What Affects Mobile Application Downloads? The Role of In-Store Information

Full papers

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Abstract

Given the increasing importance of mobile applications in people's daily life and the unique characteristics of the mobile environment, surprisingly little research has been conducted to investigate consumers' downloading behavior in mobile application stores. In this study, by combining predictors of product performance with customer value framework, we consider both text and non-text information in examining the effect of in-store information on application downloads. We apply latent semantic analysis technique to find out the meaningful, valuable information embedded in customer review and product description for five types of applications. We also find that for different types of applications, customers weight information at various levels when they make downloading decisions. This study makes contributions by revealing the role of in-store information in mobile application downloads and providing application developers with useful guidance to improve in-store information management.

Keywords

Mobile application, in-store information, downloading behavior, customer value, latent semantic analysis

Introduction

As mobile overtakes fixed Internet access, mobile applications have permeated people's daily lives due to the increase in mobile users, the frequent interaction between users and applications, and the increasing number of available applications in mobile application stores (Lella and Lipsman 2014). As of July 2015, there are 1.5 million applications available in the Apple Application Store and 100 billion applications have been downloaded from it (Statista 2016). Among mobile applications, the number of downloads ranges from hundreds to hundreds of millions, which directly represents customers' purchasing decisions in mobile application stores and has an influence on revenue generated from applications. Therefore, what factors cause this huge difference in customers' download behavior and application performance in the mobile environment becomes a critical problem worth of investigation and discussion.

Customers' purchasing behavior in the mobile environment has drawn attention in both industry and academia since mobile commerce has become increasingly prevalent amongst customers and provided ample potential for marketers and researchers (Wang et al. 2015). For example, Nilashi et al. (2015) examined the role of security, design, and content factors on customer trust in mobile commerce. Wang et al. (2015) investigated how mobile shopping affects customer purchase behavior. Although the salient factors affecting sales of products and customers' purchasing behavior in the context of e-commerce have been studied a lot (Duan et al. 2008; Mudambi and Schuff 2010), we do not know whether these factors are still valid in the mobile environment and have an influence on customers' purchasing behavior. Mobile customers' behaviors are different from those in the context of the web environment due to the unique characteristics of mobile devices as well as the mobile environment. A mobile device's relatively small screen makes it impossible to display information from multiple resources synchronously and restricts users' access to rich multimedia contents (Pham et al. 2000). Therefore, due to the inconvenience of searching for information from multiple resources, users rely on in-store information

only to distinguish applications when they make their downloading decisions. However, little research discusses how exactly in-store information influences customers' decision-making. Therefore, the principal objective of this study is to fill in this gap in both theoretical and practical fields by investigating what information about applications valued by customers has an impact on application downloads.

In this study, we apply customer value theory to analyze the impact of in-store application information, considered as the predictor of application performance, on the number of downloads. We collected various types of information for 2,500 applications in top 5 categories in the Google Play Android Application Store. We use the latent semantic analysis approach to investigate text information and apply the ordinal logistic regression method to analyze the combined impact of text and non-text information on application downloads. Our study makes theoretical contributions by revealing customers' purchasing mechanisms across different application categories in the mobile environment. Our study also makes practical contributions by providing mobile application developers with useful guidance on taking effective actions to increase the number of downloads.

The rest of this paper is organized as follows: First, we briefly review the customer value theory and propose our hypothesis. Next, we give details about data collection, variable description, text mining methodology, and regression methodology. Then we present the empirical results and related discussion. Finally, we discuss theoretical and practical contributions and limitations in this study, as well as possible directions for future research.

Conceptual Background

Customer value has been considered a critical predictor of customers' purchasing behavior in e-commerce literature (Babin et al. 1994; Dodds et al. 1991; Kim et al. 2007). Customer value comes from different sources associated with the products or the process of exchanging products, such as information about products, characteristics of products, interactions with people and environment during the transaction, and possession transfer (Smith and Colgate 2007). Specifically, customer value coming from products is created by value-chain activities associated with product development (Smith and Colgate 2007). Therefore, the predictors of product development success, such as product, strategy, process and marketplace characteristics (Henard and Szymanski 2001), could be the source of customer value, influencing the customers' purchasing behavior. In this study, we identify predictors of product performance and merge them into a customer value framework. We propose that in-store information describing a mobile application's characteristics is the source of customer value and has an influence on mobile users' downloading behavior.

Customer Value Theory

Customer value has been defined differently in existing literature. In this study, we consider customer value as "a customer's perceived preference for and evaluation of those product attributes, attribute performance, and consequences arising from use that facilitate (or block) achieving the customer's goal and purposes in use situations" (Woodruff 1997). Based on this definition, a large number of studies have been conducted to identify key precursors of customer value and propose a related framework, to demonstrate that the perceived customer value has an influence on an individual's purchasing behavior (Chen and Dubinsky 2003; Schechter 1984). Specifically, Smith and Colgate (2007) built a comprehensive framework of customer value and proposed four types of customer value: functional value, experiential value, symbolic value, and cost value.

Predictors of Product Performance

Due to the increasingly important role of product innovation in sustainable business success, a large number of studies have been conducted to explore the drivers of product development success (Cooper and Kleinschmidt 1987; Montoya-Weiss and Calantone 1994). Although the drivers are different among related research, it is widely accepted that most drivers can be grouped into four categories: product, strategy, process, and marketplace (Henard and Szymanski 2001). Of which, process and marketplace mainly describe elements and activities associated with new product development process as well as the response of a target market to new products. In this study, the research object is mobile applications, not new mobile applications. The performance drivers of process and marketplace are not within our research

scope. Therefore, we only consider the performance drivers within the first two categories: product characteristics and strategy characteristics. In this study, an application's performance is a function of product characteristics and strategy characteristics, which are the sources of customer value.

Hypotheses

Functional Value

Functional value, considered a key influence on consumer choice (Kim et al. 2007, Sweeney and Soutar 2001), refers to the extent to which a product or a service has desired characteristics or performs a desired function (Smith and Colgate 2007). The functional value of a product comes from its characteristics or attributes, which can be measured in functional terms like quality (Mazid 2012). In this study, we use functional quality to indicate functional value, which is the perceived overall excellence and expected performance of an application.

In the digital world, consumers have various ways to express their opinions on products, such as giving a rating and writing an online review, which addresses their perceived functional quality of the product. Previous studies show that use-generated content, such as online rating and review, are salient factors in e-commerce, having a significant influence on product sales and consumer decision-making (Ye et al. 2009; Dellarocas 2003, Duan et al. 2008). By analyzing the information generated by online users, organizations can have a deep understanding of consumers' perceptions of products and identify consumer's purchasing behavior (Chin et al. 2015). Additionally, the distribution of word-of-mouth increases consumer awareness and reflects the popularity of a product (Liu 2006). Hanson and Putler (1996) demonstrated that consumers use the relative popularity of products as an indication of both the quality and the appropriateness of the product when making their choices. The number of raters demonstrates consumer awareness and reflects the popularity of an application, which is another indicator of consumers' perception of products and influences product sales. For example, the popularity of an album is positively associated with its sales (Oberholzer-Gee and Strumpf 2007). Therefore, we hypothesize that

Hypothesis 1a (H1a): An Average rating has a positive impact on the number of downloads.

Hypothesis 1b (H1b): Helpful information in online customer reviews has a positive impact on the number of downloads.

Hypothesis 1c (H1c): The number of raters has a positive impact on the number of downloads.

Experiential Value

In the framework proposed by Smith and Colgate (2007), experiential value refers to the extent to which a product or a service creates appropriate experience, feelings, and emotions for the customer. This value depends principally on how the product looks and how it relates to customers. In the mobile application store, to attract potential users and impress them, the developers have the option of uploading a demonstration video and screenshots to provide a vivid description of their applications. According to advertising strategies, vivid information can be used to influence consumers' attitudes towards brands and products (Appiah, 2006). Many advertising scholars and marketing professionals hold a general assumption that increasing the vividness of a message enhances its persuasiveness (Appiah, 2006). Video-based information enhances message effectiveness and makes the message more attractive, vivid, and salient. Xu et al. (2015) argue that dynamic and moving videos can capture human attention by vividly presenting stimuli for different processing channels like hearing and seeing to enhance cognition, which is also associated with feelings and experience. Therefore, uploading a demonstration video and screenshots is a good strategy to attract potential users' attention, provide appropriate feelings, and increase the number of downloads.

Besides the vivid information, the developers can also use words to describe their applications. Product description is complementary to a demonstration video and screenshots, considering the availably of network and data traffic in the mobile environment. When customers have limited access to the Internet, they can look at product description to get information about applications. From the product description,

users can get helpful information about various aspects of applications, such as functions, operations, privacy policy, etc. Therefore, we hypothesize that:

Hypothesis 2a (H2a): A demonstration video has a positive impact on the number of downloads.

Hypothesis 2b (H2b): Helpful information in product description has a positive impact on the number of downloads.

Hypothesis 2c (H2c): The number of screenshots has a positive impact on the number of downloads.

Symbolic Value

Symbolic value refers to the extent to which customers attach psychological meaning to a product, which helps customers enhance self-concepts (Smith and Colgate 2007). For example, purchasing goods with a "recycle" icon on the package is a way to express a person's self-concepts and self-worth related to environment protection, which make them feel good about themselves. The top developer badge indicates the application developer has the qualification of providing qualified applications. The privacy policy shows customers how their information will be collected and used. The "good quality" and "privacy protection" icons make people who are care about these aspects feel good about themselves by downloading applications with these two indicators. Therefore, we argue that people who care about quality and privacy are more likely to download applications with top developer badge and privacy policy, which increases the download volume. Therefore, we hypothesize that:

Hypothesis 3a (H3a): The Top Developer badge has a positive impact on the number of downloads.

Hypothesis 3b (H3b): The privacy policy has a positive impact on the number of downloads.

Cost Value

Cost value refers to the transaction cost involved in the purchase, ownership, and use of a product (Smith and Colgate 2007). The cost value is the perceived utility of a product based on its cost associated with purchase and ownership. The literature on price sensitivity claims that consumers will tend to focus on the price when there is little other information available to distinguish products, and lower price leads to higher favorability (Dodds et al. 1991). In mobile application store, mobile users have limited information from other sources to distinguish applications. Therefore, the price can be considered as an important factor that influencing a potential customer's downloading decision. Therefore, we propose that:

Hypothesis 4: The price has a negative effect on the number of downloads.

Methodology

Data Collection

In this study, we collected the data from Google Play Android Application Store, which dominates the application markets in terms of the number of available applications and the number of users. Millions of mobile applications in the store are classified into thirty categories, such as Games, Books & References, Businesses, etc. To have a representative dataset that demonstrates the majority of mobile users' downloading behavior, we chose to analyze the five most popular application categories ranked by the download volume: Games, Communication, Tools, Entertainments, and Social (Distimo, 2014). Within each category, we collected the in-store information about top 500 applications from the top-grossing list, which included both free and paid applications and ranked them according to their generated revenue. For each application, the collected data includes price, average rating, number of raters, number of screenshots, demonstration video, Top Developer badge, privacy policy, product description, and online customer reviews.

Variable Summary

Regarding the dependent variable, we categorized the number of downloads into 19 groups (order them from 0 to 18) based on the range of raw numbers of downloads. We used download group instead of a raw number of downloads because the latter one shown in the application store is a lower boundary of the

range, which cannot reflect actual and real-time information about downloads. For example, in the Google Play Store, the raw number of downloads will be shown as 50,000, if the actual number falls between 50,000 and 100,000. Therefore, the raw number of downloads for an application having 99,000 downloads will be the same with that for an application having 51,000 downloads. The raw number of downloads thus indicates a range or a group. Therefore, it is reasonable to use categorical download group as the dependent variable in this study.

Text Mining

Latent Semantic Analysis (LSA) is a statistical approach to investigate relationships between a set of documents and their terms by transforming text information into a measurable interval data type (Deerwester et al., 1990). LSA projects a term-document matrix into a small factor space and represents an original term-document matrix by a smaller dimension of a factor-document matrix (Lee et al., 2009). In this paper, we followed the procedure proposed by Evangelopoulos et al. (2012), implementing the LSA in three steps: pre-LSA textual data qualification, core LSA, and post-LSA quantitative analysis. In this study, an open source software R was used to conduct all three stages of analysis.

The specific tasks conducted in each step are shown in Figure 1. In pre-LSA textual data qualification step, we started the analysis from document decomposition, transforming sentences in a text file that contains all documents with the same type (e.g. product description of all communication applications) into a list of terms. We then conducted a series of activities to clean the data in a basic manner, which includes removing all non-English characters, transferring all words to lower characters, and removing punctuation and numbers. As a second step, we examined and solved typo issues like misspelling, letter repetition, and scriptio continua. As a third step, we identified and eliminated the unique terms that appear in only one document (Sidorova et al. 2008). In the fourth step, we removed trivial English words and customized stopwords that would not add any useful information to our further analysis from the data, such as names of people, names of countries, and terms like "application." In the fifth step, we eliminated term suffixes by applying Porter stemmer (Porter, 1980). Finally, we weighted all text files by applying two widely accepted transformations: inverse document frequency (tf-idf) and log-entropy transformation. By comparing the results generated from each transformation, we chose the one that represents semantic meaning in a better way to conduct regression analysis. In the core LSA step, singular value decomposition (SVD) was applied to reduce the complexity of the weighted matrix and reduce noise in the matrix. In the post-LSA step, we conducted a factor analysis to find the association between terms and factors. Refer to Sidorova et al. (2008) for more details about singular value decomposition, rotation, and factor analysis.
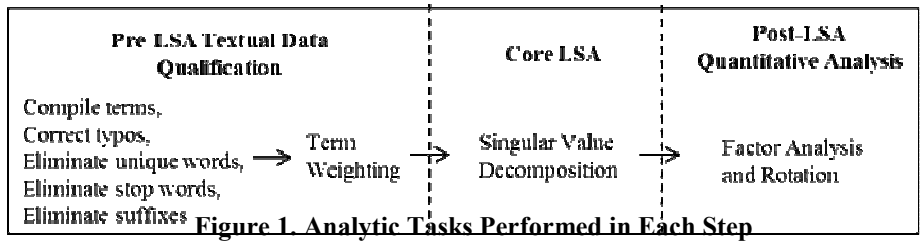

Figure 1. Analytic Tasks Performed in Each Step

Empirical Models

An ordinal logistic regression (OLR) model is employed to investigate the relationship between in-store information and download groups. Given a set of independent variables, an ordinal logistic regression model predicts the probability of an ordinal distributed download group. ORL is an extension of the binary logistic regression model, allowing the dependent variable download group to be 19 values, ranging from 0 to 18. Equation (1) and (2) demonstrates the basis of OLR approach applied in this study.

$$g(\Pr(Y \leq i \mid x) = \alpha_i + \beta' x, \ i = 0, 1, ..., 18 \tag{1}$$

where Y is the download group rank, the ranks are denoted by 0, 1 ... 18, α_i is the intercept parameters, β is the vector of slope parameters, β' is the transpose of β, and x is the vector of in-store information. The function $g = g(\mu)$ is the link function, representing the probabilities that result in a linear model in the parameters. In this study, we used logit function. $\Pr(Y \leq i \mid x)$ is the probability that download group rank Y is smaller or equal to i, conditioning on x. Equation (2) shows how logit function is used as a function to link the random component on the left side of the equation and the systematic component on the right.

$$g_i(\Pr(Y \leq i \mid x) = \ln \frac{(\Pr(Y \leq i \mid x)}{(\Pr(Y > i \mid x)} = \ln \frac{(\Pr(Y \leq i \mid x)}{1 - (\Pr(Y \leq i \mid x)} = \ln \frac{\phi_0(x) + \phi_1(x) + ... + \phi_i(x)}{1 - \left(\phi_0(x) + \phi_1(x) + ... + \phi_i(x)\right)} = \alpha_i + \beta'x$$

(2)

where $i = 0, 1, ..., 18$; $\phi_i(x)$ is the probability of being in the download group i given x.

Results and Discussion

By comparing the factor solutions generated from different settings (using different weighting methods and a different number of factors), we demonstrate the optimal final results in Table 1. All factor solutions displayed are generated by applying the log-entropy weighting method, indicating that log-entropy weighting method is a better weighting method in analyzing text information in the context of mobile environments. Due to the characteristics of a mobile environment, application developers and users tend to use concise, easy-to-read, and widely accepted terms to ensure their ideas will be easily understood, such as support, share, device, etc. Therefore, a few terms appear frequently in the text information in a mobile environment, making the log-entropy weighting method more appropriate than tf-idf weighting method in this study. This result confirms the argument in previous studies: the log-entropy weighting method works well when a small number of factors are obtained by analyzing a few frequently used terms (Evangelopoulos et al., 2012). The document loadings in the final factor solutions will be used in the OLR analysis.

	Category	Factor	Factor Label	High-loading Terms
Product Description	Game	F2.1	Fun - Easy Fun	free, slot, friend, win, featur
		F2.2	Fun - Hard Fun	Battl, power, player, build, hero
	Communication	F2.1	Usability	phone, call, messag, free, text
		F2.2	Interoperability	support, android, featur, devic, set
	Tools	F2.1	Usability	devic, support, file, server, set
		F2.2	Interoperability	phone, devic, android, locat, remot
	Entertainment	F3.1	Usability	devic, android, featur, support, free
		F3.2	Fun	plai, game, love, stori, charact
		F3.3	Functionality	friend, feature, free, share, fun
	Social	F3.1	Usability	free, call, text, chat, messag
		F3.2	Internet Connectivity	wifi, share, transfer, wirelessly,
		F3.3	Functionality	friend, locat, phone, track, famili
Customer Review	Game	F2.1	Fun	game, love, fun, addict, great
		F2.2	Experience	time, update, fix, load, crash
	Communication	F2.1	Experience	updat, time, fix, version, set
		F2.2	E-Service	free, fix, problem, help, keep
	Tools	F2.1	Interoperability	work, phone, version, android, devic
		F2.2	Usability	star, rate, feature, updat, support
	Entertainment	F3.1	Usability	game, free, pai, charact, voltag

		F3.2	E-Service	screen, time, fix, update, show
		F3.3	Fun	love, fun, game, time, funni, star
	Social	F2.1	Functionality	twitter, work, tweet, follow, updat
		F2.2	Usability	messag, chat, profil, phone, log

Table 1. Results of Text Mining

We included all text and non-text independent variables in the OLR model for the five application categories, including four continuous variables (price, the number of screenshots, the number of raters, average rating), three dummy variables (demonstration video, top developer badge, private policy), and semantic variables generated from LSA. Table 2 shows the parameter estimates of OLR.

Parameters	Games	Communications	Tools	Entertainment	Social
Price	-.515***	-.230***	-.133***	-.207***	-.797***
# of Screenshots	.010	-.023	.004	.002	.000
Average Rating	-.114	.280***	-.727***	-.379**	-.075
# of Raters	.000***	.000***	.000***	.000***	.000***
TopDeveloper=0	-.923***	-.275	-.051	-.090	.582
DemoVideo=0	-.361*	-.238	-.029	-.245	-.353
PrivacyPolicy=0	-.435*	-.794***	-.403**	-.300	-.475**
PD: Fun – Easy Fun	-.085				
PD: Fun – Hard Fun	.064				
PD: Fun				.081	
PD: Usability		.192**	.271**	-.207*	.157
PD: Interoperability		-.100	.120		
PD: Functionality				-.073	-.282**
PD: Internet Connectivity					.297***
CR: Fun	.014				
CR: Experience	.006	.043			
CR: E-Service		.455***		.000	
CR: Interoperability			.010***		
CR: Usability			.433***	.036	.024
CR: Fun				.362***	
CR: Functionality					-.272***

Note: *:p<0.1; **:p<0.05; ***:p<0.01; PD = Product Description; CR = Customer Review

Table 2. Parameter Estimates of OLR

Seven findings are summarized below. First, customers are more sensitive to price when free alternatives are available in the mobile environments. For all applications, the estimate for price is significantly negative. It indicates that price has a negative impact on application downloads, no matter which category the application belongs to. However, the intensity of impact varies across application categories. Users become more sensitive to price when they download game and social applications, compared with when they download tools, communications, and entertainment applications. In our dataset, the percentage of free applications across five categories is: 96% for game, 62% for social, 60% for entertainment, 45% for communication, and 41% for tools. Therefore, when more free alternatives are available, people will become more hesitant to pay for the download, which is consistent with previous literature (Dodds et al. 1991).

Second, consumers do not care about vivid information in the mobile environments. Except for the game category, in the other four application categories, neither number of screenshots nor demonstration video has a significant impact on download volume. The possible reasons could be network accessibility and limited screen size. It is inconvenient and costly for users to watch demonstration videos if they have

limited network accessibility. Furthermore, customers cannot be attracted if their screen size is too small to clearly display screenshots. Therefore, vivid information does not work as we proposed in the mobile environment. Mobile users pay little attention to screenshots and demonstration videos when they make downloading decisions.

Third, average rating does not always have a significant impact on downloads in the mobile environment. The impact of average rating varies among five categories. This finding is only partially supported by previous research, which indicates that the average rating is a salient factor in influencing the sales of the product (Ye et al., 2009). For communication applications, a higher rating leads to a higher download volume. For the game and social category, an average rating has no significant impact on download volume. It is caused by the small variance of rating. For example, among 499 game applications, 456 have a rating between 4.0 and 4.6. Therefore, it is hard for mobile users to distinguish applications by checking their average rating. For tools and entertainment applications, the estimate of an average rating is negative, which is opposite with the findings in previous studies. It is because there are some extreme cases in these two categories. It is possible that newly launched applications with low download volumes and a low number of raters have a high average rating. Extreme high rating makes potential users consider the application as immature products, and they hesitate to download. Based on our results, the impact of the average rating on download volume depends on the rating pattern of the application and specific situations in the application categories.

Fourth, application popularity is important but its impact on application downloads is very small. For all application categories, the estimate of number of raters becomes significant, but the estimate is close to 0. It indicates that although mobile users count on the number of raters when they make downloading decisions, having one more rater will not influence their decision.

Fifth, awards or icons are meaningless if they are not widely recognized in the mobile environments. It is interesting to find that the top developer badge only has a positive impact on download volume for game applications. For the game category, the proportion of applications having this badge is 61%, much higher than that in other categories, which ranges from 0.01% to 10%. Therefore, when most applications within one category have the icon indicating high quality, not having it will become a disadvantage in competitions. When the icon is not a widely recognized criterion, it does not have much meaning for potential users and has no impact on their downloading decision.

Sixth, privacy is important for mobile customers. The estimate for "without privacy policy" is negative for game, communications, tools, and social applications, demonstrating that uploading a privacy policy will increase the number of downloads in these four categories. Specifically, the impact of providing a privacy policy on the communications category is the strongest since communication applications are used to call, text and chat with friends, and share information with others. Most activities involve private and personal information collection. The potential users will have more willingness to download the application if the application developer provides a privacy policy to address data collection and data usage issues. For the entertainment category, a privacy policy does not have a significant impact on download volume since most entertainment applications do not involve collecting users' information, such as movie applications and painting applications.

Finally, customers focus on different aspects of text information when they download different types of applications. To increase download volumes, application developers should provide information that is valuable to customers. The estimates for some of the semantic variables are significant while others are not. For game applications, no semantic factor in product description or online customer reviews become significant. It demonstrates that the current content of product description and online customer reviews are not the information that can increase the number of downloads. When downloading game applications, users may pay more attention to non-test information (5 out of 7 non-text independent variables become significant). For the communications and tools categories, introducing usability in the product description and having more online customer reviews that address e-service, interoperability, and usability will increase the download volume. It is because communications and tools applications are designed to provide helpful utility for users to finish certain tasks. Mobile users focus on the information about usage, outcomes, and available assistance. For entertainment applications, introducing usability in the product description and having more online reviews mentioning the fun of usage is helpful in increasing download volume. For social applications, mentioning functionality in both product description and online customer review has a negative impact on downloads.

Conclusion and Limitation

In this paper, we examine an important research question of what specific information influences application downloads. We address this question by investigating the impact of in-store mobile application information on application download. The role of in-store information was investigated. This study included both text and non-text information in the analysis. Text mining techniques and ordinal logistic regression model are employed to investigate approximate 500,000 online reviews of 2,500 mobile applications within five categories. Several theoretical and practical implications can be derived from this study.

First, the major contribution of this study is to provide more understanding on important factors that attract more downloads across application categories in the mobile environment. Little research has been conducted to investigate customers' purchasing behaviors in mobile environments, which is different from those in the context of e-commerce. Our study makes theoretical contributions by filling this gap.

Second, this paper highlights the importance of detailed content in product descriptions and online customer reviews. Our study demonstrates that to fully understand in-store information in the mobile environment, it is necessary to analyze the text information embedded in online customer reviews and product descriptions, even though the text is relatively concise. Our findings indicate that the information embedded in in-store text information varies across application categories, and customers focus on different aspects of applications when they download different types of applications. Therefore, it is critical to reveal specific content addressed in the product description and customer reviews.

Third, our study reveals that the influential factors having impact on sales depend on characteristics of products like categories and characteristics of context like limited information sources. For example, in the e-commerce environment, the average rating usually works as an important factor that influences product sales. However, in the mobile environment, an average rating may not work in an expected way in some application categories.

Fourth, for different application categories, salient factors influencing download volumes are different due to the characteristics of applications as well as the characteristics of the dataset in each category. Therefore, there is no unified approach to increase the number of downloads across all application categories. This study provides empirical implications that guide mobile application developers in improving the in-store information management, which may increase download volume. It helps prevent mobile application developers from making vain efforts in in-store information management since some significant information having an impact on downloads in one category may not work as desired in other categories.

This study can be improved from some perspectives and its limitations also call for future research. First, there is some other information in the mobile application store have not been considered in this study, such as the quality of screenshots. The information embedded in screenshots is also available for customers and may also influence the number of downloads. Second, customers may download applications purely based on the information from other sources, such as public media and social network. In future research, it is necessary to consider all information that probably has impacts on application downloads at the same time to have a comprehensive understanding of the role of in-store information in the mobile environment.

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