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What in Consumer Reviews Affects the Sales of Mobile Apps: A Multifacet Sentiment Analysis Approach

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ABSTRACT: With the rapid adoption of smartphones, developing mobile apps has become an attractive arena for entrepreneurs. Many factors drive the sales of mobile apps, one of which is online word of mouth (eWOM). This research examines the effect of textual consumer reviews on the sales of mobile apps. Noting the inconsistent findings on the effect of textual reviews in previous literature, this study inspects how the sentiments of different topics in online reviews affect app sales. We develop a multifacet sentiment analysis (MFSA) approach to measure the dimensions in consumer reviews. Specifically, we are interested in the comments on product quality and service quality in this research. Employing a real-world data set of seventy-nine paid and seventy free apps from an iOS app store, we found that although consumers' opinions on product quality occupies a larger portion of consumer reviews, their comments on service quality have a stronger unit effect on sales rankings. The empirical analysis illustrates the value of our proposed MFSA approach for better understanding of the effect of textual consumer reviews on mobile app success.

KEY WORDS AND PHRASES: Consumer reviews, electronic word of mouth, eWoM, mobile app sales, opinion analysis, sentiment analysis, text mining.

Smartphones and mobile applications (apps) are increasing in use and popularity. International Data Corporation's (IDC) 2015 survey reported that the global smartphone vendors shipped a total of 334.4 million smartphones worldwide in the first quarter of 2015, up 16.0 percent from the 288.3 million units in the first quarter of 2014 [34]. Mobile apps are software applications that run on smartphones to achieve certain purposes. Since their invention in 2008, a huge market for mobile applications has emerged [56] and become an attractive arena for entrepreneurs. By mid-2014, Apple announced that users had downloaded 75 billion applications, users visited the App Store 300 million times per week, and there were 9 million registered developers, up 47 percent from the previous year [53]. Successful mobile apps become important assets for companies. For example, in 2014 Facebook spent US$19 billion to acquire WhatsApp, a popular mobile app for online chatting [13].

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Many factors affect the success of apps. One factor that differs from those that affect traditional software systems is online word of mouth (eWOM). Apps are often distributed through app stores that allow consumers to post comments about apps. As a result, consumers often consult customer reviews in making their purchase decisions.

Several marketing studies have recognized the influence of eWOM on consumers' purchases beyond inherent product and brand effects and other marketing tactics [16, 27, 73]. Chen and Xie [7] argued that consumer reviews provide product-matching information for consumers to find products that match their needs. Such supplementary information helps consumers reduce uncertainty about products and facilitates sales. In fact, previous research has reported that consumer comments are more trustable than expert opinions in many cases [6].

Despite such theoretical arguments, prior studies on sentiment in textual reviews have shown conflicting results [72], and the effect may be negligible when controlling for numerical ratings [44]. Inconsistent findings may be due to inadequate or inaccurate sentiment analysis techniques. We argue that previous studies often investigate the overall aggregated sentiments of comments. Such an approach cannot provide more information from textual content than numerical ratings provided by users, as the aggregation process may lose some important information on different aspects of the product that are considered in consumers' decision making.

To fill this gap, we propose a multifacet sentiment analysis (MFSA) of consumer feedback to deepen our understanding of textual consumer reviews and examine their influence on app sales. In particular, based on previous studies, we focus on two dimensions of sentiments in app eWOM: product quality and service quality. This differentiation is important for mobile apps because many apps rely on a server (or cloud) to store user information and distribute product information. Service is an inherent part of apps and plays a role quite different from customer service for traditional software applications. We extract such sentiments from consumer reviews and conduct an empirical study on a data set of iOS apps. Findings from the data set support our conjecture and indicate that eWOM sentiment is a good predictor of iOS app sales, given that sentiments are differentiated to different aspects such as product quality and service quality.

The contribution of this article is threefold. First, we argue that sentiment analysis on consumer reviews needs to consider different aspects of consumer concerns. An aggregative view of sentiment analysis is too coarse to fully reveal the value of consumer reviews. Second, we find that both product and service reviews have effects on app sales rankings, which differ for free and paid apps. Free app users rely more on online reviews and care more about service quality of apps. Third, we propose a framework to help identify multifacets of sentiments from consumer reviews, which can be applied to other business applications.

Related Work

eWOM in Electronic Commerce

In marketing literature, WOM has been well recognized as influencing consumers' purchasing behavior [59]. Cunningham [14] pointed out that consumers are likely to generate conversations related to products and to request information from friends and relatives if they are not sure about a purchase. Bone [5] found that WOM influences short-term and long-term product judgments, especially when a customer faces uncertainties.

Many scholars consider eWOM as a determinant of product success [16, 27, 30, 73] that is moderated by the characteristics of products [73] and consumers [71]. External WOM sources have been found to have a significant effect on retail sales [29]. Recent studies have also analyzed the interplay between online consumer reviews and recommender systems in consumers' decision making [3] and the formation of helpfulness of online product reviews [41].

As argued by Amblee and Bui [2], eWOM can convey the reputation of the product, the brand, and complementary goods. This reputation can be conveyed in both the volume and valence of eWOM [1]. Volume means the amount of eWOM, such as the number of online reviews, which reflects the popularity of the product. In prior studies, Godes and Mayzlin [26] found that the volume of eWOM has a positive influence on TV show viewership. Liu [44] and Duan, Gu, and Whinston [21] both showed that the volume of eWOM has a significant influence on movie box office revenue.

Valence is an affective indicator to show whether the reviewer's sentiment is positive or negative. Because eWOM is often anonymous, consumers are more comfortable sharing both negative and positive opinions. Recent research reports that affective factors have a significant influence on the adoption of eWOM (e.g., [23, 60]). Review sentiment can often be reflected through numerical ratings provided by users. Previous research has drawn consistent conclusions about the influence of rating valence. Chevalier and Mayzlin [8] showed that consumer ratings significantly influence book sales at Amazon.com. Dellarocas, Zhang, and Awad [17] added online review ratings to a basic forecasting model and found that its accuracy was significantly improved. Through experiments in a mobile app setting, Huang and Korfiatis [33] found that review valence and consistency alter the emotional process during trial attitude formation but do not affect the cognitive process. They identified the moderating role of online reviews on product trial experience, which in turn influences the formation of product attitudes.

Online reviews convey more information than reputation. Chen and Xie [7] argued that consumer reviews provide product-matching information that helps consumers find products that match their needs. Such supplementary information helps consumers reduce uncertainty about products and facilitates sales. As a result, the extent of subjectivity, informativeness, and readability of reviews is found to influence sales [25]. Berger, Sorensen, and Rasmussen [4] show that even negative reviews can have positive effects on sales because they may increase product publicity, especially for lesser-known products. In addition, the variances in review ratings [12] and the diversity of textual reviews [72] are found to positively affect product sales because they provide extra information. The effect of rating dispersion varies on hedonic vs. utilitarian products, where highly dispersed ratings are perceived as more positive on hedonic products [11].

However, the findings on how textual comments affect sales have not been fully illustrated through textual valence. For instance, Liu [44] studied the influence of WOM on movie box office revenue based on manually coded textual review sentiments. Liu et al. [45] further studied review sentiment using text-mining techniques. Both studies found that the textual-based measures did not affect product sales. In Table 1, we summarize previous studies related to the sales effect of eWOM, which show inconsistent findings on textual valence.

We project one reason, that is, previous studies investigate the overall aggregated sentiments of comments without differentiating the multiple dimensions of their content. Such an approach cannot provide significantly more information from textual content than numerical ratings provided by users. Previously, Park and Kim [51] and Park and Lee [52] classified eWOM into attribute-centric and benefit-centric. The attribute-centric reviews provided additional information on product features, whereas benefit-centric reviews focus on emotional and subjective recommendations. Different emotions can be associated with different aspects of a product in product reviews. The aggregation process may lose some important supporting information in consumers' decision making. Analysis of eWOM at a finer granularity could provide new insights, which is the research gap we want to fill in this research in the context of mobile apps.

Text Mining and Opinion Analysis

Text mining is an effective and efficient method to automatically process the large number of textual comments that consumers read (and write). Product features can be extracted from online comments (e.g., [64]). Opinion analysis based on natural language processing [50] has been applied to summarize opinions from textual content.

There are two primary methods of opinion analysis: learning-based and lexicon-based methods. Learning-based methods use machine-learning techniques such as probabilistic models and support vector machines to build classification models. Many previous studies have focused on positive/negative sentiment classification [15]. For example, Turney [63] presented a PMI-IR algorithm to calculate the semantic orientation of phrases based on their association with the two human-selected seed words (poor and excellent) in a large corpus. Pang and Lee [48] used a graph-cut approach to classify document sentiments. Some studies, such as Pang and Lee [49], inferred people's attitude to a multipoint scale. Yang et al. [66] applied

Table 1. Summary of Previous Research on WOM's Impact on Sales.

Paper	Volume	Numerical valence	Textual valence	Variance	Others	Application	Results related to textual valence
Chevalier and Mayzlin [8]		√				Book	
Godes and Mayzlin [26]	√					TV show	
Clemons, Gao, and Hitt [12]				√		Beer	
Liu [44]	√		√			Movie	Not significant
Dellarocas, Zhang, and Awad [17]	√	√				Movie	
Duan, Gu, and Whinston [21]	√					Movie	
Chintagunta, Gopinath, and Venkataraman [9]	√	√		√		Movie	
Liu et al. [45]	√	√	√			Movie	Not significant
Zhu and Zhang [73]	√	√		√		Video game	
Zhang, Craciun, and Shin [71]		√			√	Book	
Amblee and Bui [2]	√	√				Book	
Ghose and Ipeirotis [25]	√	√			√	Hi-Fi, Camera, DVD	Textual subjectivity is related to Hi-Fi sales
Gu, Park, and Konana [29]	√	√			√	Camera	
Zhang, Li, and Chen [72]	√	√	√	√		Book and Movie	Not significant
Sun, Song, and Huang [61]	√	√	√			Movie	Not significant

association rules and a naive Bayes classifier to identify the sentiment of consumer reviews and found good accuracy.

The learning-based method has a major constraint. It needs manually coded training data to build learning-based models, which is often unavailable in eWOM studies. Thus a lexicon approach, which uses lexicons and predefined rules to annotate sentiments of terms in text, is often easier to apply [72]. For example, Hu and Liu [32] built a seed list with a set of common adjectives (e.g., positive adjectives include great, fantastic, nice; negative adjectives include bad, dull, tardy), then used WordNet [10] to determine the semantic orientation for each opinion word. Demers and Vega [20] used a lexicon approach to measure the tone of news for firm valuation.

Another issue related to this research is that Chinese-language processing is different from that of English. One major challenge of processing Chinese texts is to segment sentences to words [68]. In computational linguistics, several text-segmentation methods have been proposed to address this problem, such as Chinese Knowledge Information Processing (CKIP) [46]. Another challenge for Chinese opinion analysis is the lack of established Chinese sentiment lexicons. In order to handle these challenges, Zagibalov and Carroll [69] proposed an unsupervised classification method to build sentiment lexicons from a small seeding lexicon. Taking a learning-based paradigm, Ku, Huang, and Chen [38] employed morphological and syntactic structures to analyze opinions in Chinese words and sentences. Xu et al. [65] proposed a procedure to annotate opinions from online Chinese product reviews. These studies provide basic techniques to handle Chinese eWOM in our study.

Theoretical Basis and Hypotheses

To study the multiple facets of eWOM sentiments, we need to find a perspective to differentiate topics and illustrate the influence of their related comments on app sales. In this research, we take a theory-driven approach and focus on the differentiation of product quality (such as the functional correctness and usability of the app) and service quality [35, 40] (such as service reliability, customer service responsiveness, etc.). The two aspects of information technology (IT) artifacts have been widely studied in previous research [35, 40]. A few theoretical lenses support the differentiation of product and service as two distinct dimensions that affect consumer decisions.

First, product-based view and service-based view are two viewpoints on software [62]. A traditional view of software, especially consumer software, is that it is an off-the-shelf product, where firms design and develop applications and consumers hold, use, and maintain the software together with associated data. With the development of the Internet, the concept of software-as-a-service (SaaS) is increasingly popular in the IT industry, where firms maintain some parts of software modules and/or user data on the server side for users' remote access and use. In such a context, the concept of "service" is quite different from software maintenance and customer service for traditional software applications. In this study, we want to assess the influence of eWOM sentiments of the two aspects on app sales.

In ex ante literature, product quality is a key construct in modeling consumer utility and behavior [55]. For regular products, one important role of online reviews is to provide information about the product to support sales [6]. Viewing a mobile app as a type of software product, its product quality comes from the development process and directly affects user satisfaction and experience [37], which need to be carefully managed [58]. In the literature on information system success in organizations, DeLone and McLean [19] also employed system quality and information quality to measure characteristics of information systems and examined their influence on users' satisfaction and intention to use. Obviously consumers' reviews on software systems could affect potential consumers' perceptions of product quality. The user comments with positive sentiments on product quality should affect people's assessment and increase their purchase intention. Thus, we propose:

> *Hypothesis 1:* The sentiment of comments on product quality is positively correlated with app sales.

Service is another important dimension in marketing literature that affects consumer behavior [70]. Traditional information systems (IS) literature also values service quality. In research on information system success in organizations, Pitt, Watson, and Kavan [57] argued that service quality (such as user support) affected IS success, which was later included in the IS success model [18]. In IT outsourcing, service quality is one important factor affecting consumers' decisions [28]. In the context of mobile apps, many apps take such a model, either storing the user data in the "cloud" or distributing information products (such as weather broadcasts) from the backend to the users. This makes it difficult for users to separate the service element from the value they receive from the product, which is different from the traditional customer service quality often measured in IS literature [36, 54]. Thus, service quality plays a more important role in decisions on mobile app purchases than on traditional software applications. The existence of online reviews on service actually provides a rating of the service, which complements the terms of the service level agreement (SLA) [43]. The user comments with positive sentiments on service quality should affect people's assessment and increase their purchase intention. Thus, we propose:

> *Hypothesis 2:* The sentiment of comments on service quality is positively correlated with app sales.

Research Methodology

In order to test the hypotheses, we develop a multifacet sentiment analysis (MFSA) approach and collect real data from the Apple Store to evaluate the approach.

Data Set

We collected a data set on iOS app sales in Taiwan from App Annie (www.appannie.com) to test the aforementioned hypotheses. App Annie has archived information on apps, such as sales rank, prices, reviews, and version changes, in different geographic locations since 2009. The iOS app store only reports the sales rank of the top 500 bestselling apps. In this research, we collected information on the bestselling free and paid apps in Taiwan for each week in 2011. However, many apps only appeared on the leaderboard for a couple of weeks, leaving the other weeks with missing data. We thus kept apps appearing more than thirty-five weeks (i.e., two-thirds of the year) in the data set for a relatively longer panel for our study. We collected reviews that appeared in 2011 and examined their effect on sales rank. Note that in the first couple of weeks, some app reviews were actually published before 2011, which caused some missing data. We removed these app-weeks from the data set. After cleaning, our data set contains seventy-nine paid apps and seventy free apps.

According to FaberNove [22], iOS store app rankings are based on the weighted sum of the past four days' sales, that is, *day k's ranking sales* = *day k's sales* * 8 + *day k* – 1*'s sales* * 5 + *day k* – 2*'s sales* * 5 + *day k* – 3*'s sales* * 2. Thus, we can safely measure the effect of reviews (and other information) from Sunday on the sales (represented by sales rank) of the next Thursday. In this paper we label them with week subscript $t - 1$ and t, respectively. We collected these average ratings and the number of reviews to capture the effect of existing numerical measures' influence on consumers. The data set is an unbalanced panel. We report the descriptive statistics of the data set in the Results section.

MFSA for Opinion Analysis

A key component of MFSA is an appropriate opinion analysis to differentiate the two types of facets, product quality and service quality. In our data set, user comments are in Chinese (mixed with English). There is no comprehensive lexicon of Chinese sentiment words. Therefore, we adapted a procedure as shown in Figure 1 to build lexicons and then code customers' online textual comments. This approach allows us to process a large number of reviews after building the lexicon. Then, the coding of lexicons requires substantial effort, especially in differentiating between similar concepts. Thus, we choose to differentiate only product quality and service quality and do not get into multiple, more detailed subdimensions of each construct. We leave the examination of other subdimensions of lexicon coding to future research.

To build the lexicon, we took a semimanual approach; we first identified the candidate words and then invited human subjects to code. We employ the 3,284 reviews of the top-ten most popular apps to build the lexicon. First,

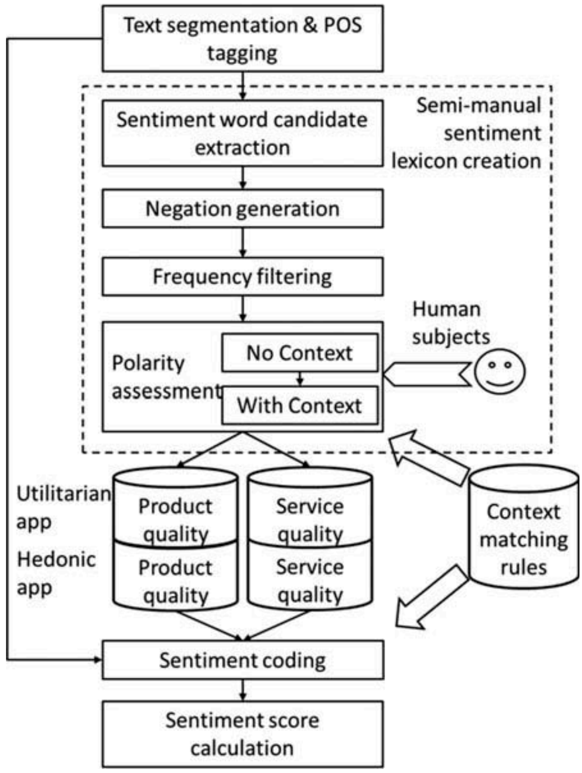


Figure 1. Procedure for Sentiment Analysis

we fed the reviews to CKIP API to conduct text segmentation and part-of-speech (POS) tagging [46]. We then extracted the candidate sentiment words according to their POS. Note that the symbolic POS system developed in Taiwan is different from that developed in Mainland China or in English. Many words that are considered as adjectives in those two systems are deemed intransitive verbs (Vi), which are considered to carry most of the sentiments in a sentence [47] and employed as our candidate sentiment words. If the consumer reviews contained English terms, we considered the English adjectives as reflecting sentiment. Then we added negation prefixes (e.g., 不/non-/ir-/dis-) to the extracted candidate sentiment words.

It is possible that a word's sentiment or product/service classification could not be judged by itself. Thus, we used the heuristics [47] in Table 2 to identify phrases as the context of sentiment words to help the human subject's judgment. Note that the rules in Table 2 were used recursively, where identified noun or Vi phrases are then used to identify longer terms. According to [47], the use of contextual information significantly improves sentiment assessment in Chinese.

The process provides us with a list of extracted candidate sentiment words (including the ones after adding or removing negation words). Some of the terms are associated with contexts that were extracted from

Table 2. Rules for Identifying Phrases as Contexts of Words.

Tagging system	Rule	Type	Examples (English translation)
CKIP (for Chinese)	N + N	N	應用(utility) + 軟體 (software)
	N + N + N	N	遊戲 (game) + 音樂 (music) + 音效(sound effect)
	Vi + Vt	Vi	努力(endeavor) + 嘗試 (try)
	Vi + Vi	Vi	暢快 (smooth) + 過癮 (enjoyable)
	Vt + Vi	Vi	覺得 (feel) + 有趣 (interesting)
	N + Vi	Vi	印象 (impression) + 深刻 (vivid)
	Vi + N	Vi	好玩 (fun) + 遊戲 (game)
	Vi + ADV + Vi	Vi	覺得 (look) +太 (too) + 醜 (ugly)
	Vt + ADV + Vi	Vi	期待 (expect) + 好 (so) + 久 (long)
	N + ADV + Vi	Vi	遊戲 (game) +太 (so) + 爛 (bad)
	ADV + Vi	Vi	太 (too) + 爛 (bad)
	Vi + T + Na	Vi	糟糕 (terrible) + 的(-) +中文化 (Chinese localization)
Yahoo (for English)	A + N	N	Good game

Notes: The POS tags used by CKIP are explained at http://ckipsvr.iis.sinica.edu.tw/papers/category_list.doc. N: Noun; Vi: Verb-intransitive; Vt: Verb-transitive; A: Adjective; ADV: Adverb; Na: Generic noun; T: Interjection.

the reviews. We invited ten college and postgraduate students to code the polarity of these words (positive vs. negative) and whether they were related to product quality or service quality. In Taiwan, college students are a major consumer group of apps. We consider that their judgments of app reviews are reliable enough and reflect the perception of reviews by most app users. The coding results naturally contain some ambiguous words with inconsistent understanding across coders. To address this concern, we required mutual agreements from seven out of ten coders to decide the polarity and/or product/service classification. For example, if seven out of ten coders agree that a term is positive (while the others consider it negative or neural), the term is labeled as positive. By keeping only the high-agreement terms, we consider that the majority of college student coders are able to reveal the majority of public perceptions when seeing a term.

In our coding process, the candidate sentiment words are in their original language, mostly Chinese. The few English words are generally simple and easy terms that were embedded in the Chinese comments. All ten coders are native Chinese speakers with sufficient education to understand the simple English terms in our coding process; they expressed no concerns about understanding terms. The users coded the terms independently, without exchanging ideas on the coding offline. We first asked them to judge terms without context. Then context information was provided for the terms that could not be judged. (When using the coded lexicons to assess reviews in our experiments, the terms identified with context are applied before the ones identified without context, since they represent more specific meaning of a term in a particular sentence.) Noticing the difference in term usage between hedonic (i.e., game) and utilitarian apps, we built separate lexicons for these two types of apps for the subjects to code.

From these, the coders identified 50 positive terms and 30 negative terms on utilitarian app product quality and 9 positive terms and 14 negative terms on utilitarian app service quality. By providing contexts of words as a reference, the coders further identified 17 positive terms and 19 negative terms on utilitarian app product quality and 6 positive terms and 13 negative terms on utilitarian app service quality. For the hedonic apps, the coders identified 53 positive terms and 14 negative terms on product quality without context, 12 positive terms and 14 negative terms on service quality without context, 16 positive terms and 15 negative terms on product quality with context, and 5 positive terms and 15 negative terms on service quality with context.

After creating the lexicons, we coded the sentiments of reviews for each app each week. After segmentation and POS tagging, the sentiment words without context can be directly annotated. For the words that need to be determined based on context, we checked whether the context of the word in the review contains any of the listed phrases in our coding tables. We then aggregated the sentiment words by extending Demers and Vega [20] semantic score measures. As argued by Lee, Ku, and Chen [39] and Yao and Lou [67], adverbs strengthen the effect of positive and negative sentiments in Chinese. Thus, we considered the number of adverbs used before the sentiment words as in the following equation:

$$Score = p + 0.5^{*}adv_p - n - 0.5^{*}adv_n, \tag{1}$$

where p is the number of positive words appearing in a product's reviews; adv_p is the number of adverbs before positive words; n is the number of negative words in a product's reviews; and adv_n is the number of adverbs before negative words. We get scores for both product quality and service quality, represented as *ProdScore* and *ServScore*, respectively.

Table 3 shows the ten online reviews for Angry Birds retrieved on August 7, 2011. These reviews were treated as one piece to measure the WOM information in this research. The text contains ten sentiment word occurrences on product quality that can be determined without context: 好玩/Fun (2 times), 欲罷不能/can't help myself from playing it, Fun (3 times), 棒/great (2 times), good (2 times), 糟/bad. The term 動腦/think hard needs to be determined with sentence context, which is retrieved using the rule (*Vi* + *N*) from our lexicon. The phrase is a positive term related to product quality. These words are associated with three adverbs: 太好玩/so interesting, Very fun, 很棒/so great, which adds an extra 1.5 positive score to the total. We determined the sentiment words and their associated adverbs for service quality in a similar manner. Eventually, we calculated the product quality and service quality scores for Angry Birds reviews on August 7, 2011, as:

$$ProdScore = 11 + 0.5^{*}3 - 0 - 0.5^{*}0 = 12.5$$

$$ServScore = 1 + 0.5 - 2 - 0.5 = -1$$

Table 3. An Example of Computing Semantic Score.

1. {太} [好玩] 了，令人[欲罷不能]
(It's so interesting that I can't help myself from playing it.)
2. [Fun]
3. 好刺激的破關方式，實際玩時需要動[動腦]
(What an exciting way of finishing the mission. One needs to think hard to play.)
4. {很 }[棒]，比周杰倫還[棒]
(Very great, greater than Jay Chou.)
5. 這遊戲感覺到{非常} [物超所□]
(This game is very much worth the price.)
6. [good]
7. [中文化字體糟]透了，讓人糾結
(The Chinese font is terrible, which makes people frustrated.)
8. 娛樂性滿分，[good]
(Full score in entertainment, good)
9. [Fun]，[中文化字體很醜]，不如不要
(Fun. The Chinese font is ugly, which is better to throw away.)
10. {Very}[fun]，好玩
(Very fun, interesting)

*Sentiment terms in square brackets; adverbs in curly brackets; English translation in parentheses.

Our proposed method essentially is a lexicon-based method. Its cost comes mainly from the labor of manual coding, which also ensured the high quality of the lexicon. The general process of our approach is based on previous research that has been validated. In this study, our major purpose is to differentiate comments on product quality and service quality, which is not a common task in text mining. No gold standard exists that can directly support a learning-based method. Although it is possible to cluster the terms before coding or employ a semisupervised approach to train machine-learning models employing a small set of coded data, lexicons built from such methods still need human validation to ensure their quality. We left such technical improvements to future research.

The Econometric Model

In order to assess whether MFSA can better interpret the effect of two types of textual reviews on app sales, we collected panel data in a weekly manner and used econometric models to control the confounding factors. We employed the logarithmic transformation of sales rank as an indicator of app sales (downloads). A higher value in sales rank indicates a lower sales volume. As shown in several previous studies [24], there is a power relationship between sales rank and sales. Thus we can use *LogRank* to replace *LogSales* as a dependent variable.

The two independent variables of the studies are two types of textual sentiment measures: *ProdScore* and *ServScore*. Since the two measures are calculated based on the last ten reviews from each week, they reflect the influence of recent reviews. In 2011, app store reviews were sorted in chronological order. It is natural to expect that recent reviews had a higher chance of being referenced and influencing consumer decisions.

We control the variables commonly used in marketing literature for eWOM. First, most economic literature supports the idea that price affects the sales of products; a higher price will reduce sales. Since not all apps cost the same amount, it is also important to include variable *Price* in our model. Second, we control the valence of consumer numerical ratings *AvgRating* (i.e., the average number of stars), which reflects the reputation of the product and is often controlled in previous studies [8]. Third, we control the volume of consumer ratings/reviews. Since the number of reviews is countable data, we take a log transformation (*LogNumRev*) to make its distribution closer to normal distribution. We project that the volume of ratings/reviews will have two effects in our model: (1) as a number reported in the app store interface, it directly affects consumers who view it; and (2) the number of ratings reflects the popularity of apps. However, as a cumulative measure, directly using the number of ratings for this purpose may combine past and current popularity. From this perspective, the change of number of ratings better represents the popularity of the app in a short period. Thus, we include both *LogNumRev* and Δ*LogNumRev* as control variables. Since a logarithmic transformation is conducted, Δ*LogNumRev* also reflects the growth rate of number of reviews. Last, considering that some apps have upgrades during the year, we included a binary variable, *Upgrade*, to capture its effect.

In the basic model, we applied a two-way fixed-effect model:

$$\begin{aligned} LogRank_{i,t} = {} & \alpha + \beta_1 ProdScore_{i,t-1} + \beta_2 ServScore_{i,t-1} + \gamma_1 Price_{i,t-1} \\ & + \gamma_2 Upgrade_{i,t-1} + \gamma_3 AvgRating_{i,t-1} + \gamma_4 LogNumRev_{i,t-1} \\ & + \gamma_5 \Delta LogNumRev_{i,t-1} + \mu_i + \eta_t + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

where i represents an app and t represents a week; μ_i represents the product characteristics that do not vary across time; η_t represents the time-variant factors that influence the entire market; and $\varepsilon_{i,t}$ is the random noise left. Since free apps and paid apps are ranked separately, their relations between sales rank and sales may be different. We conduct separate analyses for free and paid apps.

One might argue that the variables related to reviews in Equation (2) may be endogenous. We conduct two types of robustness checks to address this concern. First, we employ a random-effect model, adding app categories as control variables to enrich the possible omitted missing variable bias. Second, we employ the lags of these variables as instrumental variables and apply 2SLS (using Stata's xtivreg2 package) to estimate the coefficients. Such variables are likely to have serial correlations and will not be correlated with the error terms at time t, since their appearances are replaced by the variables in the time point t when a consumer read the reviews.

In order to show the effect of differentiating user comments to product quality and service quality, we build a measure of overall sentiment topics by using the lexicon built in the previous section. Since we do not need to differentiate product quality from service quality in this model, we only used the sentiment words and ignore the context words in doing the sentiment coding. We replicated the analysis with the developed *TotalScore* variable.

Results

Descriptive Statistics

We applied the MFSA framework as discussed in the previous section on the weekly app reviews and obtained the product score and service score. Table 4 reports the descriptive statistics of the data. Our data set contains 79 paid apps and 70 free apps. The average sales rank of paid apps is 133 and the average sales rank of free apps is 199. The price of paid apps varied from 0 (for special promotions) to US$15.99 with an average of US$2.64. The average rating was 4.14 stars in the 10 most recent reviews. The apps on average have about 200 reviews, with an average rating of about 3.9. The paid apps have higher textual scores than free apps. The *ProdScore* is about 8–9, the *ServScore* is about 0.2–0.8, and the *TotalScore* is about 17–20. Note that the *TotalScore* does not equal the sum of *ProdScore* and *ServScore* because it covers more information than the product and service dimensions that are restricted in our coding process. The probability for an app to have an upgrade during a week is 0.13. With our limitation that the app has to appear in more than 35 weeks, on average paid apps appeared in 42 weeks and free apps appeared in 45 weeks.

Table 5 reports the correlation coefficients among the variables. In general, there is no strong concern about the collinearity problem. The correlation between *AvgRating* and *ProdScore* is about 0.6, which is still acceptable for

Table 4. Descriptive Statistics of the Data in the Last Week.

	Paid apps					Free apps				
Variables	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
SalesRank	3,321	133.00	107.10	1	500	3,098	199.32	112.13	2	500
LogRank	3,321	4.48	1.05	0	6.21	3,098	5.09	0.71	0.69	6.21
Price	3,321	2.64	2.86	0	15.99	3,098	0	0	0	0
NumRev	3,321	194.59	316.03	1	3,249	3,098	223.79	431.14	1	5,585
LogNumRev	3,321	4.47	1.29	0	8.09	3,098	4.76	1.11	0	8.63
AvgRating	3,321	3.96	0.91	1	5	3,098	3.90	0.76	1.5	5
ProdScore	3,321	9.27	6.90	-8.5	52.5	3,098	8.12	5.94	-13.5	36.5
ServScore	3,321	0.84	1.97	-6	11.5	3,098	0.16	1.32	-20	10.5
TotalScore	3,321	19.81	11.72	-11.5	112.5	3,098	17.20	11.88	-16.5	236.5
Upgrade	3,321	0.13	0.33	0	1	3,098	0.13	0.33	0	1
NumWeek	3,321	42.61	4.91	35	51	3,098	44.79	4.73	35	52

Table 5. Correlation Matrix.

		V1	V2	V3	V4	V5	V6	V7	V8
Paid Apps									
LogRank	**V1**	1							
TotalScore	**V2**	−0.053	1						
ProdScore	**V3**	−0.033	0.533	1					
ServScore	**V4**	0.011	0.427	0.210	1				
Upgrade	**V5**	−0.054	0.027	0.015	0.018	1			
Price	**V6**	−0.016	0.110	−0.146	0.045	0.032	1		
AvgRating	**V7**	−0.057	0.190	0.623	0.19	0.027	−0.094	1	
LogNumRev	**V8**	−0.213	−0.054	0.171	−0.16	0.005	0.237	0.281	1
Free Apps									
LogRank	**V1**	1							
TotalScore	**V2**	0.035	1						
ProdScore	**V3**	0.048	0.376	1					
ServScore	**V4**	0.005	−0.071	0.096	1				
Upgrade	**V5**	−0.018	−0.011	−0.009	−0.014	1			
Price	**V6**	-	-	-	-	-	-		
AvgRating	**V7**	0.089	0.040	0.595	0.025	−0.003	-	1	
LogNumRev	**V8**	0.161	−0.100	0.072	−0.062	−0.025	-	0.283	1

regression analysis and shows that the ratings of reviews to a large extent reflect product quality.

Regression Results

Table 6 shows the results on the paid and free apps using the fixed-effect model, random-effect model, and instrumental variable regression. (For the instrumental variable regression, after underidentification and overidentification tests, we choose lags 1 to 3 and lags 1 to 2 of *ProdScore*, *ServScore*, *AvgRevRating*, *LogNumRev*, and Δ*LogNumRev* as instrumental variables for the paid and free apps, respectively. In such a setting, the endogeneity test is significant.) The overall results are consistent across the two data sets. Reviews on both product quality and service quality generally show a significant negative correlation with the sales rank, that is, a positive correlation with app sales. More positive comments on the product and service quality lead to higher sales. The results show the significant influence of textual reviews, particularly the two dimensions of the textual reviews on app sales. Hence, H1 and H2 are confirmed.

The results on our control variables also fit previous findings and our intuition. App price is positively related to app sales rank and negatively related to app sales; that is, a higher price leads to lower sales. The appearance of new versions of apps significantly improves app sales (and reduces sales

Table 6. The Effect of Differentiated Sentiments on App Sales.

	Paid apps			Free apps		
	(I) Fixed effect	(II) Random effect	(III) IV-2SLS	(I) Fixed effect	(II) Random effect	(III) IV-2SLS
ProdScore	-0.005*	-0.005*	-0.004	-0.005**	-0.005**	-0.007**
	(0.056)	(0.068)	(0.271)	(0.014)	(0.014)	(0.033)
ServScore	-0.014*	-0.014*	-0.025**	-0.021***	-0.020***	-0.019**
	(0.061)	(0.068)	(0.026)	(0.001)	(0.001)	(0.027)
Price	0.168***	0.146***	0.130***			
	(0.000)	(0.000)	(0.000)			
Upgrade	-0.066*	-0.065*	-0.033	-0.047**	-0.046*	-0.051**
	(0.064)	(0.070)	(0.404)	(0.044)	(0.051)	(0.028)
AvgRating	-0.211***	-0.163***	-0.138	-0.308***	-0.256***	-0.111*
	(0.001)	(0.006)	(0.137)	(0.000)	(0.000)	(0.052)
LogNumRev	-0.125***	-0.163***	-0.191***	-0.060**	-0.058**	-0.137***
	(0.000)	(0.000)	(0.000)	(0.030)	(0.026)	(0.000)
ΔLogNumRev	-0.802***	-0.831***	-2.125***	-0.669***	-0.674***	-1.770***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time dummy	√	√	√	√	√	√
App id dummy	√		√	√		√
App category dummy		√			√	
Num Apps	79	79	79	70	70	70
Num Obs	3,113	3,113	2,610	2,973	2,973	2,767
R-square	0.1862	0.1854	0.1505	0.3552	0.3548	0.3158
Endogeneity test			0.0271**			0.0038***

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; *p*-values are in parentheses; √ means the variable is controlled.

rank). The average rating of the reviews also influences the app's sales rank, where a higher rating leads to lower sales rank and higher sales. Furthermore, our results show that both the existing number of reviews and changes of number of reviews have a negative effect on sales rank of apps, which indicates the existence of an interface effect (to show a total number of reviews) and the network effect caused by the current popularity of apps.

Table 6 allows us to compare paid apps and free apps. A major difference we can see is the much higher *R*-square on the models of free apps. Note that the variables reported in this research are generally available on app stores. For free apps, a user may make quick decisions based on such available information. However, for paid apps, one may pursue information from other channels, such as third-party review websites, before making a purchase. As a result, the predictive power of our model is higher on free apps than paid apps.

We also notice that review volume and valence have different effects on paid and free apps. In general, the average rating's effect is much larger on free apps, whereas the review volume's effect is much larger on paid apps.

Our results indicate that free app users are more influenced by ratings, which may be due to the low cost of downloading, trying, and switching. However, it is not easy to drop paid apps without perceiving loss. The large volume of reviews indicates the large user base. Knowing that many people have purchased the app will increase the users' confidence in purchasing.

On the two hypotheses we want to test, free app and paid app users are generally consistent. We also notice free app users generally have slightly higher concerns about the app service (*ServScore*). We believe this is because app service quality occupies the major part of the free app users' cost. In general, it is relatively easy to figure out an app's product quality after a quick trial. However, service quality takes longer to determine. If there is any service problem, free app users are usually less protected. Then, the time they spend to find and fix a service quality problem becomes a major portion of their cost. Therefore, free app users tend to focus more on service quality.

To further illustrate the value of differentiating user comments to product quality and service quality, we experiment using the overall sentiment measure *TotalScore*. Model (IV) in Table 7 reports the use of *TotalScore* in a fixed-effect model. The results on the random-effect model and instrumental variable model (2SLS) are consistent. It is found that the *TotalScore* measure can help predict sales rank on paid apps but not on free apps. We further conducted a nonnested *J*-test between model (I) and model (IV). In a *J*-test, the predicted value of one model is included as an independent variable in another model to investigate whether it can bring further predictive power as compared with existing variables. Models (V) and (VI) in Table 7 report the results of the *J*-test. Consistent with model (IV), *TotalScore* provides extra predictive power over *ProdScore* and *ServScore* on paid apps. *ProdScore* and *ServScore* provide extra predictive power over *TotalScore* on free apps. To a certain extent, the results show the value of our proposed MFSA approach that decomposes online reviews into multiple facets for sentiment analysis.

Discussion

To understand the implications of our findings, we visualize the data set's product quality and service quality sentiments in Figure 2. The two measures have a very small correlation (correlation coefficient = 0.210 and 0.096, respectively in Table 5). The product quality sentiments (on average 9.27 and 8.12, respectively) are much stronger and more positive than those on service quality (on average 0.84 and 0.16, respectively). In other words, if we do not differentiate these two types of sentiments, the positive product quality sentiments will dominate the overall sentiments and overshadow consumers' opinions on service quality. Using an overall sentiment measure of textual reviews will cause biased prediction of app sales.

The larger scale of the product quality score shows that a majority of consumer comments are on product quality, which is the basis for the success of mobile apps. However, the service score coefficient is three to four times larger (in absolute value) than that of the product score in Table 6, suggesting that negative comments on service hurt sales more and mobile

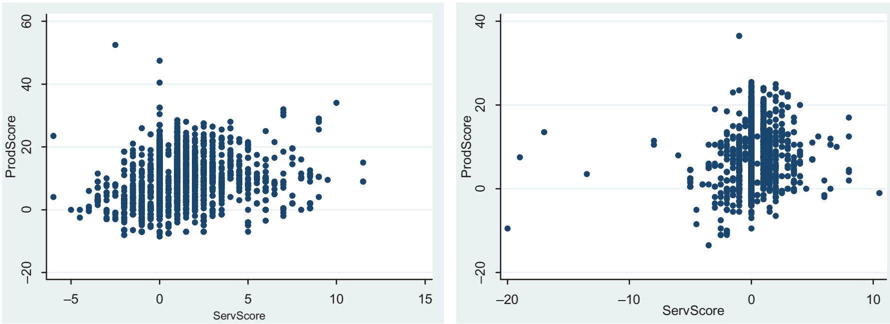
Table 7. J-test: Total Sentiment vs. Separated Sentiment in a Fixed-Effect Model.

	Paid apps			Free apps		
	IV	V	VI	IV	V	VI
TotalScore	-0.006***		-0.005***	0.000		0.001
	(0.000)		(0.002)	(0.578)		(0.203)
ProdScore		0.001			-0.006***	
		(0.661)			(0.005)	
ServScore		-0.007			-0.020***	
		(0.389)			(0.002)	
Price	0.166***	-0.003	0.138*			
	(0.000)	(0.961)	(0.069)			
Upgrade	-0.064*	0.000	-0.053	-0.046*	0.077	0.002
	(0.071)	(0.994)	(0.239)	(0.050)	(0.406)	(0.931)
AvgRating	-0.213***	-0.002	-0.175	-0.334***	0.598	0.011
	(0.001)	(0.983)	(0.148)	(0.000)	(0.364)	(0.898)
LogNumRev	-0.133***	0.001	-0.111*	-0.059**	0.102	0.005
	(0.000)	(0.989)	(0.087)	(0.034)	(0.399)	(0.873)
ΔLogNumRev	-0.805***	0.009	-0.671*	-0.674***	1.161	0.037
	(0.000)	(0.973)	(0.065)	(0.000)	(0.382)	(0.833)
Predicted Value of Model (IV)		1.016***			2.711	
		(0.001)			(0.168)	
Predicted Value of Model (I)			0.166			1.049***
			(0.707)			(0.000)
Time dummy	√	√	√	√	√	√
App id dummy	√	√	√	√	√	√
Num Apps	79	79	79	70	70	70
Num Obs	3,113	3,113	3,113	2,973	2,973	2,973
R-square	0.1887	0.1889	0.1887	0.3511	0.3557	0.3556

$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; *p*-values are in parentheses; √ means the variable is controlled.

app companies definitely need to put emphasis on improving their service quality. Previously, Li and Hitt [42] argued that showing multidimensional numerical ratings could reduce the bias of ratings caused by product price, which can provide consumers with better references for purchase decisions. In this study, we further illustrate the importance of differentiating the multiple facets of textual reviews to help us better understand consumers' opinions and predict demand. This finding should be considered in future text-mining studies.

Based on our data set, consumers take the comments on features related to both product quality and service quality of mobile apps seriously. This finding highlights the importance of service in the mobile app business, in addition to the product quality measure valued in e-commerce. To succeed in the highly competitive mobile app business, it is necessary to improve both product and service quality. We found that service quality comments have a slightly stronger influence on free app users than paid app users. The



a) Paid Apps b) Free Apps

Figure 2. Scatter Diagram of *ProdScore* and *ServScore*

nonnested *J*-test shows that it is more valuable to differentiate product quality and service quality when predicting free app sales. Mobile app companies should carefully maintain their online reputation to succeed in the mobile app business.

Conclusion

This research explores the relationship between textual reviews and mobile app sales. We developed a multifacet sentiment analysis method for analyzing textual sentiments from the perspective of product quality and service quality. Using a data set from the iOS app store in Taiwan, we found that after differentiating product quality and service quality, consumer textual reviews show a significant influence on app sales rankings. Our study shows that app users care about service quality in addition to product quality, especially for free apps. To succeed in the mobile app market, it is necessary to improve both product and service quality.

Our study provides support for using multifacet sentiment analysis to understand eWOM. Previous research on understanding textual eWOM has often been conducted in an aggregative way. Existing studies have failed to show the additional value of textual reviews over numerical ratings, which may be due to the canceling of (conflicting) information in the aggregation. In this paper, through the analysis of app reviews, we show that sentiment analysis needs to get into the details of different aspects of consumer opinions. Analysis of eWOM at a finer granularity could provide new insights and may improve theoretical explorations of e-commerce applications.

Among the different types of concerns in consumer reviews, this study focuses on features related to product and service quality based on previous studies of IT artifacts. It provides a textual analysis method to code eWOM and assess the two types of information from customer reviews. This method can be employed in future studies on other types of IT artifacts, especially in languages without extant lexicons or sentiment analysis models. For example, in SaaS ERP systems, users are concerned about both the service security and system functionality (user experience). In intelligent transportation solutions, users care about both the quality of (map-based) software functionality and interface and the accuracy of the provided traffic information. In such scenarios, a similar differentiation of product quality and service quality can be conducted, where our proposed approach can be applied.

In this research, we took a theory-driven approach and explored only two dimensions in app reviews. We built lexicons for each of the two quality measures. It is possible to extend our framework to more detailed subdimensions of product and service features in future research. To do so, it is necessary to develop multiple lexicons and further clarify where terms belong in each of the subdimensions of a construct, which will require substantial coding efforts of both IS and computer science researchers. However, such fine development of lexicons may empower us with more business insights from product reviews. From a text-mining perspective, it is also possible to incorporate richer textual features from reviews depicting consumer concerns related to IT artifacts' characteristics. Exploring richer features and more advanced sentiment analysis models could lead to more effective predictions.

For the empirical findings we derived on mobile apps, it should be noted that our data consisted of iOS apps in Taiwan. It is possible that the effects of eWOM on sales vary across regions. It is also possible that Android apps might show characteristics that differ from iOS apps. In future studies we plan to extend this research to more platforms and regions. We only collected sales rank data on the top 500 apps due to limitations of the iOS app store data. It is possible the effects of eWOM differ on less popular apps, which is worth studying. In this study, we only consider product reviews of app stores. It would also be valuable to examine eWOM in other channels, such as blogs, Web forums, Twitter, and so on, and to examine their influence on mobile app sales, which is also deferred to future research.

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