MOBILE REPUTATION SYSTEM AND ITS EFFECT ON MOBILE APP PURCHASES

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ABSTRACT

Apple Appstore and Google Android Market[1] are digital distribution platforms that provide users a central location to effectively browse, purchase, download and update their mobile applications. They play a critical role in driving mobile app adoption and usage. However, there are about 600,000 mobile apps currently available in Apple Appstore, and over 450,000 apps in Google Android Market, choosing the right collection of apps to suit their individual needs can be quite daunting for smartphone users. In a mobile environment, reputation systems embedded in application stores may play a critical role in influencing app consumption. This paper intends to examine the importance of mobile reputation systems in app discovery and purchases. After reviewing literature on reputation systems and its application in mobile setting, a survey of student mobile app users for their preferences in app discovery and purchases is presented. The preliminary findings of our survey suggest that mobile reputation systems embedded in application stores play important roles in various stages of app purchase decision making process. Additional data collection and analysis are planned in the next phase of our research.

Keywords: Mobile Reputation Systems, Mobile Apps

INTRODUCTION

According to a recent survey conducted by the Pew Research Center's Internet & American Life Project, nearly half (46%) of American adults are smartphone[2] owners, and 2012 marks the first time that smartphone users outnumber traditional mobile phone users within the overall adult population in US (Smith, 2012). Even though hardware improvement related factors, such as

[1] Google Android Market is currently a part of the Google Play store, which was introduced in March 2012 when Google merged the Android Market and Google Music services into Google Play.[

[2] According to the survey, smart phone include the iPhone and Blackberry, as well as phones running the Android, Windows or Palm operating systems.

better processing power, larger wireless network bandwidth etc., have also contributed to the popularity of smart mobile devices, fundamentally, it is the ability to run large selection of feature-rich mobile applications that really differentiates "smart" mobile devices from "dumb" ones (Charland, 2011; Holzer and Ondrus, 2011). Not surprisingly, as the demand for smartphone soars, so too will the interest in mobile applications and services. Indeed, An IDC study forecasts annual mobile app downloads to rise from 38 billion in 2011 to nearly 183 billion in 2015 (Ellison, 2011).

In many ways, mobile applications are very different from their desktop counterparts. Because they tend to be used in short spurts, more frequently, but with limited screen size, it is important for mobile applications to deliver simple and focused functionalities for accomplishing specific tasks, rather than general and complex features in a combined fashion (Salmre, 2005). In addition, modern smartphones are equipped with embedded sensors that are traditionally not part of desktop computers, such as an accelerometer, digital compass, gyroscope, GPS navigation, microphone and camera, it's possible for developers to create large array of exciting applications to address virtually every aspect of mobile users' personal as well as professional needs. Since mobile applications first debuted in Apple's app store and Google's Android Market in 2008, there has been an explosion in innovative mobile apps in the areas of healthcare, social networking, environmental monitoring and transportation (Lane, et al, 2010). Other popular mobile app categories also include games, music, banking, shopping, and productivity (Nielsen Report, 2010).

Apple Appstore and Google Android Market are digital distribution platforms that provide users a central location to effectively browse, purchase, download and update their mobile applications. They play a critical role in driving mobile app adoption and usage. Currently, over 25 billion apps have been downloaded from Apple Appstore alone[3]. This is not surprising because majority of mobile apps are free or cost less than a cup of Starbucks coffee[4], they are very affordable to average consumers. However, there are about 600,000 mobile apps currently available in Apple Appstore, and over 450,000 apps in Google Android Market, choosing the right selection of apps to suit their individual needs can be quite overwhelming for smartphone users. Not to mention, the increasing presence of "copycat" or "clone" apps could further mislead consumers into making wrong app purchase decisions (Dredge, 2012).

A reputation system provides a framework of references to gauge the credibility of reputation objects such as a product, a people, or a thing etc. In a web environment, reputation systems are important mechanisms that take advantage of user generated content to aggregate reputations of products, individuals, and organizations and help people to decide whom to trust, and to encourage trustworthy behavior (Farmer and Glass, 2010). Essentially, these systems form "large-scale online word-of-mouth communities in which individuals share opinions on a wide range of topics, including companies, products, and services (Dellarocas, 2003). Some of the best known examples of online reputation system include Amazon's product reviews and eBay's feedback score (Resnick et al 2000; Zheng and Jin, 2009). In fact, the overall commercial

[3] Apple Press Release, "Apple's App Store Downloads Top 25 Billion," March 5, 2012.

[4] According to the App Store Stats Summary, the current average app price is $2.03, see http://148apps.biz/app-store-metrics/, last accessed on 03/29/2012.

success of eBay and Amazon are largely attributed to the design of their reputation systems (Resnick et al 2000; Dellarocas 2003; Farmer and Glass, 2010).

In a mobile environment, reputation systems established by application stores also play a critical role in influencing app consumption, especially because searching application stores on their phones are found to be the most popular method of app discovery and adoption for mobile users (the Nielsen Report, 2010). Both Apple's Appstore and Google's Android Market (or Google Play) have provided reputation information for their mobile applications. Naturally, features and designs of reputation systems embedded in their stores are crucial in guiding mobile users to decide which apps to purchase or download. For example, a mobile reputation system may include user generated reputation cues such as average user ratings of a mobile app, as well as vender generated reputation cues such as featured app ranking by the application store.

This paper intends to examine this new breed of reputation systems under the context of mobile application stores. While they bear a lot of resemblance with web based reputation systems, they are also subject to the limitations of mobile applications in general. Here after a brief review of reputation systems and its development in mobile settings, we present the preliminary result of a survey that is conducted to investigate the design features of the reputation system of mobile application stores and its impact on users app adoption behavior.

RELATED LITERATURE

Online Reputation Systems

Reputation represents "the beliefs or opinions that are generally held about someone or something" (Oxford English Dictionary). It is "a collective measure of trustworthiness based on the referrals or ratings from members in a community." (Josang et al., 2007, p. 621). Although individual reputation measure is often characterized as context-specific, multifaceted, and dynamic for the evaluated object (Windley, Tew, & Daley, 2007), reputation aggregated at a community level can be more consistent and stable for the object evaluated within that community, for example, people or organizations with similar profiles tend to use similar criteria as they are judging a product and view the same product similarly. Such aggregated reputation appears to have more "credits" than individual reputation measures to many people regardless of the accuracy of aggregated reputation. As a result, people tend to follow "the herd" in their purchase decision making. As they do so, they essentially compromise the inaccuracy and non-trustworthy of aggregated reputation in exchange of saving on their individual cost of searching, evaluation and verification etc. It is also noted that when compared to a product with similar aggregated reputation scores, the product that has more bad evaluation can be viewed more negatively in consumers' purchase decision even if it could have more good evaluation at the same time.

Existing online reputation systems have heavily relied on the aggregation of explicit information that is entered by a user, e.g. rating score or vote. That explicit information, once entered, can be summarized, and used to generate reputation scores that reflect the past behavior of a participant based on certain modeling equations. As an example, sellers' reputation on ebay primarily depends on buyers' rating on their transaction from negative to neutral and positive. While important to their initial business success, Ebay's and other similar reputation systems have been criticized for their weakness such as misrepresented feedback, pseudonyms, lack of portability and inaccurate reputation calculation (Resnick et al. 2000, Malaga 2004). Often, the reputation generated by those systems are thought to misrepresent the performances of community participants and subjected to artificial inflation or deflation by malicious actions. Since participants in many online communities are permitted to provide reputation scores with anonymity, it is also difficult for their reputation systems to identify participants and aggregate their reputation inputs accurately.

To remedy their weaknesses discussed above, online reputation systems have gone beyond simple scores or votes to include more user generated content such as review comments, testimony, audio and video evidences, and reciprocal interaction among users etc. Those attempts help to enhance existing reputation systems to some extent (Zheng and Jin 2009). Besides, some online reputation systems also take advantages of users' network behavioral data that is without their explicit knowledge. Examples of such implicit information are: how a user navigates through a series of web pages, how much time a user spends in an online store, or how frequent a user visits a site (Jensen, Davis, & Farnham, 2003). Frequently, online reputation systems will release some basic access statistics including popularity by evaluating view rankings, number of visitors, and number of comments in conjunction with their e-rating and e-voting scores. However, the scope and depth of implicit information used in today's online reputation systems are very limited.

Mobile Reputation System of Apple AppStore

As discussed earlier, reputation systems established by mobile application stores have included features of traditional online reputation systems, which may include: user generated reputation indictors, vender generated reputation indicators, explicit reputation indicators, implicit reputation indicators, as well as peripheral reputation indicators. However, due to limitations of being a mobile application, a mobile reputation system has to be carefully redesigned or simplified. It is argued that mobile application should only include "what is absolutely necessary" to support user's mental models and activities (Hoekman, 2010). Since the primary function of an application store is to facilitate selling of mobile applications, we first discuss the app purchase processes of mobile users briefly, and then we will examine Apple's Appstore in detail to look at how the design of its reputation system support user's app purchase processes and activities.

As illustrated in Figure 1, the traditional buyer purchase decision processes include: 1) Need Recognition; 2) Information Search; 3) Evaluation of Alternatives; 4) Purchase Decision; 5) Post-Purchase Behavior (Kotler and Armstrong, 2005). Under the context of mobile application purchases, mobile users have many different ways to recognize their needs for mobile apps. The need could be driven by internal stimuli, for example, consumers may feel the need for a restaurant recommendation app when they are hungry. On the other hand, the need could be externally influenced by friends' recommendations, app advertisements etc.

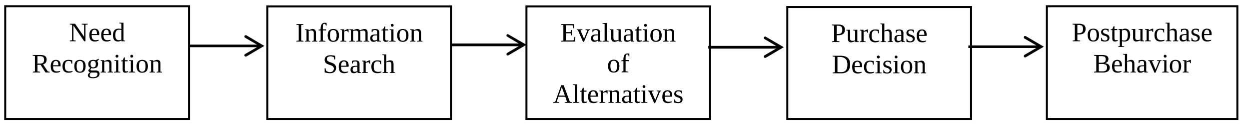


Figure 1. Buyer Decision Processes

During the information search process, consumers may choose to obtain more information from various sources, including personal sources (family, friends or colleagues), commercial sources (advertising on web, TV or magazine, display in Apple store), public sources (mass media, social media, app review blogs and forums), and experiential sources (try or use an app on somebody else's phone). However, Kotler and Armstrong (2005) acknowledge that if consumers find satisfying products during the need recognition stage, they may not search for additional information.

In general, information search will help consumers to narrow down their choices into a smaller set of apps. During the alternative evaluation stage, consumers will compare the alternative apps in their "choice set" in detail before finalizing their purchase decision. After apps are purchased or downloaded, consumers may engage in post-purchase activities, such as app reviews or updates.

Next, we will examine how the same app purchase decision processes are supported under the context of mobile application stores. In particular, we take Apple's Appstore as an example to illustrate our points.

Figure 2. Apple Appstore Bottom Navigation Menu

Inside Apple's Appstore, the primary function of its bottom menu is to guide users through the navigation. Before starting information search about mobile apps, users need to identify a mode in which they would like to begin the search. The four different modes are: Featured, Categories, Top 25, and Search (Updates belong to post-purchase behavior). The "Search" mode allows users to search apps through a keyword, this could be particularly efficient if users know the exact name of the app they are purchasing. The "Categories" mode enables users to search mobile apps based on the 22 categories set by Apple, ranging from books, music, to social networking and weather. The users who choose this mode to start their searches typically already have a general direction in terms of which type of apps they are interested in. While users who navigate through "Featured" mode are more acceptive to apps "featured" or recommended by Apple, users who choose “Top 25” tend to put more faith in most popular (most downloaded) apps.

After users select the mode of navigation, Appstore display a list of apps to facilitate the information search process. For each listed app, several app descriptive and reputation indicators are displayed:

- App icon: this could be a peripheral reputation indicator. An effective icon design not only makes an app stand out from the list, but also helps to infer level of quality of an app.
- Developer name: the name of the company who designed the app. This could also serve as a peripheral reputation indicator, again, a trusted developer brand may help to infer app quality. For example, users may trust apps developed by Apple or Disney more than the ones developed by unfamiliar companies.

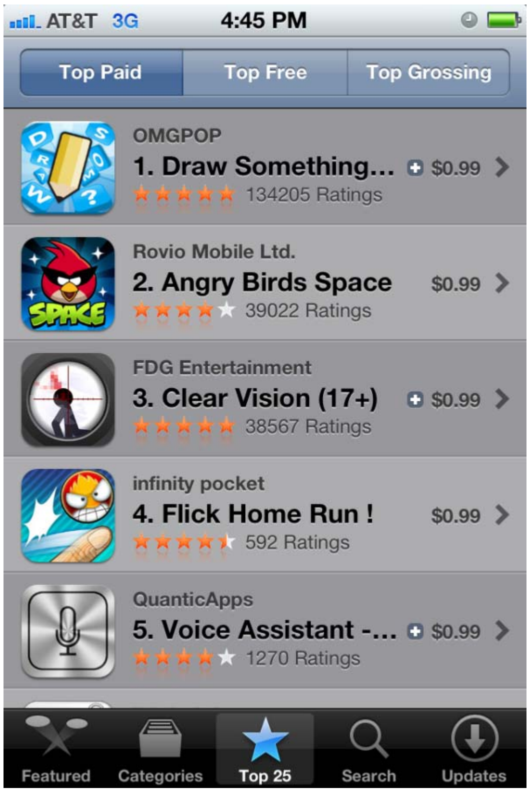


Figure 3. Apple Appstore “Top 25” List under “Top Paid” Category

- App name: this is a descriptive indicator.
- App price: this is a descriptive indicator, but may also serve as a peripheral reputation indicator. It has been established that users tend to infer quality from price of a product.
- Average user rating: this is a well-known explicit reputation indicator generated by users.
- Total number of ratings: this is an implicit reputation indicator that aggregates how many users have submitted reviews. It could be used to infer the popularity of an app.
- App rankings: the order in which an app is displayed in a list is determined differently, depending on which navigation mode a user chooses. The "Featured" rankings display relatively "new" or "trending" apps recommended by editorial staff from Apple, the criteria based on which the apps are selected and the orders are determined is unclear. The "Top 25" rankings (top paid, top free, and top grossing) reveal what Appstore thinks are the most popular apps. Again, according to Reisinger (2012), the rankings are calculated based on a closely held algorithm Apple has developed, which may include factors such as an app's download amount, the number of news articles about the app, whether it has been featured by Apple, and user ratings. Apparently, the apps that rank high on the lists tend to generate more revenue (Reisinger, 2012), therefore, they are very important vender generated reputation indicators.

After users go through apps listed, for the ones that interest them, they may navigate to the App "Info" page to compare app details.

Figure 4. Apple Appstore "Craigslist+" App Info Page (Beginning)

As shown in Figure 4, after repeating important information such as app name, developer, average user rating, total number of ratings, and price, an app info page will first showcase the credentials, awards, and testimonials from various professional sources, which are also powerful reputation indicators. After that, the page will explain in detail various functions that an app performs. Besides App descriptions, the detailed App Info page may also include 1 – 5 screen shot images that may help user better understand the "look and feel" of some key features of a mobile app, as illustrated in Figure 5. Note that images are also important peripheral reputation indicators that potentially give users the sense of using a product before it is purchased (Zheng and Jin, 2009).

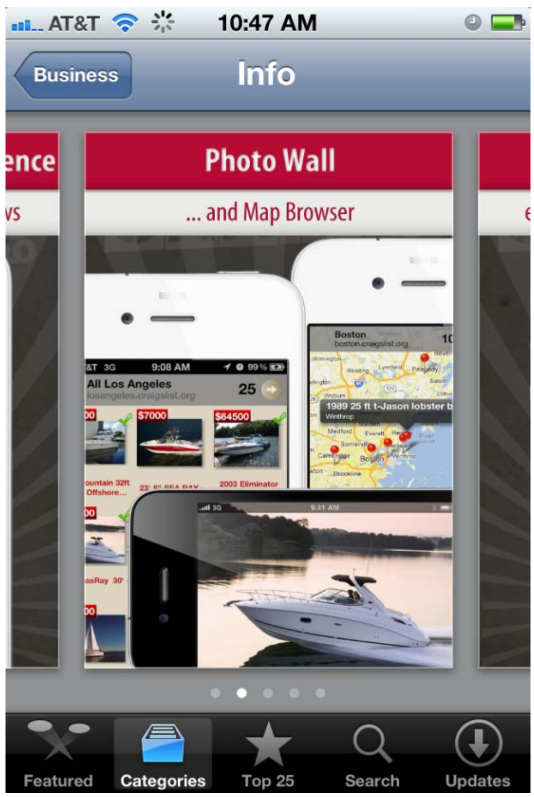


Figure 5. Apple Appstore "Craigslist+" App Screenshot in its Info Page

As shown in Figure 6, toward the bottom of the info page, users can choose to read the details of text comments of each reviewer. In addition, they could engage in activities to influence other people's app purchase decision, such as "Tell a friend" or "Gift This App", or to request support from app developers. Lastly, some essential technical details of an app are also included, such as version and file size of an application.

In our previous discussion, we reviewed various features of the mobile reputation system as presented in Apple's Appstore. Next, we describe an exploratory survey conducted with university students to investigate the impact of mobile reputation systems on their app purchase decisions. The result of the survey is reported in the preliminary finding section of the paper.

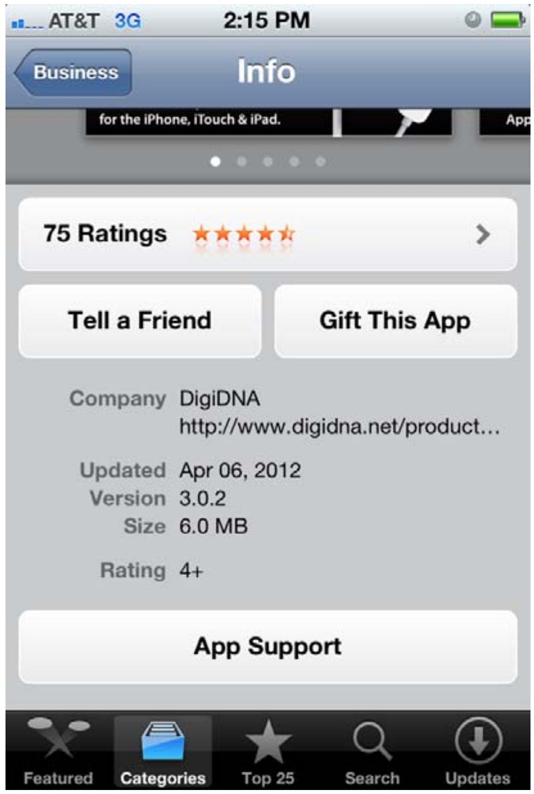


Figure 6. Apple Appstore "FileApp Pro" App Info Page (End)

METHODS

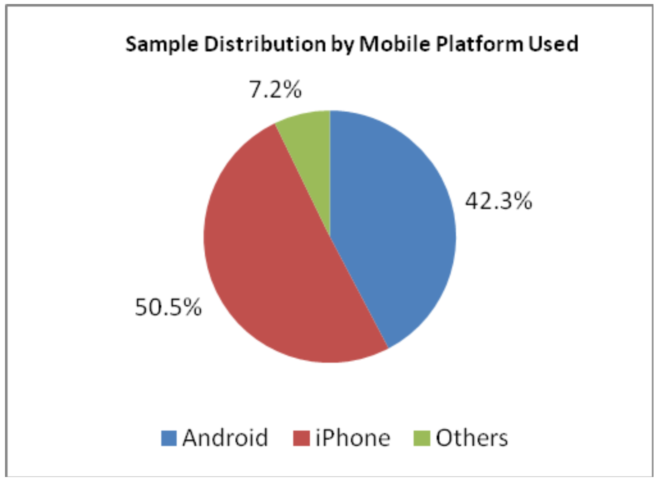
In order to investigate the role of reputation system in users' mobile app purchase, we started out with a survey conducted in two different universities at both west coast and Midwest of the U.S. The survey was made accessible to 166 students from both universities online. Students are asked to fill in the survey with their identification by the end of 2011 fall semester. A total of 146 students (88.6 % response rate) filled the survey. After examining the questionnaires collected, those incomplete were removed from sample pool, resulting in a total 97 valid samples. In addition to the survey, we have also interviewed a few representative students for their experiences with mobile apps reputation systems. Together, those findings are used for further analysis

PRELIMINARY FINDINGS

An initial observation of the data collected revealed that our samples have reflected similar market shares and patterns suggested by early research reports (Nielsen Report, 2010). First, the mobile phone platform markets are dominated by two major players—iOS and Android. Together, they took about 93% of mobile phone users in our sample population, leaving all the other platforms in less than 8% market. Since most mobile apps have to be designed for specific platform for compatibility, it is not a surprise to see that the app store market followed similar mobile phone platform. Again, with about 90% market shares, both Apple Appstore and Android Market are far ahead from the other app store available. Table 1 and figure shows that pattern:

Table 1: Sample Distribution by Mobile Platforms and App Stores

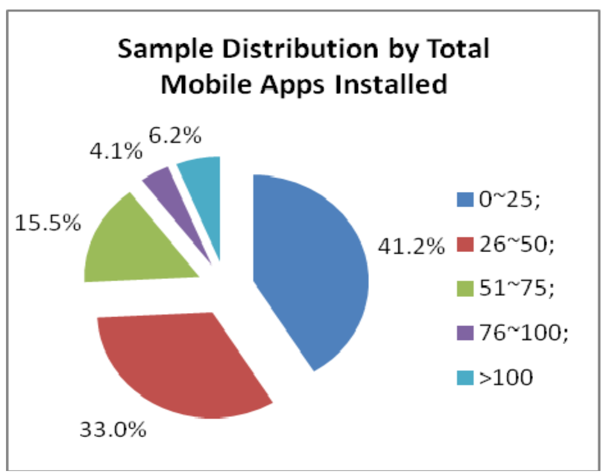
		Frequency	Percent
Platform	Android	41	42.3%
	iPhone	49	50.5%
	Others	7	7.2%
AppStore	Android	37	38.1%
	iPhone	50	51.5%
	Others	10	10.3%
Total		97	100%



Second, when it comes to purchase of a mobile app, users' prior experiences with mobile apps and mobile app reputation systems can be influential to their decisions. Therefore, we asked how many mobile apps the respondents have previously installed in their mobile phone. Only 41% of users had installed less than 25 mobile apps in total in the past. The majority of users installed 25 to 75 apps in their phone. See Table 2 for our sample distribution by Total Mobile Apps Installed.

Table 2 Sample Distribution by Total Mobile Apps Installed

		Frequency	Percent
Total Installed	0~25;	40	41.2%
	26~50;	32	33.0%
	51~75;	15	15.5%
Mobile Apps	76~100;	4	4.1%
	>100	6	6.2%

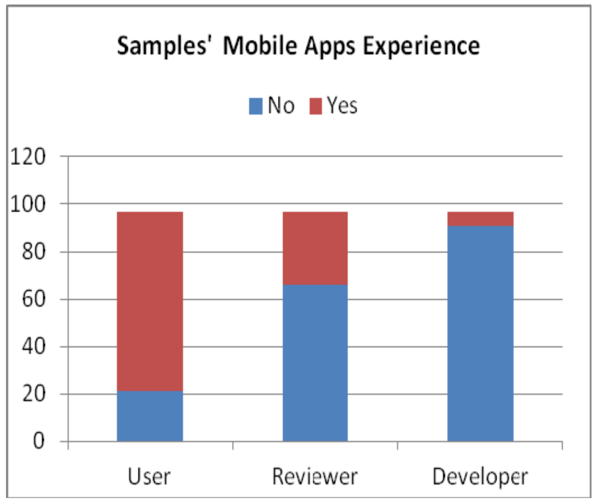


In addition to the number of mobile apps a user installed, the nature of their app experience also matters to their attitudes towards mobile app reputation systems. Our survey asked the respondents what their prior experiences are in using, reviewing or even developing a mobile app. According to our survey data, while the majority of users (78.4% of total samples) are users only, there are a high percentage of users (32% of totals) had app review experiences, and only 6% who ever developed a mobile app. Table 3 displays that distribution of our samples.

Third, since economic driver has played important role in mobile app users' purchases, we asked our respondents their expenditures on mobile apps on both the percentage of paid mobile apps in their total mobile apps downloads and the percentage of in-app store purchases within their total purchases.

Table 3: Sample Distribution by Mobile Apps Experiences

		Freq	Percent
User Experience	No	21	21.6%
	Yes	76	78.4%
Reviewer Experience	No	66	68.0%
	Yes	31	32.0%
Developer Experience	No	91	93.8%
	Yes	6	6.2%
Total		97	100%

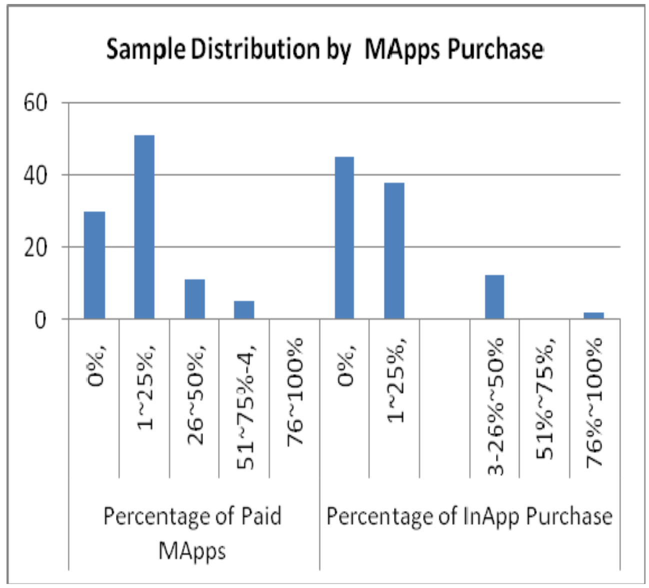


The first percentage is relevant to our study because it can reveal the purchase tendency of a respondent as he or she was downloading a mobile app. The second percentage can help us to understand if the respondent will more likely continue to purchase in the same app environment after they made their purchase of that mobile app. Our data suggests that while mobile app purchases are not uncommon to many app users, the rate of purchase stays relatively low at less than a quarter of total downloads. It is not surprising though since our respondents are all students, who may be subject to financial limitations. These findings are captured in Table 4.

Interestingly, in-App purchase seems a working strategy for many mobile app developers. According to our data, 39% of all downloads are in-App purchases . It is less than the rate of total paid apps in all downloads. However, a further look at the data suggests that as high as 80% of all paid apps are from in-App purchases. Table 4 shows such mobile app purchase patterns.

Table 4: Sample Distribution by Mobile Apps Purchases

	Percentage of Total Download	Freq	Percentages
Paid Users	0%	30	30.9%
	1~25%	51	52.6%
	26~50%	11	11.3%
	51~75%	5	5.2%
	76~100%	0	0.0%
InApp Purchase	0%	45	46.4%
	1~25%,	38	39.2%
	26%~50%	12	12.4%
	51%~75%,	0	0.0%
	76%~100%	2	2.1%
Total		97	100%



Fourth, besides economic drivers, users' interests in mobile apps can motivate their discovery of a mobile app on their phones. On a 1 to 5 Likert Scale, mobile users' highest interest in mobile apps download/purchase comes from social networking and communication needs of users, followed by the needs of entertainment/music/sports and mobile games. Figure 7 gives the relative scale of users' interests in mobile apps.

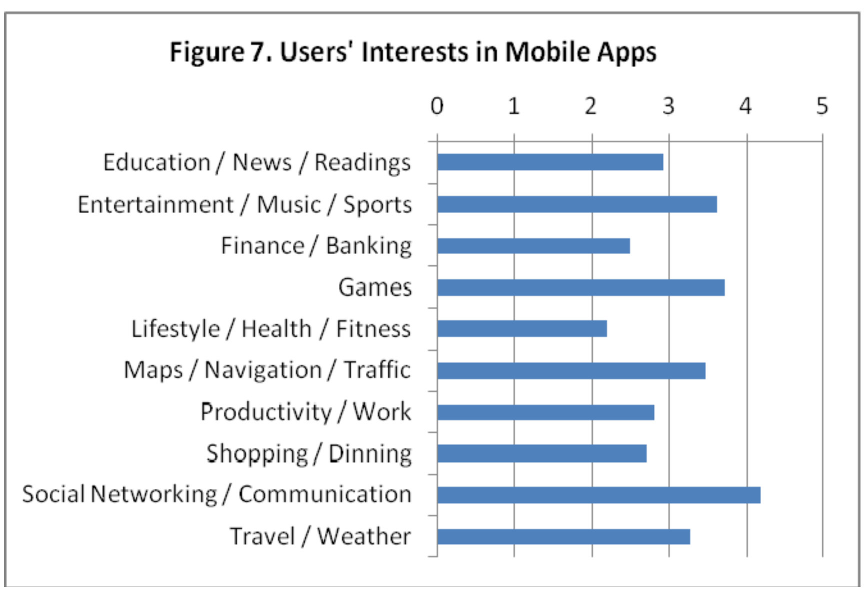


Figure 7. Users' Interests In Mobile Apps

Fifth, mobile application stores essentially provide a framework in which mobile app users can complete buyer purchase decision processes, from need recognition, information search, evaluation of alternatives, all the way to purchase decision and post-purchase activities. To what extent users take advantage of information search and alternative evaluation capabilities provided by the application store depends on the level of external influences, such as recommendations from friends or social networks. In other words, if users have decided what apps to buy before they open their application store app, the built in reputation systems would not have the chance to influence their purchase decisions.

Our survey results shown in the Figure 8 indicate that mobile apps are indeed most frequently discovered inside application stores through user initiated searching and browsing. Therefore, the reputation system features of a mobile application stores are important mechanisms to influence user app purchase behavior. In addition to application store searching and browsing, both physical social network (such as friends and family) and online social network also play important roles in mobile app purchase decision making processes.

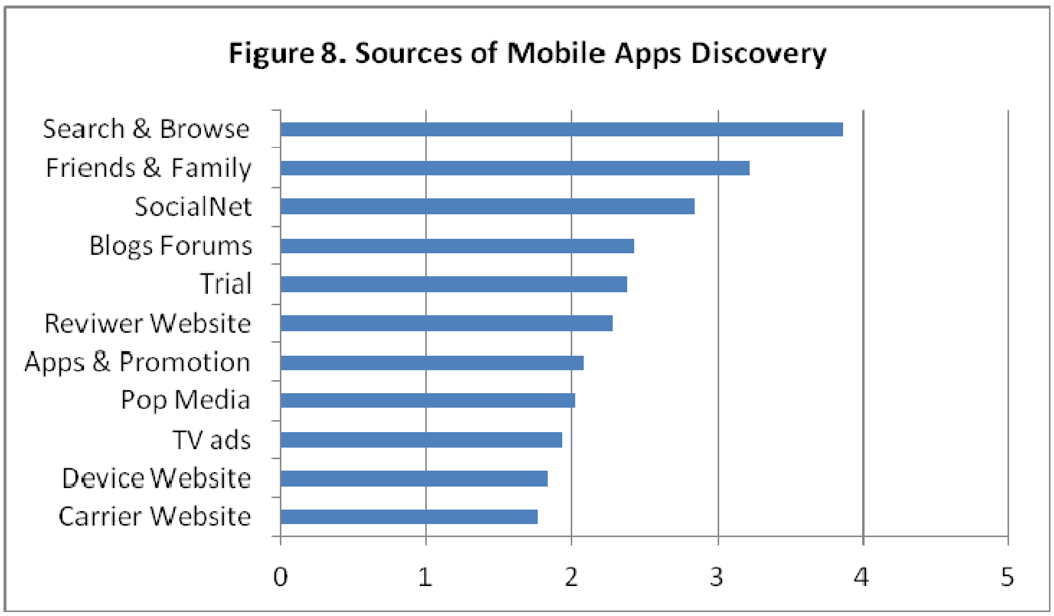


Figure 8. Sources of Mobile Apps Discovery

As illustrated in Figure 9, the role of mobile reputation systems can be examined by comparing the navigation modes to see which ones are the most influential in terms of helping users during the app discovery stage. According to our survey data, among the major application store navigation modes that help users to discover a mobile app, Top download is ranked the highest in its effectiveness. As we discussed earlier, even though top download rankings are generated by vender like Apple, the algorithm itself aggregates important reputation indicators generated by users and third parties. Compare to Top download, the low rating of keyword search seem suggesting that users tend to choose following the herd more than engaging in targeted search. What is more interesting is the lowest rating of Featured.

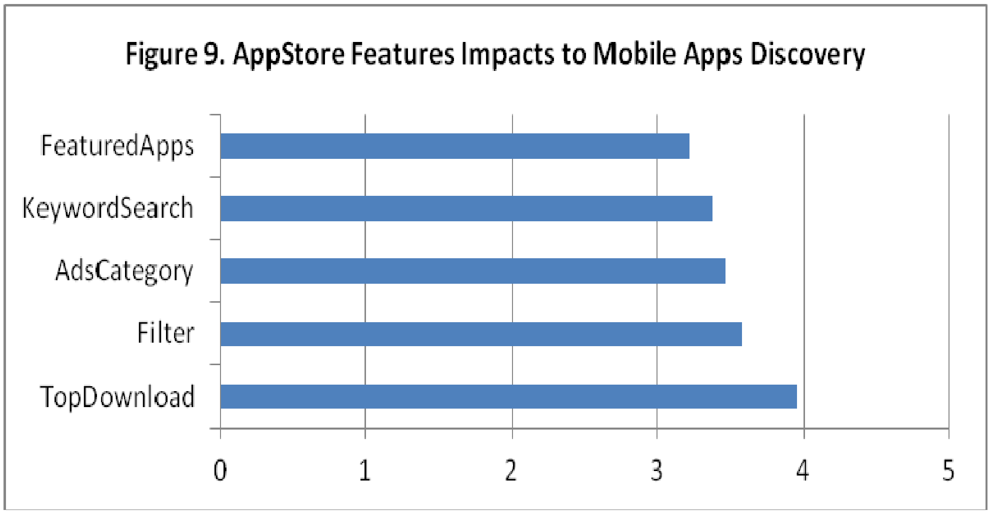


Figure 9. AppStore Features Impacts to Mobile Apps Discovery

apps, a list handpicked by application stores to recommend relatively new or trending mobile apps. Such a low rating might suggest that users trust popular apps more than new ones.

As shown in Figure 10, during the information search stage, users may pay attention to various reputation indicators, such as average user ratings, price, total number of ratings, icon design, as well as the developer brand. Our survey shows that among all apps' properties, average rating a mobile app gets from other users has the highest impact on their decision, following by app price. In addition, both average ratings and total number of ratings are more important than name, app icon, and brand of app developers. Both average rating and total number of ratings are classic user generated reputation indicators. Their high ranking in our sample data confirms the importance of reputation systems to mobile apps discovery and purchase.

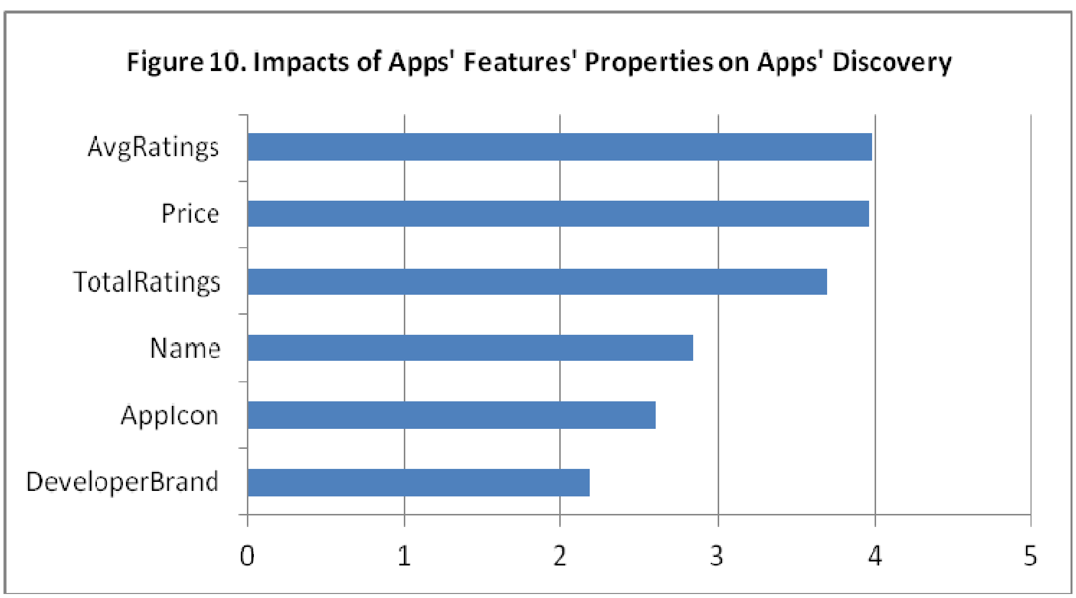


Figure 10. Impacts of Apps' Features' Properties on Apps' Discovery

As Figure 11 indicates, among those mobile app details, smartphone users rely most on the other users' review details to make up their mind for purchase. While they do look at the function descriptions, the other users' reviews are more influential on their purchase decision than the other details, such as screenshots, and technique specifications.

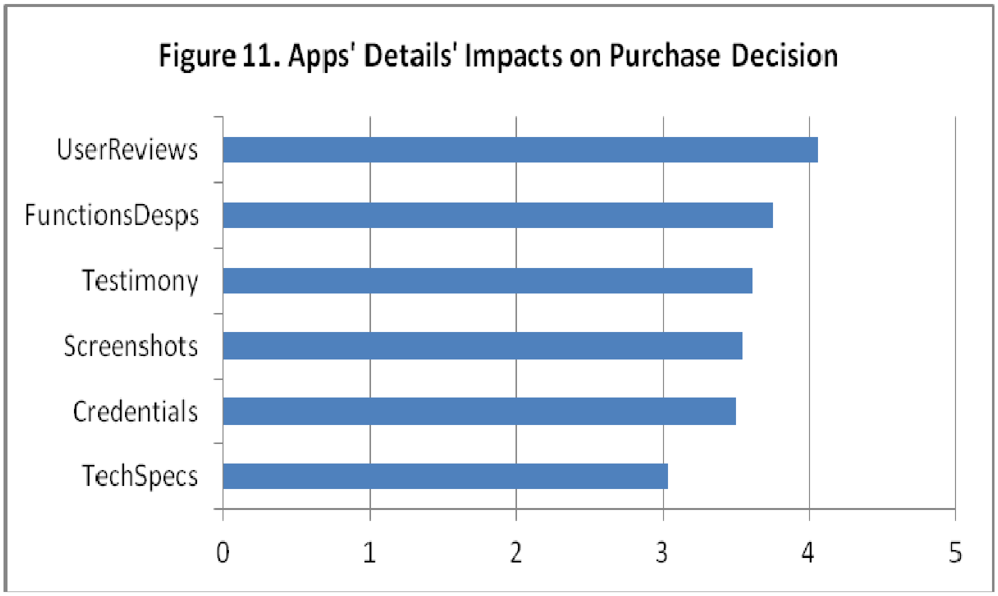


Figure 11. Apps' Details Impacts On Purchase Decision

CONCLUSION

The paper set out to understand the importance of mobile reputation systems in app discovery and purchases. After reviewing literature on reputation systems and its application in mobile context, a survey of student mobile app users for their preferences in app discovery and purchases is presented. The preliminary findings of our survey suggest that mobile reputation systems embedded in application stores play important roles in various stages of app purchase decision making process. Additional data collection and analysis are planned in the next phase of our research.

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