choices [40]. In addition, this argument is supported by the fact that CNETD professional reviews are usually posted at the early stages of selected software programs' life cycles and don't change much over time. CNETD claims that if a reviewed product has a substantial technology update, CNETD editors update their reviews within two business days. However, this didn't occur in our data, as we failed to observe any update of CNETD professional rating after being posted during the data collection period.

Finally, we followed the prior studies [40] to use a one-week lag between independent variables and dependent variables of software download and WOM. This can better represent the actual decision-making process and help control for the potential feedback effect of the dependent variable on the relevant independent variables, given the dynamics between online WOM and online user choices suggested by the literature [18, 40]. Therefore, combined with the calculation need for $WEEKLYUSERVOL_{i,t}$, we only kept software programs that existed in three consecutive weeks. Overall, we were able to compile a longitudinal data set of those two sources of online WOM information over 24 weeks to analyze the dynamics of online user choices.

# 4 Empirical Model and Results

## 4.1 Model

We followed the full procedures of mediation analysis suggested by Baron and Kenny [4] to empirically test our mediation model of the relationship among professional reviews, online user reviews, and online user choices. We first conducted some preliminary steps by individually testing the path *c* when path *a* and path *b* of Figure 1 are not considered, and the path *a* when path *b* and path *c* are not considered [4, 32]. The results show that professional reviews are correlated with online user choices and with volume of online user reviews, respectively. Hence, as the main step of the mediation analysis [4], we proceeded to test the full mediation model as below, which is a system of four equations.

$$
\begin{aligned}
&\text{Software Download Equation:}\\
&LOG(WEEKLYDOWNLOAD_{i,t}) = \beta_1^t + \beta_2 * USERD_{i,t-1} + \beta_3 * USERD_{i,t-1} * USERVAL^R_{i,t-1}\\
&\quad + \beta_4^t * USERD_{i,t-1} * USERVAL^R SQ_{i,t-1} + \beta_5 * PROD_{i,t-1} + \beta_6 * PROD_{i,t-1} * PROVAL_{i,t-1}\\
&\quad + \beta_7 * LOG(WEEKLYUSERVOL_{i,t-1}) + \beta_8 * LOG(TOTALDOWNLOAD_{i,t-1}) + \beta_9 * WEEKLYRANK_{i,t-1}\\
&\quad + \beta_{10} * WEEKLYRANKSQ_{i,t-1} + \beta_{11} * FREEPRICED_{i,t} + \beta_{12} * AGE_{i,t} + \beta_{13} * AGESQ_{i,t} + \varepsilon_{i,t}\\
&\text{Volume of User Reviews Equation:}\\
&LOG(WEEKLYUSERVOL_{i,t}) = \lambda_1 + \lambda_2 * PROD_{i,t-1} + \lambda_3 * PROD_{i,t-1} * PROVAL_{i,t-1}\\
&\quad + \lambda_4 * LOG(WEEKLYUSERVOL_{i,t-1}) + \lambda_5 * USERD_{i,t-1} + \lambda_6 * USERD_{i,t-1} * USERVAL_{i,t-1}\\
&\quad + \lambda_7 * LOG(TOTALDOWNLOAD_{i,t-1}) + \lambda_8 * WEEKLYRANK_{i,t-1} + \lambda_9 * WEEKLYRANKSQ_{i,t-1}\\
&\quad + \lambda_{10} * FREEPRICED_{i,t} + \lambda_{11} * AGE_{i,t} + \lambda_{12} * AGESQ + \delta_t + \sigma_{i,t}\\
&\text{Lower Level Equations:}\\
&\beta_j^t = \alpha_1^j + \alpha_2^j * WEEKLYVARETY_t + \delta_j^t\\
&i = 1,\ldots,I;\ j = 1,3;\ t = 3,\ldots,26
\end{aligned}
\tag{1}
$$

In particular, we constructed the first two equations to systematically model the proposed mediation relationship: software download equation and volume of user reviews equation. Specifically, in the software download equation, volume of user reviews ($LOG(WEKKLYUSERVOL_{i,t-1})$) is the mediator and software download ($LOG(WEEKLYDOWNLOAD_{i,t})$) is the outcome variable. Volume of user reviews is shown to be endogenous with respect to contemporaneous online user choices, due to the potential reverse causality that user choices can affect the review volume at next time period [18, 40]. To address this issue, our model adopts the time lag between those two variables ensures that the independent variable $LOG(WEKKLYUSERVOL_{i,t-1})$ occurs before the dependent variable $LOG(WEEKLYDOWNLOAD_{i,t})$. Therefore, $\beta_7$ can measure the impact of volume of user reviews on software download (path *b* in Figure 1). Two variables concerning professional reviews are included to capture path $c$: $PROD_{i,t-1}$ and $PROD_{i,t-1}*PROVAL_{i,t-1}$. As suggested by the mediation literature [4, 32], the direct impact of professional rating is measured by $\beta_6$, and the direct impact of whether the software received professional review is captured by $\beta_5+\beta_6*PROVAL_{i,t-1}$.

The second equation, volume of user reviews equation, is used to capture path $a$ in Figure 1. Following the mediation analysis literature [4, 32], we used the mediator of software download equation, ($LOG(WEKKLYUSERVOL_{i,t-1})$, as the outcome variable and professional review ($PROD_{i,t-1}$ and $PROD_{i,t-1}*PROVAL_{i,t-1}$) as the independent variables. As a result, the indirect impact of professional rating on online user choices is measured by $\beta_7 * \lambda_3$ (path $a$->$b$), mediated by volume of online user reviews. We also allowed the error terms of those two equations ($\varepsilon_{i,t}$ and $\sigma_{i,t}$) to be correlated as below, to account for any unknown shocks that simultaneously affect both weekly downloads and volume of user reviews. The correlation between error terms can be thus calculated as $\sum \varepsilon\sigma / \sqrt{\sum \varepsilon\varepsilon \sum \sigma\sigma}$ .

$$\begin{bmatrix} \varepsilon_{i,t} \\ \sigma_{i,t} \end{bmatrix} \sim MVN\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sum_{\varepsilon\varepsilon} & \sum_{\varepsilon\sigma} \\ \sum_{\sigma\varepsilon} & \sum_{\sigma\sigma} \end{bmatrix} \right) \tag{2}$$

To robustly estimate the mediation relationship, several control variables are added in both two equations. Specifically, we included nine control variables in the volume of user reviews equation (path $a$). In particular, we first added $LOG(WEEKLYUSERVOL_{i,t-1})$ to control for the impact of last week's volume of user reviews. $USERD_{i,t-1}$ and $USERD_{i,t-1}*USERVAL_{i,t-1}$ are included, because the valence of user reviews are argued to influence volume of user reviews that a product receives [18]. If the product has not received one single user review yet, $USERD_{i,t-1}$ is zero. The value of $USERVAL_{i,t-1}$ is thus technically irrelevant to the estimation and treated as zero. In addition, $LOG(TOTALDOWNLOAD_{i,t-1})$) is added to be a proxy for product quality as well as help control for the overall user base. We also added $WEEKLYRANK_{i,t-1}$ and its square term $WEEKLYRANKSQ_{i,t-1}$ to control for the influence of product popularity [19]. Another control variable is a dummy variable, $FREEPRICED_{i,t-1}$, to control for the free trial license difference in the software. Product age $AGE_{i,t-1}$ and its quadratic term $AGESQ_{i,t-1}$ are also included to control for the impact of the stage in product life cycle. Lastly, we used a time-fixed effect to control for any unobserved heterogeneity over time, denoted by $\delta_t$ in the equation.

Similarly, software download equation (path *b* and *c*) also includes several control variables. We also included $WEEKLYRANK_{i,t-1}$ and its square term $WEEKLYRANKSQ_{i,t-1}$, and $FREEPRICED_{i,t}$ to control for any download difference caused by product popularity and free trial license difference [51]. Product age $AGE_{i,t-1}$ and its quadratic term $AGESQ_{i,t-1}$ are also included to control for product diffusion [19]. To control for the network effect, the log-transformed accumulative number of downloads ($LOG(TOTALDOWNLOAD_{i,t-1})$) is added [9, 20].

In addition, in this equation, we also adopted the same technique of using $USERD_{i,t-1}$, a dummy variable, and treated $USERVAL_{i,t-1}$ as zero to account for the case where user rating is not available. We further captured the nonlinear impact of valence of online user reviews by including the linear and quadratic terms of average user rating, $USERD_{i,t-1}*USERVAL^{R}_{i,t-1}$ and $USERD_{i,t-1}*USERVAL^{R}SQ_{i,t-1}$, and by controlling for the moderation effect of product variety. We adopted product variety as an identified contextual moderator in this study by following a previous research, which was also conducted in the similar context of CNETD to find product variety as a valid moderator for online user ratings [55]. In particular, we managed to control for this context heterogeneity by applying a hierarchical structure [23]. We first modeled the potential linear and nonlinear moderation effect of product variety by allowing coefficients on both $USERD_{i,t-1}*USERVAL^{R}_{i,t-1}$ and $USERD_{i,t-1}*USERVAL^{R}SQ_{i,t-1}$ to vary over product variety. However, the results showed that product variety moderates valence of online user reviews only in the quadratic way. Therefore, we only kept the hierarchical structure on the coefficient of $USERD_{i,t-1}*USERVAL^{R}SQ_{i,t-1}$ ($\beta_4^t$) in the software download equation above to capture the quadratic moderation effect of product variety. Specifically, we allowed the coefficient on $USERD_{i,t-1}*USERVAL^{R}SQ_{i,t-1}$ ($\beta_4^t$) to be random over weeks and explained it by a lower level equation with product variety as the independent variable. The error term $\delta_3^t$ can control for all omitted time-variant moderators within the lower level equation. The literature regarding hierarchical model methodology suggests completely separating the lower level dimension (the time dimension) from the estimation of the software download equation [49]. As a result, the intercept term ($\beta_1^t$) in the software download equation also varies with weekly product variety and an error term $\delta_1^t$. This time-variant intercept ($\beta_1^t$) can thus help control for any unobserved time-variant demand shock.

Overall, in the above main step of a mediation analysis, we are particularly interested in the coefficients on $PROD_{i,t-1}$, $PROD_{i,t-1}*PROVAL_{i,t-1}$ and $WEEKLYUSERVOL_{i,t-1}$ ($\beta_5$, $\beta_6$, $\beta_7$) in software download equations, and the coefficients on $PROD_{i,t-1}$ and $PROD_{i,t-1}*PROVAL_{i,t-1}$ ($\lambda_2$, $\lambda_3$) in volume of user reviews equation[4, 32].

## 4.2 Estimation results

We employ a Bayesian framework in this study, mainly because it is technically more feasible and efficient to implement mediation analysis, compared to the frequency framework. It is always a challenge to robustly estimate the standard error for the mediated impact (path *a->b*) by frequency statistics [43]. Specifically, it can be difficult to estimate the standard error for the indirect impact of professional rating in the frequency framework, measured by $\lambda_3*\beta_6$, because the distribution of the product of two normally distributed variables is unknown. In addition, the Bayesian framework is also shown to particularly fit the hierarchical model for better capturing moderation effects [23]. Therefore, we choose to estimate the whole model by using the MCMC method, which is a widely adopted computational simulation method in Bayesian statistics [22, 49]. It constructs a large number of MCMC chains whose stationary distribution approximates the posterior distribution of the unknown parameter. The posterior mean of the unknown parameter is thus approximately calculated by the mean value of the MCMC chains that converge to the stationary. Hence, to estimate the mediation effect, the MCMC method can simply calculate a product of $\lambda_3$ and $\beta_7$ from each MCMC draw, which produces a sample of a new quantity: $\lambda_3 * \beta_7$. And the standard error of $\lambda_3 * \beta_7$ can be easily computed. Specifically, in each category, we first run the MCMC chain of 15,000 burn-in draws and use an additional 15,000 target draws to characterize the posterior distributions of parameters. Before discussing the results, we use history and autocorrelation plots as well as the results of the Gelman-Rubin diagnostic to make sure that our MCMC draws have achieved the convergence and thus the estimates are reliable [21,49].

We present the results of coefficients in Table 4 through the posterior means and standard deviations. We primarily focus on the mediation process illustrated by three paths in Figure 1, as the main step of a classic mediation analysis. In the software download equation, the coefficient on $LOG(WEEKLYUSERVOL_{i,t-1})$ ($\beta_7$) is significantly positive in each category, indicating the positive impact of volume of online user reviews on software downloads, which supports path *b* in Figure 1. This result is consistent with previous findings [40]. The coefficients on $PROD_{i,t-1}$ ($\beta_5$) and $PROD_{i,t-1} * PROVAL_{i,t-1}$ ($\beta_6$) in this equation are also significant for each category. Specifically, $\beta_5$ indicates that whether the product is selected by experts for reviews directly matters to software downloads, and $\beta_5$ shows an increase in professional rating has a positive direct impact on software downloads. Path *c* in Figure 1 is thus verified.

Insert Table 4 about here

In the volume of user reviews equation, the coefficients on $PROD_{i,t-1}$ ($\lambda_2$) and $PROD_{i,t-1}*PROVAL_{i,t-1}$ ($\lambda_3$) are significant, in every category supporting path *a* in Figure 1. Specifically, the positive $\lambda_3$ denotes a positive impact of professional ratings on volume of user reviews, which sheds some lights on the competing implications from two theories of generation of online user reviews as discussed in section 2.3. We find that online users are more willing to share their feedback on products that have received higher professional ratings. For example, in the category of File Compression, nearly 10% more consumers will write reviews on the product if its professional rating increases by one star, indicated by ($e^{\lambda_3}-1$). However, the negative sign of $\lambda_2$ on $PROD_{i,t-1}$ implies that receiving a very negative professional review can discourage online users to share their experiences, which will be extensively discussed in the paragraph for interpreting the indirect impact of receiving a professional review.

Based on the coefficients on path *a* and *b* estimated in the full model, we find that the indirect impact of professional ratings on downloads ($\lambda_3*\beta_7$) is significantly positive, mediated by volume of user reviews through path *a->b*. The total impact of professional rating is thus shown to be significantly positive, indicated by $\beta_6+\lambda_3*\beta_7$. For instance, if a product receives an increase of one star in the professional rating, its downloads can increase by up to 30% in the category of Digital Media Player, indicated by ($e^{(\beta_6+\lambda_3*\beta_7)}-1$). In addition, we find that the indirect impact of professional rating ($\lambda_3*\beta_7$) is generally smaller than its direct impact ($\beta_6$) in all categories. However, it still has a significant weight in the total impact and thus should not be neglected. For example, in the category of MP3 Finder, the indirect impact of professional rating accounts for around 20% of its corresponding total impact. Thus, while using both online user reviews and professional reviews to explain online user choices, omitting the path *a*, i.e. the mediation role of user review, may cause a serious underestimation in the impact of professional rating. This result supports the finding of Reinstein and Snyder [48] that the estimated impact of professional reviews for dramas and narrow release movies is shown to be surprisingly larger, because it can embodies both direct and indirect impact. Overall, those estimations successfully support three paths in Figure 1 [4, 32].

As the last step of testing a mediation model [4, 32], we also estimated an additional last-step model that doesn't include path *b* and compared it with the above mediation model. The detailed model illustrations and estimation results of this last-step model are reported in Appendix 1. The classic mediation analysis requires that the impact of professional reviews on software downloads in the last-step model should be more significant, than the estimated direct impact in the full mediation model (eq. 1). The key rational is that if the mediation model is valid, the impact of professional reviews estimated in the last-step model actually includes both the direct impact and the indirect impact that are individually estimated by the mediation model. Our comparison in Appendix 1 finds supportive evidence and thus helps verify our proposed mediation model. [32].

We also look into the indirect, direct and overall impact of whether the product receives professional reviews. Naturally, all of them depend on the specific professional rating, measured by $(\lambda_2+\lambda_3*PROVAL_{i,t-1})*\beta_7$, $\beta_5+\beta_6*PROVAL_{i,t-1}$ , and the sum of those two terms, respectively. For a better illustration, we present a series of estimations for each of those three impacts at every possible professional rating, that is, 0.5, 1,…, 4.5, 5, by a series of caterpillar plots, which are reported in Appendixes 2, 3 and 4 respectively. In terms of the indirect impact, in most categories, although products are better off receiving higher professional ratings, receiving a very negative professional review can have a negative indirect impact on software downloads through volume of user reviews; while receiving a positive professional review has a positive indirect impact on downloads. The sign of the indirect impact of receiving a professional review is actually determined by the sign of its impact on volume of user reviews, given the positive $\beta_7$. Because of the negative $\lambda_2$, in those categories, receiving a very negative professional review can discourage user participation in online WOM activities, denoted by the negative value of $(\lambda_2+\lambda_3*PROVAL_{i,t-1})$; on the other hand, receiving a positive professional review can encourage active user-generated WOM. However, we find a slightly different result in one category, Download Manager. In this particular category, the indirect impact of receiving a professional review is negative, as compared to not receiving a professional review, even if it is a 5-star professional rating, due to the much larger magnitude of $\lambda_2$ with respect to $\lambda_3$. We believe this can be related with the discussion over the "bandwagon" effect versus the "underdog" effect [44, 45]. In some categories (markets), online users prefer to review the winner products; in other categories, they may prefer to review those underdogs that are not selected by experts.

The caterpillar plots in Appendix 3 show a very consistent result for the direct impact of receiving a professional review among all four categories. Receiving a negative professional review is directly worse than not receiving. However, receiving a positive professional review directly benefits the corresponding product. The total impact of receiving a professional review is measured by the sum of the indirect and direct impact, $\beta_5+\beta_6*PROVAL_{i,t-1}+(\lambda_2+\lambda_3*PROVAL_{i,t-1})*\beta_7$, illustrated by Figure 5 in Appendix 4. We observe a very similar pattern as the direct impact. Overall, receiving negative professional reviews can hurt a product's performance, whereas products with positive professional reviews tend to receive more user choices. For example, in the category of File Compression, overall, receiving a one-star professional review leads to about 40% fewer software downloads than not receiving the professional review, all else being equal. Receiving a five-star professional rating can almost double the number of downloads of not being selected by experts for a professional review.

We also find support for the moderated impact of valence of online user reviews, being consistent with the literature [55]. The marginal impact of valence of user reviews, denoted by $\beta_3+2*\beta_4^t*USERVAL^R$, is shown to vary over weeks, given that $\beta_4^t$ is significantly positive over every single week in all categories. As expected, $\alpha_2^3$ in the lower level equation for estimating $\beta_4^t$ is significant in each category, indicating the nonlinear moderation effect of product variety on the impact of valence of user reviews. The increase in product variety enforces the impact of positive user reviews on downloads, while it diminishes the impact of negative user reviews.

Finally, we also conduct a brief robustness check by using a different MCMC prior specification and the pooled data. Specifically, in the first robustness check model, we use the student *t* distribution to replace current normal prior distribution for all unknown parameters and error terms in the software download equation [21, 34]. The CNETD software download distribution may have a heavier tail than the normal distribution, as implied by the long tail phenomenon [55]. In the second model, we pool all data of four categories together to run the model and add category dummies to control for the category-specific effect. The results of both models remain qualitatively similar to the results of the full model summarized in Table 4, in terms of the sign and the statistical significance.

## 5 Discussion and Implications

The major contribution of this study is to deepen the understanding of the impact of online user reviews and professional reviews. It relaxes the assumption used in previous studies that those two sources of WOM information independently influence user choices. Instead, focusing on the mediation role of online user reviews, we show that whether experts pick the product to review and the corresponding professional rating play a significant role in online user decisions about sharing feedback online. Therefore, professional reviews are shown to indirectly affect online user choices via influencing volume of user reviews, in addition to their direct impact that has been documented in the literature. We find that the direct impact of professional reviews, which was interpreted as the total impact in many previous studies, can be significantly underestimated, up to 20% smaller than the actual total impact.

This study provides three broad implications for managers. First, our results suggest that firms' WOM strategy towards online user-generated contents needs to go hand in hand with proactively seeking positive professional reviews. In recent years, firms have been put more and more resources to encourage online user-generated content by advertising review collection, offering monetary incentive to share feedback, etc. Our results imply that firms have to proactively solicit positive professional reviews and reduce negative reviews, in order to effectively accumulate online user conversations. Favorable reviews from experts not only directly deliver a good image of product quality and thus promote user adoptions directly, but also generally encourages more users to share experience. This can greatly increase the effectiveness of firms' efforts towards stimulating online user conversations. On the contrary, a negative opinion from the expert, possibly related with the poor communication between firms and experts, can easily offset firms' efforts on generating online user feedback. Therefore, firms are suggested to carefully manage the interaction and communication with experts for them to recognize the merit of the product.

Second, our findings also caution firms that conventional understandings of offline market may not be directly applied to interpret online market. The reach of the internet can greatly change how people find and process information. Our work provides a good example. In the offline channel, professional reviews are generally believed to have no impact on the generation of user feedback [40]. The underlying reason is that most of users are not aware of the professional reviews. As a result, professional reviews are of little use to encourage user experience sharing. However, the online channel has greatly expanded the reach of professional reviews. Many websites clearly highlight the reviews written by experts. Moreover, the prevalence of electronic commerce in recent years also provides online users abundant experience and sufficient skills to use various online tools, e.g. search engines, to fetch needed information. Therefore, the reason underlying the insignificant relationship between professional reviews and volume of user reviews in offline channel does not hold any more in online market. Our findings imply that it is important to re-examine conventional thinking in the online context.

Finally, managers should utilize professional reviews, in addition to user reviews, to predict a product's performance and allocate resources accordingly. Accurate predictions of user choices are important for firms' marketing and R&D strategies; however, it is normally difficult to obtain real-time sales and transaction data. Since volume of user reviews only partially mediates the impact of professional reviews, our results demonstrate that information on online user reviews alone is not sufficient to accurately predict the market outcome.

Although we show these results in the context of an online third-party software website, the implications are potentially broader. Our results can be applied to interpret the relationship between professional reviews and volume of online user reviews in the contexts where online users extensively resort to WOM for product information. Some attributes can differ between software programs and other types of experience goods, which suggests a more significant indirect impact of professional reviews in retail websites selling those experience goods, such as books and movies. First, those products do not have many objective measures, for example, technology features that software programs normally have, and thus are more subject to personal preferences. Second, consumers also make decisions more carefully and conservatively on purchasing products, compared to adopting products for free, as is the practice in our research context. As a result, while purchasing those types of products at retail websites, consumers tend to rely more heavily on user reviews to locate products matched to their preferences and have greater appreciation of the reviewers' contribution. In turn, they perceive greater psychological benefit from writing reviews on those retail websites. Therefore, receiving affirmative professional reviews can encourage sharing opinions to a larger extent than we have observed in the current research context, leading to a more significant indirect impact of professional reviews through online user reviews.

The data used in this study suggest some limitations and future research directions. First, we find that both valence of past user reviews and being selected for professional reviews have a differential impact on volume of user reviews in different category. In some categories, online users are shown to more likely write reviews on products that are positively reviewed by prior users and that are picked by experts for professional evaluations. However, in some categories, people tend to write reviews towards unfavorably reviewed products and products that are not picked by experts to be reviewed. This echoes the divergent conclusions regarding whether people prefer to review winner products or underdogs. A potential explanation can be that the "underdog" effect competes with the "bandwagon" effect to different extent in different product category [44, 45]. For the future research, it would be interesting to separate those two opposite effects and further compare them in depth. It can also be useful to examine the role product category plays in this line of research. Second, we don't have the information on the textual content of either user reviews or professional reviews. It is therefore also important to expand this study to incorporate the rich product information and personal preference information from the review text. Third, we do not have information on user visit history and WOM information on external websites. We thus cannot directly observe the sequence of users' downloading and sharing behavior. Also, it is likely that CNETD users also read user-generated content and comments by critics on external websites, which can possibly affect their downloading decisions on CNETD. Last but not least, it would be very interesting to re-examine the mediation relationship proposed by this study using a more recent dataset.

**References**


1. Amblee, N., and Bui, T. Freeware downloads: An empirical investigation into the impact of expert and user reviews on demand for digital goods. In *Proceedings of Americas' Conference on Information Systems.* Colorado*:* 2007, pp. 27.

2. Amblee, N., and Bui, T. Harnessing the influence of social proof in online shopping: The effect of electronic Word of Mouth on sales of digital microproducts. *International Journal of Electronic Commerce*, 16, 2 (2011), 91-113.

3. Baek, H., Ahn, J., and Choi, Y. Helpfulness of online consumer reviews: readers' objectives and review cues. *International Journal of Electronic Commerce*, 17, 2 (2013), 99-126.

4. Baron, M., and Kenny, D. A. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51, 6 (1986), 1173–1182.

5. Basuroy, S., Chatterjee, S., and Ravid, S. A. How critical are critical reviews? The box office effects of film critics, star power and budgets. *Journal of Marketing*, 67, 4 (2003), 103–117.

6. Baum, D., and Spann, M. The interplay between online consumer reviews and recommender systems: An experimental analysis. *International Journal of Electronic Commerce*, 19, 1 (2014), 129-162.

7. Benlian, A., Titah, R., and Hess, T. Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study. *Journal of Management Information Systems,* 29, 1 (2012), 237-272.

8. Boatwright, P., Basuroy, S., and Kamakura, W. Reviewing the reviewers: The impact of individual film critics on box office performance. *Quantitative Marketing and Economics*, 5, 4 (2007), 401–425.

9. Brynjolfsson, E., and Kemerer, C. F. Network externalities in microcomputer software: An econometric analysis of the spreadsheet market. *Management Science*, 42, 12 (1996), pp. 1627-1647.

10. Chakravarty, A, Liu, Y., and Mazumdar, T. The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluation. *Journal of Interactive Marketing*, 24, 3 (2010), 185–197.

11. Chen, Y., Liu, Y., and Zhang, J. When do third-party product reviews affect firm value and what can firms do? The case of media critics and professional movie reviews. *Journal of Marketing*, 75, 2 (2012), 116–134.

12. Chen, P. Y., Wu,, S. Y., and Yoon, J. The impact of online recommendations and consumer feedback on sales. In *Proceedings of International Conference on Information Systems*. Washington DC: 2004, pp. 58.

13. Chevalier, J. A., and Mayzlin, D. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43, 3 (2006), 345–354.

14. Clemons, E., Gao, G., and Hitt., L. When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information Systems*, 23, 2 (2006), 149–171.

15. Cui, G., Lui, H,. and Guo, X. The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, 17, 1 (2012), 39-58.

16. Dichter, E. How Word-of-Mouth advertising works. *Harvard Business Review*, 44, 6 (1966), 147–166.

17. Dimensional Research. *Survey: 90% of customers say buying decisions are influenced by online reviews*. 2013, Last Accessed on http://marketingland.com/survey-customers-more-frustrated-by-how-long-it-takes-to-resolve-a-customer-service-issue-than-the-resolution-38756.

18. Duan, W., Gu, B., and Whinston, A. B. The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, 84**,** 2 (2008), 233–242.

19. Duan, W., Gu, B., and Whinston, A. B. Informational cascades and software adoption on the Internet: an empirical investigation. *MIS Quarterly*, 33, 1 (2009), 23–48.

20. Gallaugher, J. M., and Wang, Y. M. Understanding network effects in software markets: Evidence from web server pricing. *MIS Quarterly*, 26, 4 (2002), 303–327.

21. Gelman, A., and Rubin, D. B. Inference from iterative simulation using multiple sequences, *Statistical Science*, **7,** 4 (1992), 457–472.

22. Ghose, A., Ipeirotis, P. G., and Li, B. Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Science*, 31, 3 (2012), 493–520.

23. Ghose A., Goldfard, A., and Han., S. P. How is the mobile Internet different? Search costs and local activities. *Information Systems Research*, 24, 3 (2013), 613–631.

24. Godes, D., and Mayzlin, D. Using online conversations to study word of mouth communication. *Marketing Science,* 23, 4 (2004), 545–560.

25. Goes, P. B., Lin, M., and Yeung, C. A. "Popularity effect" in user-generated content: Evidence from online product reviews. *Information Systems Research*, 25, 2 (2014), 222–238.

26. Gu, B., Park, J., and Konana, P. The impact of external word-of-mouth sources on retailer sales of high-involvement products. *Information Systems Research,* 23, 1 (2012), 182–196.

27. Hann, M. A., Dijkstra, S. G., and Dijkstra, P. T. Expert judgment versus public opinion-evidence from the Eurovision song contest. *Journal of Cultural Economics,* 29, 1 (2005), 59–78.

28. Hennig-Thurau, T., Gwinner, K. P., Walsh, G., and Gremler, D. D. Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, 18, 1 (2004), 38–52.

29. Hill, S., and Ready-Campbell, N. Expert stock picker: The wisdom of (experts in) crowds. *International Journal of Electronic Commerce*, 15, 3 (2011), 73.

30. Holbrook, M. B. Popular appeal versus expert judgments of motion pictures. *Journal of Consumer Research,* 26, 2 (1999), 144–155.

31. Holbrook, M. B. The role of ordinary evaluations in the market for popular culture: Do consumers have "good taste." *Marketing Letter*, 16, 2 (2005), 75–86.

32. Judd, C. M. and Kenny, D. A. *Estimating the Effects of Social Interventions*. Cambridge, UK: Cambridge University Press, 1981.

33. Kwon, O. and Sung, Y. Shifting selves and product reviews: How the effects of product reviews vary depending on the self-views and self-regulatory goals of consumers. *International Journal of Electronic Commerce*, 17, 1 (2012), 59-82.

34. Lange., K. L., Little, R. J. A., and Taylor, J. M. Robust statistical modeling using the t distribution. *Journal of the American Statistical Association*, 84, 408 (1989), 881–896.

35. Lee, Y. J. and Tan, Y. Effects of different types of free trials and ratings in sampling of consumer software: An empirical study. *Journal of Management Information Systems*, 30, 3 (2013), 213-246.

36. Li, M., Huang, L., Tan, C., and Wei, K. Helpfulness of online product reviews as seen by consumers: Source and content features. *International Journal of Electronic Commerce*, 17, 4 (2013), 101-136.

37. Li, X., Hitt, L. M., and Zhang, Z. Product reviews and competition in markets for repeat purchase products. *Journal of Management Information Systems*, 27, 4 (2011), 9-41.

38. Liebowitz, S. and Margolis, J. Winners, Losers and Microsoft: Competition and Antitrust in High Technology (2nd ed.). Oakland, CA, USA: Independent Institute, 1999.

39. Litman, B. R. Predicting the success of theatrical movies: An empirical study. *The Journal of Popular Culture*, 16, 4 (1983), 159–175.

40. Liu, Y. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, 70, 3 (2006), 74–89.

41. Luo, X., and Zhang, J. How do consumer buzz and traffic in social media marketing predict the value of the firm? *Journal of Management Information Systems*, 30, 2 (2013), 213-238.

42. Ma, X., Khansa, L., Deng, Y., and Kim, S. S. Impact of prior reviews on the subsequent review process in reputation systems. *Journal of Management Information Systems*, 30, 3 (2013), 279-310.

43. MacKinnon, D. P., Fairchild, A. J., and Fritz, M. S. Mediation analysis. *Annual Review of Psychology,* 58, 1 (2007), 593–614.

44. McAllister, I., and Studlar, D. T. Bandwagon, underdog, or projection? Opinion polls and electoral choice in Britain, 1979-1987. *The Journal of Politics*, 53, 3 (1991), 720–741.

45. Moe, W.W., and Schweidel, D. A. Online product opinions: Incidence, evaluation and evolution. *Market Science*, 31, 3 (2012), 372–386.

46. Moon, S., Bergey, P. K, and Lacobucci, D. Dynamic effects among movie ratings, movie revenues, and viewer satisfaction. *Journal of Marketing*, 74, 1 (2010), 108–121.

47. Park, D., Lee, J., and Han, I. The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International Journal of Electronic Commerce*, 11, 4 (2007), 125.

48. Reinstein, D. A., and Snyder, C. M. The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *The Journal of Industrial Economics,* 53, 1 (2005), 27–50.

49. Rossi, P. E., Allenby, G. M. and McCulloch, R. *Bayesian Statistics and Marketing*. Chichester, England: Wiley, 2005.

50. Sundaram, D. S., Mitra, K., and Webster, C. Word-of-mouth communications: A motivational analysis, *Advances in Consumer Research*, 25, 1 (1998), 527–531.

51. Tucker, C., and Zhang, J. Long tail or steep tail? A field investigation into how online popularity information affects the distribution of customer choices. *Working Paper No. 4655-07*, Massachusetts Institute of Technology, Boston, MA, 2007.

52. WOMMA. *The state of word of mouth marketing 2014*. 2014, Last accessed on https://www.ama.org/resources/White%20Papers/Pages/state-of-word-of-mouth-marketing-2014.aspx.

53. Xu, Y., Zhang, C., and Xue, L. Measuring product susceptibility in online product review social network. *Decision Support Systems*, forthcoming (2013).

54. Zhang, J., Fang, X., and Sheng, O. R. L. Online consumer search depth: Theories and new findings. *Journal of Management Information Systems*, 23, 3 (2007), 71-95.

55. Zhou, W., and Duan, W. Online user reviews, product variety, and the long tail: An empirical investigation on online software downloads. *Electronic Commerce Research and Applications*, 11, 3 (2012), 275–289.

56. Zhu, F., and Zhang, X. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, 74, 2 (2010), 133–148.

## Tables and Figures

**Figure 1. Mediation Model**

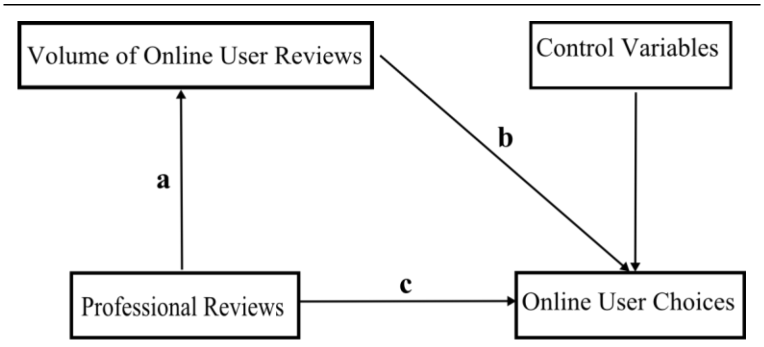

**Table 1. Summary of WOM Literature**

| Literature | User reviews | Professional reviews | Independent | Products | Focus |
|---|---|---|---|---|---|
| Duan et al. 2008 | Yahoo Movies | | Y | Movie | The dynamics between volume of online user reviews and movie performance |
| Chevalier & Mayzlin 2006 | Amazon, BN | | Y | Book | A difference-in-difference approach to study the sales impact of online user reviews |
| Zhu & Zhang 2010 | GameSpot | | Y | Video game | Contextual moderators for online user-generated WOM effect |
| Baek et al. 2013 | Amazon | | Y | Multiple categories | The helpfulness of online user reviews |
| Luo & Zhang 2013 | CNET | | Y | Software, hardware | The interaction between online user reviews and web traffic |
| Basuroy et al. 2003 | | *Variety* | Y | Movie | The dual role of professional reviews: influencer and predictor |
| Reinstein & Snyder 2005 | | Siskel and Ebert | Y | Movie | The correlation between unobserved quality and professional reviews |
| Boatwright et al. 2007 | | *Variety* | Y | Movie | The role of professional reviews depending on the individual expert reviewer |
| Amblee & Bui 2007 | CNETD | CNETD | Y | Software | The independent impacts of two WOM sources |
| Moon et al. 2010 | Yahoo movies | Rotten tomatoes | Y | Movie | The dynamics between valence of WOM and sales |
| Li et al. 2013 | Lab experiment | Lab experiment | Y | Mobile phone, laptop | The helpfulness of two WOM sources by a laboratory experiment |
| Liu, Y. 2006 | Yahoo movies | *Variety* | N | Movie | The explanatory power of WOM and the antecedents of WOM activities |
| Chakravarty et al. 2010 | Lab experiment | Lab experiment | N | Movie | Conflicts between professional reviews and online user reviews |
| **This Study** | **CNETD** | **CNETD** | **N** | **Software** | **Volume of online user reviews mediates the indirect impact of professional reviews on user choices** |

**Table 2. List of Variables Used in the Analyses**

| Variable name | Meaning |
|---|---|
| *I (1,…,I)* | Software program index |
| *T (3,…26)* | The week when software *I* is posted |
| $LOG(WEEKLYDOWNLOAD_{i,t})$ | Natural log transformation of number of weekly downloads of software *i* at week *t* |
| $LOG(WEEKLYUSERVOL_{i,t})$ | Natural log transformation of number of weekly user reviews software *i* has received at week *t* |
| $PROD_{i,t}$ | A dummy variable to indicate software *i* receives CNET editorial review at week *t* |
| $PROVAL_{i,t}$ | CNETD editorial rating software *I* receives at week *t* (one to five scale with half points) |
| $WEEKLYVARIETY_{t}$ | Total number of software programs listed in the category at week *t* |
| $USERD_{i,t}$ | A dummy variable to indicate software *i* receives at least one user review by week *t* |
| $USERVAL_{i,t}$ | Average user rating for software *i* at week *t* (one to five scale with half points) |
| $USERVAL^{R}_{i,t}$ | $USERVAL_{it} - 3$ |
| $USERVAL^{R}SQ_{i,t}$ | Square term of $USERVAL^{R}_{it}$ |
| $LOG(TOTALDOWNLOAD)_{i,t}$ | Log transformation of cumulative number of downloads of software *i* at week *t* |
| $WEEKLYRANK_{i,t}$ | Weekly download rank of software *i* at week *t* |
| $WEEKLYRANKSQ_{i,t}$ | Square term of $WEEKLYRANK_{i,t}$ |
| $FREEPRICED_{i,t}$ | A dummy variable to indicate software *i* is free to try for limited time, instead of free for lifetime, at week *t* |
| $AGE_{i,t}$ | Days since software *i* has been posted |
| $AGESQ_{i,t}$ | Square term of $AGE_{it}$ |

**Table 3. Summary of the Weekly Software Download Sample**

| Variable | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|
| Digital Media Player (N = 10,286) | | | | |
| $WEEKLYDOWNLOAD_{i,t}$ | 1,478.26 | 9,948.40 | 0 | 222,979 |
| $USERD_{i,t}$ | 0.31 | 0.46 | 0 | 1 |
| $USERVAL_{i,t}$ | 3.24 | 0.68 | 1 | 5 |
| $WEEKLYUSERVOL_{i,t}$ | 0.24 | 2.29 | 0 | 124 |
| $PROVAL_{i,t}$ | 3.59 | 0.89 | 2 | 5 |
| $PROD_{i,t}$ | 0.10 | 0.29 | 0 | 1 |
| $WEEKLYVARIETY_{t}$ | 436.80 | 51.76 | 242 | 466 |
| Download Manager (N = 2644) | | | | |
| $WEEKLYDOWNLOAD_{i,t}$ | 1,375.70 | 6,334.58 | 0 | 211,640 |
| $USERD_{i,t}$ | 0.59 | 0.49 | 0 | 1 |
| $USERVAL_{i,t}$ | 3.34 | 0.67 | 1.5 | 5 |
| $WEEKLYUSERVOL_{i,t}$ | 0.38 | 1.75 | 0 | 40 |
| $PROVAL_{i,t}$ | 3.66 | 0.72 | 2 | 5 |
| $PROD_{i,t}$ | 0.22 | 0.41 | 0 | 1 |
| $WEEKLYVARIETY_{t}$ | 215.29 | 33.04 | 150 | 256 |
| File Compression (N = 4,052) | | | | |
| $WEEKLYDOWNLOAD_{i,t}$ | 3,032.77 | 26,253.80 | 0 | 385,226 |
| $USERD_{i,t}$ | 0.28 | 0.45 | 0 | 1 |
| $USERVAL_{i,t}$ | 3.68 | 0.73 | 1.5 | 4.5 |
| $WEEKLYUSERVOL_{i,t}$ | 0.17 | 1.10 | 0 | 36 |
| $PROVAL_{i,t}$ | 3.66 | 0.75 | 2 | 5 |
| $PROD_{i,t}$ | 0.24 | 0.43 | 0 | 1 |
| $WEEKLYVARIETY_{t}$ | 174.48 | 22.17 | 95 | 193 |
| MP3 Finder (N = 2040) | | | | |
| $WEEKLYDOWNLOAD_{i,t}$ | 9,355.88 | 61,137.00 | 0 | 909,295 |
| $USERD_{i,t}$ | 0.55 | 0.50 | 0 | 1 |
| $USERVAL_{i,t}$ | 3.42 | 0.58 | 1.5 | 5 |
| $WEEKLYUSERVOL_{i,t}$ | 1.48 | 8.47 | 0 | 125 |
| $PROVAL_{i,t}$ | 3.28 | 0.76 | 2 | 4 |
| $PROD_{i,t}$ | 0.13 | 0.34 | 0 | 1 |
| $WEEKLYVARIETY_{t}$ | 89.04 | 11.47 | 52 | 97 |

*Note:* N=Total observations over time

**Table 4. The Impact of Professional Reviews and Online User Reviews**

| | Digital Media Player | Download Manager | File Compression | MP3 Finder |
|---|---|---|---|---|
| **Software download equation** | | | | |
| $USERD_{i,t-1}$ ($\beta_2$) | -0.57(0.11)* | 0.45 (0.11)* | -0.48 (0.21)* | 0.57 (0.26)* |
| $USERD_{i,t-1}$*$USERVAL^R_{i,t-1}$ ($\beta_3$) | 0.08(0.02)* | -0.05(0.02)* | 0.07(0.02)* | -0.01 (0.04) |
| $PROD_{i,t-1}$ ($\beta_5$) | -0.57(0.08)* | -0.23 (0.09)* | -0.60 (0.10)* | -0.82(0.22)* |
| $PROD_{i,t-1}$ * $PRODVAL_{i,t-1}$ ($\beta_6$) | 0.24 (0.02)* | 0.07 (0.02)* | 0.21(0.03)* | 0.36(0.07)* |
| $LOG(WEEKLYUSERVOL_{i,t-1})(\beta_7)$ | 0.43(0.02)* | 0.25(0.01)* | 0.49(0.03)* | 0.25(0.03)* |
| $LOG(TOTALDOWNLOAD_{i,t-1})(\beta_8)$ | 0.20(4.70E-3)* | 0.15(0.01)* | 0.20(0.01)* | 0.17(0.01)* |
| $WEEKLYRANK_{i,t-1}$ ($\beta_9$) | -0.02 (2.34E-4)* | -0.04 (4.91E-4)* | -0.06 (1.03E-3)* | -0.11 (3.51E-3)* |
| $WEEKLYRANKSQ_{i,t-1}$ ($\beta_{10}$) | 2.64E-5(4.43E-7)* | 6.63E-5(1.85E-6)* | 1.55E-4(4.57E-6)* | 4.51E-4 (3.06E-5) |
| $FREEPRICED_{i,t}$ ($\beta_{11}$) | -0.12 (0.01)* | -0.23 (0.02)* | -0.13 (0.02)* | -0.11 (0.04)* |
| $AGE_{i,t}$ ($\beta_{12}$) | -7.88E-4(3.72E-5)* | -5.48E-4(5.25E-5)* | -9.99E-4(6.89E-5)* | -1.58E-3(1.24E-4)* |
| $AGESQ_{i,t}$ ($\beta_{13}$) | 2.07E-7(1.55E-8)* | 2.34E-7(2.46E-8)* | 3.21E-7(3.19E-8)* | 6.24E-7(7.95E-8)* |
| **Volume of user reviews equation** | | | | |
| $PROD_{i,t-1}$ ($\lambda_2$) | -0.08(0.03)* | -0.22(0.07)* | -0.25(0.04)* | -0.93(0.12)* |
| $PROD_{i,t-1}$ * $PRODVAL_{i,t-1}$ ($\lambda_3$) | 0.04(0.01)* | 0.04(0.02)* | 0.09(0.01)* | 0.32(0.04)* |
| Indirect Impact of Professional Ratings ($\lambda_3$ * $\beta_7$) | 0.02 (3.73E-3)* | 0.01(4.39E-3)* | 0.04 (0.01)* | 0.08(0.01)* |
| Total Impact of Professional Ratings ($\beta_6$ + $\lambda_3$ * $\beta_7$) | 0.25(0.02)* | 0.08(0.03)* | 0.25 (0.03)* | 0.44(0.06)* |
| $LOG(WEEKLYUSERVOL_{i,t-1})$ ($\lambda_4$) | 0.24(0.01)* | 0.20(0.01)* | .23(0.01)* | 0.40(0.07)* |
| $USERD_{i,t-1}$ ($\lambda_5$) | -0.16(0.02)* | -0.34(0.05)* | -0.27(0.04)* | 0.31(0.01)* |
| $USERD_{i,t-1}$*$USERVAL_{,t-1}$ ($\lambda_6$) | 0.04(0.01)* | 0.06(0.01)* | 0.07(0.01)* | -0.39(0.08)* |
| $LOG(TOTALDOWNLOAD_{i,t-1})$ ($\lambda_7$) | 0.06 (1.90E-3)* | 0.05(4.04E-3)* | 0.05(2.81E-3)* | 0.07(0.02)* |
| $WEEKLYRANK_{i,t-1}$ ($\lambda_8$) | -1.10E-3(8.46E-5)* | -0.01(3.30E-4)* | -1.56E-4(3.57E-4)* | -0.023(1.98E-3)* |

| | | | | | |
|---|---|---|---|---|---|
| *$WEEKLYRANKSQ_{i,t-1}$* ($\lambda_9$) | | 3.00E-6(1.57E-7)* | 2.03E-5(1.35E-6)* | 1.28E-5(1.62E-6)* | 2.11E-4(1.76E-5)* |
| *$FREEPRICED_{i,t}$*($\lambda_{10}$) | | -0.03(0.01)* | -0.13(0.01)* | -0.03 (.01)* | 3.69E-3(0.03) |
| *$AGE_{i,t}$* ($\lambda_{11}$) | | -2.76E-4(1.48E-5)* | -2.48E-4(4.55E-5)* | -2.29E-4(2.59E-5)* | -4.49E-4(7.13E-5)* |
| *$AGESQ_{i,t}$* ($\lambda_{12}$) | | 6.49E-8(6.10E-9)* | 8.86E-8(2.15E-8)* | 6.75E-8(1.21E-8)* | 1.75E-7(4.56E-8)* |
| **Lower level equation** | | | | | |
| Intercept | $\alpha_1^1$ | 4.50(0.39)* | 5.24(0.39)* | 4.52(0.43)* | 4.71(0.44)* |
| | $\alpha_1^3$ | -0.19(0.07)* | 0.07(0.07) | -0.13(0.07)* | -0.02(0.08) |
| *$WEEKLYVARIETY_t$* | $\alpha_2^1$ | 3.89E-3(8.40E-4)* | 3.38E-3(1.70E-3)* | 0.01(2.08E-3)* | 0.02(3.37E-3)* |
| | $\alpha_2^3$ | 3.64E-4(1.53E-4)* | 7.14E-4(2.98E-5)* | 6.97E-4(3.90E-4)* | 9.22E-4(7.81E-4)* |
| *Correlation between first two equations* | | 0.30(0.01)* | 0.52(0.01)* | 0.26(0.01)* | 0.39(.02)* |

*Notes:* *: Significance level at $p < 5\%$. Results of intercepts in the software download equation, and results of the intercept and the time fixed in the volume of user reviews equation are not reported. $\beta_4^t$ in the software download is positive in each week for all categories. Its detailed results are not included for parsimony, yet available upon request.