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Product Portfolio and Mobile Apps Success: Evidence from App Store Market

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ABSTRACT

This research empirically analyzes seller's product portfolio strategy in the mobile application (apps) market. We use cross-sectional data on the most downloaded application rankings in the Apple App Store to examine the impact of app portfolio strategy on sales performance. We find that app portfolio diversification is positively correlated with sales performance. We also find that sellers who offer a combination of free and paid apps have higher sales performance than those who deliver paid apps only. Furthermore, the results show that sellers with scale advantages compete differently from sellers in the long tail. These findings have implications for theorizing about product portfolio management in the emerging mobile app store markets.

Keywords

App store market, product portfolio management, long tail, versioning.

1. INTRODUCTION

Mobile applications are one of the most rapidly growing segments of the software market. Many of the mobile application stores, such as Google Android Market, Nokia Ovi Store, Blackberry App World, and Apple App Store that have been launched over the past few years have experienced remarkable growth over a short period of time. For example, Apple App Store has featured over 300,000 apps and 62,100 unique developers within the span of only two-and-a-half years.

According to the Wall Street Journal (2011), Apple has sold 10 billion apps since the market launched in 2008. Such a fast growth of the app market has provided many opportunities not only to sellers (i.e., developers or publishers), but also to consumers. It has broadened customers' access to a large database of apps. App Store users spent an average of $4.37 on apps every month in 2010[1].

The market structure of the mobile app store naturally lends itself to a large selection of apps. In such a market, developers would need to carefully formulate strategies for success. Online channels with low search costs and large selection of heterogeneous products create a conducive environment for the "long tail market" (Anderson 2006). Recent research attention on long tail markets has focused on book sales (Brynjolfsson, Hu, and Smith 2006) and DVD sales (Elberse 2008). A number of these studies have focused on sales distributions in the long tail with specific implications for intermediaries and, to an extent, for developers. However, content creation related to movies and books is very different from that for software development. App developers compete more directly with other developers since consumers are better able to compare product features across apps. Unlike music creators, app developers can focus on building apps under various categories. The versioning strategy for app developers affords much wider range of options than for music or movie producers. App developers can also continuously update apps to compete and keep their product offerings fresh. While some software developers publish apps across the various categories, others have chosen to only provide apps in particular categories. For example, large mobile app developers such as Chillingo Ltd. and Wizzard media sell around 200 apps across

[1] The Apple App Store Economy (January 12, 2010), Gigaom. http://gigaom.com/2010/01/12/the-apple-app-store-economy/

13 or more categories with different versions (or different prices) of apps, while several developers like Iceberg Reader and Libriance Inc. offer over 1,000 apps in 6 or less categories. Thus, a seller's app portfolio strategy and its impact on successful sales have surfaced as an important issue for researchers and market participants.

The main objective of this research is to empirically examine the impact of sellers' product portfolio on sales performance.

Consequently, this study will answer the following key research questions:

- How does a seller's assortment of apps across categories affect sales performance?
- Does offering a combination of free and paid apps increase a seller's sales performance?
- How is the impact of product portfolio on sales performance different for high-volume sellers as compared to the low-volume sellers?

We address these research questions by utilizing theories of product portfolio management, versioning digital goods, and the long tail effects.

The remainder of this paper proceeds as follows. In section 2, we discuss the relevant literature to our present work. Hypotheses are developed in section 3. In section 4, data descriptions and analyses are presented. In section 5, estimation results and discussion are presented. We discuss the implications of our results and future research direction in section 6.

2. LITERATURE REVIEW

Although research on the mobile app store market is just emerging, a large volume of literature in marketing, economics, and IS enables us to examine the key research questions theoretically. The following sections review the relevant research streams.

2.1. SELLERS' PORTFOLIO MANAGEMENT STRATEGY

Since most existing studies on software portfolio management have focused on the software product development (e.g., Vähäniitty and Rautiainen 2005), our study draws on the extant marketing literature on product portfolio. Day (1977) defined the product portfolio as a decision on the use of managerial resources for maximum long-run gains. A vast research (e.g., Lancster 1979; Quelch and Kenny 1994) is dedicated to the impact of product proliferation (or product line extension) on firm profitability.

Prior research related to product portfolio management can be broken down into two streams: product line extensions (diversification) and narrow product lines (concentration). By offering highly divergent product lines, firms can satisfy consumers' heterogeneous preferences (Quelch et al. 1994), accommodate future preference uncertainty, and gain price-setting power (Aribarg and Arora 2008). Furthermore, having a greater variety of related products helps firms to satisfy customer needs better than competitors (Rothaermel et al. 2006). However, in spite of these benefits of product line extensions, some firms take advantage of narrow product lines, which allow them to have lower production costs (Baumol, Panzaar, and Willig 1982), lower design costs, and lower inventory costs (Lancaster 1979). Hence, the success of product proliferation depends not only on the firm's market, but also on firm specific properties. Some firms may be more successful in diversifying their product lines, while others may find it advantageous to concentrate on specific product lines related to their specific specialization.

2.2. VERSIONING OF DIGITAL GOODS AND FREE CONTENT

The versioning of digital goods refers to the sales practice pursued by producers or distributors by which several versions of some specific digital products are offered to users at different prices. It allows potential users to sort themselves out to different groups according to their willingness to pay (Varian 1997). The literature on versioning and pricing of digital goods (Bhattacharjee et al. 2007; Bharagava and Choudhary 2004; Shapiro and Variance 1999) provides insights on app sellers' versioning strategy. Shapiro and Varian (1999) note that versioning enables customers to self-select the version that meets their expectation. It explains why many sellers have provided different prices for different versions of apps (e.g., trying-before-buy versions).

Many IS researchers have examined how versioning strategy can resolve inherent problems of digital goods such as media content piracy (Bhattcharjee et al.; Wu and Chen 2008) and creation of large network of customers (Bhargava and Choudhury 2004). For example, Bhattacharjee et al. (2007) argue that a digital music distributor may be able to maximize profits by offering a mixed-mode purchase and subscription service in the presence of digital music piracy. Bhargava et al. (2004) present that the versioning strategy improves intermediaries' profitability and user participation based on strong aggregation effects.

Several studies on software versioning strategy (Gaudeul 2004; Hui, Yoo, and Tam 2008) have shown that shareware can be used not only for reducing the possibility of piracy under certain conditions but also for mitigating customer uncertainty about software quality. Gaudeul (2004) argued that shareware increases a consumer's willingness to pay for products and heightens the product's attractiveness. In the app store market, sellers offer paid and free versions. Carare (2010) defines free apps as "either reduced functionality versions of paid programs or programs that display advertisements." Some developers prefer to release their apps free of charge to gain advertising. Furthermore, free versions of apps may lead to future purchases. Smith and Telang (2009) examined the impact of the availability of free content on DVD sales and found that the presence of free content can stimulate sales in the paid channel. Moreover, Parker and Alstyne (2005)'s study suggests that the increased demand in a complementary premium goods market covers the cost of investment in the free good market.

2.3. LONG TAIL EFFECT

Anderson (2006) indicated that online channel has significantly changed the shape of the demand curve because consumers can easily and inexpensively find products more closely tailored to their preferences. Much of the research investigating the long-tail effect has focused on the changing distribution of books (Brynjolfsson et al. 2006) and DVDs (Elberse 2008). There are two different perspectives on the impact of long-tail effect on sales of digital goods. Anderson (2006) and Brynjolfsson et al. (2005) showed that reduced search costs using the online channel allowed niche products to gain a higher market share and caused the demand for popular products to decrease. They predicted that niche products can better satisfy consumers' heterogeneous tastes by allowing them access to more obscure products. For example, Brynjolfsson et al. (2006) found that obscure book titles accounted for about 40% of Amazon's book sales in 2000.

Meanwhile, Elberse (2008) argued that although the online channel has increased the demand for niche products, it does not ensure that the firm offering niche products will be successful. By tracking weekly DVD sales from 2000 to 2005, Elberse and Oberholzer-Gee (2007) found that customers' preference tended to be concentrated on a few hit DVD titles over time rather than being dispersed across the spectrum of obscure titles. Similarly, Tan et al. (2010), using data from Netflix, found that the demand for hit movies increased over time, while the call for niche movies decreased. They concluded that there is no evidence that niches satisfy consumer preferences better than hits, and only a small number of consumers regularly venture into the long tail.

3. RESEARCH HYPOTHESES

The assortment of apps under various categories has the potential to affect overall sales performance for app developers. A seller developing multiple apps faces a decision on whether to specialize in specific categories or to develop a broad collection of apps under different categories. Consistent with the theories of product line extensions (Putsis 1994, Rothaermel et al. 2006), we argue that the large selection of apps across various categories and diversification of categories reduce the uncertainty about consumer demand for the seller. Furthermore, past research has found no significant relationship between product concentration and profitability (Cooper, 1985). A related stream of research has applied financial portfolio theory to product portfolio decisions (Cardozo and Smith, 1983; Devinney and Stewart, 1988). The implication of the portfolio approach is that correlations across product categories can lead to a higher risk profile for the firm. Thus, broadening app offerings across categories has the potential to improve product portfolio's risk-return profile. A counter argument to broadened product portfolio is the diminished complementarities across products. However, we believe that this is less of a concern in the app market since developers leverage the same underlying platform to build apps across various categories. Further, sales and marketing efforts are not that dissimilar across categories. While specialized skills and competencies within app categories may still be valuable, we argue that the benefits of leveraging development expertise across categories outweigh the costs of developing category specific skills.

Hypothesis 1a: Sellers providing a larger selection of apps are more successful than sellers offering only few selections.

Hypothesis 1b: Sellers diversifying across categories are more successful than sellers concentrating on a particular category.

There are three different types of sellers according to app pricing on Apple's App Store: sellers offering free apps only, paid apps only, and both free and paid apps. From our observations on App Store, we hardly see sellers proving only free apps (0.01% of sellers). Thus, we restrict our focus to paid app only, and free and paid app sellers**.** Decision on app pricing can be considered a seller's strategy that accommodates different customer preferences**.** While some price-sensitive customers may prefer free apps to paid apps regardless of the apps' functionality, some customers may want to experience or sample an app before making a purchase decision. In this context, Shapiro and Varian (1999) suggest that differentiated prices satisfy different values of a seller's product. They also argue that offering different versions (differentiated in delay, user interface, convenience, speed of operation, format capability features, annoyance, and support) appeals to different segment groups. The trial-ability of reduced functionality versions (try-before-buying versions) promotes customers to purchase full version of paid products. Thus, we predict that sellers offering both free and paid versions of apps have higher sales performance. This leads us to the following hypothesis.

Hypothesis 2: Sellers providing both free apps and paid apps are more successful than sellers selling only paid apps.

While the above hypotheses aim at addressing the impact of overall seller's product portfolio strategy (i.e., assortments of apps and pricing) on sales performance, other factors can also be relevant. We formulate the hypotheses regarding the relationship between sales performance and characteristics of different seller groups by drawing upon the theory of long tail. Previous literature on the long tail effects (Brynjoffson at al. 2006; Elberse 2008) divided sellers into popular-product sellers and niche-product sellers (tail) based on their sales revenue and rankings. A different interpretation of the long-tail, especially suited to entertainment or app markets, can classify sellers based on production volume (Kauffman et al., 2010) - small number of high volume sellers and a large number of low volume sellers (tail). We expect that popular sellers would be more successful as compared to the tail producers. As we discussed in the previous hypotheses, the sellers with large number of apps are likely to have more opportunities to diversify their apps across categories and to offer different prices than sellers who have fewer apps. In contrast, sellers in the tail would have fewer resources to develop apps to compete across all categories. In this context, Elberse (2008) recommend that sellers should focus on a few popular categories to strengthen channel presence. Further, when scale advantages exist, it is better to broaden market presence and leverage success from one category to another. Therefore, competing in the app store market may require different strategies depending on whether a seller is in the tail or at the head (from a scale perspective). We predict that sellers in the tail have higher sales performance by selling apps though popular categories, while large-scale sellers increase downloads by offering more apps across a large cross section of categories.

Hypothesis 3a: Large-scale sellers have higher sale performance as compared to sellers in the tail.

Hypothesis 3b: Concentrating on popular categories is more beneficial for the low-volume sellers as compared to the high-volume sellers.

4. DATA DESCRIPTIONS AND ANALYSIS

DATA

To conduct our research, we collected data on the top 300 apps in all categories in the U.S. Apple App Store. Based on the seller listed in the top 300, we collected all seller information in the second stage of data collection. Given our focus on product portfolio, we limited our attention to those sellers that have more than four apps across at least two categories. This resulted in a set of 3,168 unique sellers who list at least one application in the top grossing 300 (most revenue generated free and paid apps) under 21 different categories[2] on Apple's App Store from December 2010 to February 2011. We combined data from two main sources: Apple's iTunes and AppStoreHQ.com-a mobile application tracking site. These two sites provide app information on iPhone, iPod touch, and iPad devices, but we only consider apps for iPhone and iPod touch devices. From iTunes, we collected data on ranks, titles, price, category, developers, publishers (i.e., sellers), updated dates, modified dates, descriptions, number of screenshots, icons, user ratings, and file size of apps (MB). In addition, we obtained data on each seller's total number of apps, number of categories, and average rating and price of those apps from AppStoreHQ.com. Then, the dataset was re-categorized according to the individual seller. For example, we calculated each seller's total number of apps in the top 300, number of apps under each category, and portions of free and paid apps. The set of variables extracted from our dataset is shown in Table 1.

[2] Apple App Store provides 21 different categories: book, business, education, entertainment, finance, games, healthcare-fitness, lifestyle, medical, music, navigation, news, photography, productivity, reference, social-networking, sports, travel, utilities, and weather.

Variable Names	Description of Variables	Mean (S.D.)	Min.	Max.
Num_apps_top300	Number of apps in the top 300	1.68 (2.21)	1.00	49.00
Num_category	Total number of categories in seller product portfolio (diversification)	1.16 (0.49)	1.00	7.00
SD_category	Standard deviation of number of apps across the non-empty categories (focus)	0.33 (0.40)	0.21	10.40
Total_num_apps	Total number of apps in product portfolio (scale)	18.28 (146.02)	1.00	691.00
Log_avg_price	Average price of paid apps	6.09 (14.96)	0.00	299.99
Avg_user_ratings	Average user ratings for apps	3.21 (1.31)	0.00	5.0
Avg_filesize	Average file size of apps	21.91 (71.76)	0.00	1006.00
Avg_num_ screenshots	Average number of screenshots on App Store	5.43 (2.07)	1.00	10.00
Free_apps	1 if a seller offers both free and paid apps, 0 if a seller delivers paid apps only	0.25 (0.433)	0.00	1.00
Longtail_seller	1 if a seller offers less than 20 apps (tail part), 0 if a seller offers more than 20 apps (body part)	0.86 (0.34)	0.00	1.00
Popular_category	1 if a seller includes popular categories, 0 if a seller does not include popular categories	0.13 (0.25)	0.00	1.00

Table 1. Summary of Variables

DEFINITION OF MEASURES

Table 1 presents the descriptions of variables used in this research.

Num_apps_top300: The dependent variable measures sales performance. Because Apple App Store does not release sales figures, such as the amount of downloads and net revenues, for individual sellers, we measure a seller's sales performance by counting the number of apps in the top 300 apps (top gross 300) appear across the 21 categories. This top-grossing chart is based on the total revenue generated from apps, rather than the number of downloads (i.e., top-paid chart).

Num_category: The total number of categories that includes a seller's apps. This is computed by the sum of categories that contain at least one app. This measure is used as a proxy for measuring the diversification of the product portfolio.

Total_num_apps: The total number of apps offered by a seller on App Store. This is also a proxy for product diversification.

SD_category: Standard deviation of number of apps throughout categories including at least one app. This measure is an indication of the focus within each category. When a seller has a high standard deviation it is an indication of specialization. Lower standard deviation values indicate diversified portfolio strategy. We calculated this by using a following equation:

$$\sqrt{\frac{\sum_{1}^{n}[(\textit{number of apps under nonzero categories})_i - \textit{mean}(\textit{number of apps under nonzero categories})_i]^2}{n}}$$

,where n is the number of non-empty categories provided by seller i.

Log_avg_price: The average price of paid apps in seller portfolio. We consider the average price of paid apps offered by individual sellers to investigate how the average price affects sellers' sales performance. Avg_user_rating, Avg_filesize,

Avg_num_screenshots: These three variables indicate the average number of user ratings (on a scale of 1-5), the average file size of apps (in megabytes), and the average number of screenshots on App Store in the top 300 respectively.

Free_apps: a dummy variable representing whether a seller delivers both free apps and paid apps. While 75% of sellers offer only paid apps with average price of \$4.07, 25% of them include free and paid apps with average price of \$3.29. We also obtained free app sellers, but during the observation period 0.01 % of the sellers in the top 300 offer only free apps.

Longtail_seller: a dummy variable whether a seller belongs to the tail part. We separated the seller types into "head part" and "tail part" based on the number of apps they provide. Figure 1 presents a scatter plot of number of apps against the number of sellers. As an illustration, there are 183 sellers who provide 2 apps and similarly 27 sellers that offer 25 apps. This graph shows a clear illustration of the Pareto distribution (or power law probability distribution). By using a segmented regression model, we found a change point that distinguishes these two parts. While the head part includes about 13% of sellers who offer more than 20 apps with the average number of 108.7 apps, sellers in the tail part deliver less than 20 apps with the average number of 5.3 apps.

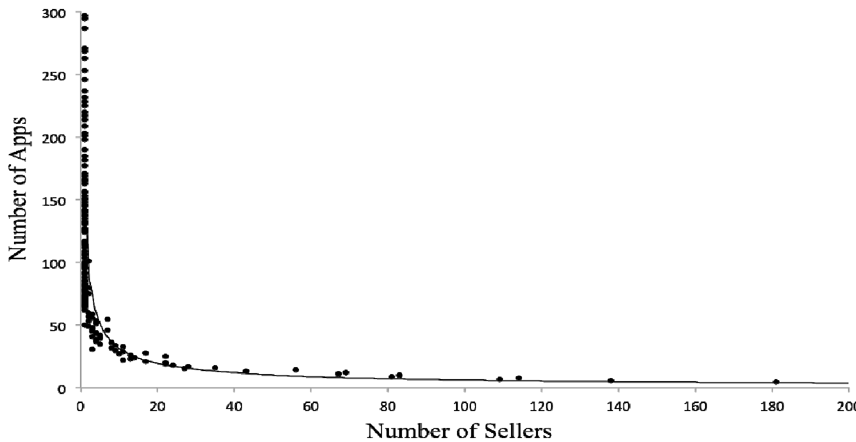

Figure 1. Pareto Distribution-Number of Apps on the Number of Sellers

Popular_category: A dummy variable representing whether a seller offers apps in the popular category. According to 148apps.biz, a mobile app information aggregator, there are three popular categories: books (56,827 apps), games (47,704 apps), and entertainment (36,749). These categories take over 40% of total apps. Our dataset shows 13% of sellers included at least one app in the popular categories, while 87% of sellers provided apps in the other 18 categories.

Longtail x Popular_category: An interaction variable between Longtail_seller and Popular_category. We describe the interaction influence of these two variables on the sales performance. About 10 % of sellers belong to the tail part and offer apps to the popular categories.

EMPIRICAL MODEL

From the defined variables, we develop a count regression model in order to explain how a seller's unique product portfolio affects the sales performance.

$$
\begin{aligned}
E(Num\_apps\_top300 \mid X)_i = {} & \beta_0 + \beta_1 (Num\_category)_i + \beta_2 (SD\_category)_i + \beta_3 (Log\_avg\_price)_i + \beta_4 (Total\_num\_app)_i \\
& + \beta_5 (Avg\_user\_rating)_i + \beta_6 (Avg\_filesize)_i + \beta_7 (Avg\_num\_screenshots)_i + \beta_8 (free\_apps)_i \\
& + \beta_9 (Longtail)_i + \beta_{10} (Popular\_category)_i + \beta_{11} (Longtail\ x\ Popular\_categoty)_i + \varepsilon_i
\end{aligned}
$$

, where X is a vector of independent variables.

Since the dependent variable is counted numbers (i.e., number of apps in the top 300), we have utilized the Poisson regression models (PRM); counts are all positive integers in our dataset, so the Poisson distribution is more appropriate for the analysis rather than the Normal distribution (the mean of Poisson is greater than zero). The typical PRM expresses the natural logarithm of the outcome of interest as a linear function of a set of explanatory variables. Thus, the PRM incorporates observed heterogeneity into the Poisson distribution function (Cameron and Trivedi 1998).

5. RESULTS AND DISCUSSION

The results of Poisson regression estimates are presented in Table 2. While we have not reported the correlation matrix, we did not find any strong correlation between independent variables; all correlations were below 0.40. Overall, our findings are consistent with the developed hypotheses. We have presented two models in Table 2 – the first model does not include the interaction term. Since Total_num_apps and SD_app_300 had high correlation (=0.3969), we examined a model that excluded Total_num_apps, but we did not find any significant changes in estimates.

Variables	Model 1	Model 2
Intercept	0.1944*** (0.0621)	0.1990*** (0.0622)
Num_category	0.2702*** (0.0154)	0.2743*** (0.0154)
SD_category	0.4481*** (0.0121)	0.4513*** (0.0121)
Total_num_app	-0.0002*** (0.0001)	-0.0002*** (0.0001)
Log_avg_price	0.0694** (0.0310)	0.0805*** (0.0311)
Avg_user_rating	-0.0105 (0.0112)	-0.0065 (0.0112)
Avg_filesize	0.0005*** (0.0002)	0.0005*** (0.0002)
Avg_num_screenshots	0.0114* (0.0069)	0.0108* (0.0069)
Free_apps	0.1239*** (0.0306)	0.1167*** (0.0307)
LongTail_seller	-0.4018*** (0.0374)	-0.4277*** (0.0383)
Popular_category	-0.0631 (0.0505)	-0.3707*** (0.0570)
Longtail x Popular_category	-	0.1741*** (0.0552)
Log Likelihood	-1227.3802	-1222.5610
AIC	8166.1795	8158.5411
BIC	8232.8489	8231.2731
Pr > Chi-Square: ***=Pr <.01, **=Pr<.05, *=Pr<.1		

Table 2. Analysis Results

The results show that as the seller creates apps in more categories, the probability of ranking more apps in the top 300 increases. Thus, portfolio diversification has a positive association with sales performance. Furthermore, the estimated coefficient of SD_category has a positive value. This implies that specialization into a specific category is associated with better sales performance as well. Anecdotal data supports this observation as well. For example, many major game developers like Gameloft and Electronic Arts have provided their applications mainly on a game category. Gameloft offers total 190 apps on Apple App Store: games (187 apps), healthcare (2 apps), and books (1 app). Gameloft has 21 apps in top 300. Meanwhile, Michael Schneider, an individual developer, has listed 12 of his 40 apps in the top 300 by offering apps in 14 different categories. Consequently, *Hypothesis 1a and Hypothesis 1b* are supported by the results.

In terms of versioning strategy (*Hypothesis 2*), the estimate of free_apps coefficient is positive, as expected, and strongly significant. This indicates that a seller who includes both free and paid apps has almost 12% higher probability of ranking one more app in the top 300. According to our observation on App Store, around 30% of top 300 apps are free apps and most of them are either lite version of paid apps or required additional payments for more features (e.g., game money or network play) when running apps. This implies that the availability of free apps could be attractive to users and makes them purchase paid apps or pay for more functions, and therefore it supports our results. Consequently, Hypothesis 2 is also supported.

For the *hypothesis 3,* we find a negative coefficient for LongTail_seller with strong statistical significance. It suggests that the low-volume sellers in the tail part have less number of apps in the most downloaded top 300 than high-volume sellers. While this is not a surprising result, the interaction effect signifies an important implication for long-tail sellers. As Elberse (2008) argued in their study, “digital channels would be more consolidating the position of a select group of sellers than that of a large group in tail part.” The coefficient of popular category is not significant by itself, however it becomes significant once the interaction term is introduced. The significant interaction term suggests that a seller who offers small number of apps can be more successful if she concentrates on the popular categories.

Our model suggests that users’ review ratings are not likely to be influential to the sales performance, but the apps properties such as file sizes and detailed descriptions (i.e., the number of screenshots) are positively correlated with the app sales. While we used these variables as controls, there is perhaps usability, feature driven influence on sales rankings that merit further exploration.

6. CONCLUSION

This research has attempted to establish the main characteristic of a seller’s strategy in the mobile app store market and its impact on the sales performance. The results of this study provide empirical evidence to substantiate that sellers’ different assortments of apps and pricing strategies influence sales performance. By offering more apps across categories and diversifying selling categories, a seller increases sales performance. Furthermore, we find that strategies have to be tailored based on whether one is competing as a major seller or a long-tail seller. Even though overall low-volume sellers have lower sales performance as compared to high-volume sellers, they find better sales performance when they concentrate on popular categories.

This study contributes to new light on the seller’s product portfolio management and versioning strategy in app store market by integrating theories of product portfolio, information good versioning, and the long tail. Our study is a first step to investigate evidence for the relationship between product portfolio strategy and sales performance in the app store market. From a business perspective, our study assists potential sellers and market makers to have a better understanding of successful product portfolio strategy in the app store.

We acknowledge some limitations of our study to provide a context for the research findings. The findings of this study are based on sellers in the U.S. Apple App Store. A seller’s app portfolio management can be affected by distinct market structures and regional differences. For example, each market has a different proportion of free apps (e.g., Google Android Market: 57 percent; Apple App Store: 25 percent) and a different number of categories (e.g., Google: 34 categories; Apple: 21 categories). Furthermore, users' preferences for apps vary around the world. For example, App Store users in North America are most willing to buy games, while navigation apps and religious apps are most popular in Europe and Africa, respectively[3]. As a result, future studies exploring sellers' portfolio management in different app markets and regional settings are necessary.

[3] Around the world in 90 App Stores: Apple’s top sellers show differences in our app tastes (January 19, 2011), The Next Web,http://thenextweb.com/apple/2011/01/19/around-the-world-in-90-app-stores-apples-top-sellers-show-differences-in-our-app-tastes/

While this study focused on the impact of sellers' strategy on sales performance, it might be interesting to examine how a seller's efforts on apps such as frequent updates and promotional price offers influence sales performance. We found that many sellers have very similar practices of displaying and selling apps: using similar icons, genres, interfaces and price. It seems leading sellers' behaviors in delivering hit apps can affect other sellers' behaviors. In this context, it would be worthwhile to examine herd behavior (Banerjee, 1992) in product portfolio management among app sellers.

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