A Long-Tail Model of Mobile Application Usage

HANNU VERKASALO
Helsinki University of Technology
Helsinki, Finland
hannu.verkasalo@tkk.fi

Abstract–**In management research, the long tail phenomenon is typically linked to the long-tail of product demand distribution, particularly under electronic distribution, storing and consumption of content. This article discusses the role of open mobile software platforms in creating a market for niche mobile applications. Open software platforms of smartphones facilitate innovation around new applications. This study makes a hypothesis that open software platforms are boosting the use of niche applications. Empirical data on smartphone usage is collected over three consequent years in Finland. The dataset of 1 145 smartphone users is analyzed in studying whether the long-tail phenomenon is evident in the demand for mobile applications. The analysis of usage-level data reveals that the application demand is more heterogenic in the newest panel study than in the earlier studies. In other words, though the top 5% of applications typically represent more than 90% of total application usage, the bottom 80% of applications (the long-tail part) already represent 2.10% of total observed application usage in 2007, whereas this tail is only 1.39% in 2006 and 0.89% in 2005. Average usage activity of niche applications has increased. The analysis reveals a U-relationship between the number of users and usage frequency of applications, meaning that many niche applications are being used actively by those who installed them, suggesting that the value of add-on applications is high.**

*Keywords-**long-tail; mobile applications; smartphones; application stores***

I. INTRODUCTION

Chris Anderson introduces the concept of long-tail in his articles [1] [2], suggesting that though typically only few top hits or instances (e.g., top movies, books, search words) dominate the rankings, particularly the digital means of content distribution and consumption have opened the doors for niche products that face demand from only few people. These products, though outside of the top rankings, are significant in number, and together form the long-tail. The value of this long-tail can be significant, because of the mere number of titles in the long-tail. Particularly in situations where the supply and demand of products is potentially infinite (huge variety), the long-tail is evident. In addition to Anderson, e.g., Kilkki [13] discusses the practical applications and mathematical modeling of the long-tail concept.

Figure 1 presents the basic logic of the long-tail phenomenon. Few titles receive very high popularity (e.g., sales), but the potentially infinite tail of the distribution can cumulatively represent a significant share of total value and volume of the market.

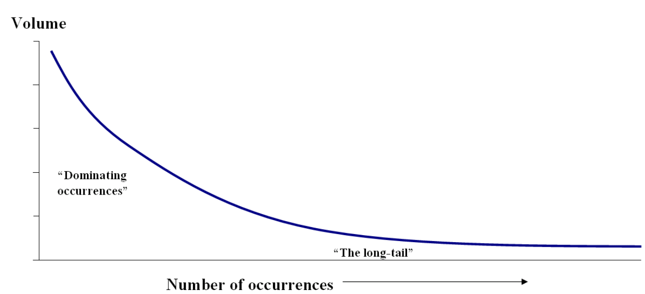

FIGURE 1 - THE LONG-TAIL PHENOMENON

The mobile industry is undergoing a major transformation, as it is converging with the Internet, media and computer industries [22]. From the perspective of this paper particularly the increasing penetration of open mobile software platforms is of importance [16], transforming mobile phones into multi-purpose smartphones. The birth of the mobile application market is the consequence of this trend. Independently of handset vendors or mobile operators, mobile software developers (3rd party companies and individuals) can create their own solutions on top of Symbian, Windows Mobile, Google Android or any other software platform. In essence, mobile phones have become programmable handheld computers, which have Internet connectivity, computing power and open APIs (application programming interfaces), providing prospective platforms for an infinite set of new mobile services and applications.

The assumption of this study is that the creation and evolution of the mobile application market, which is constantly being induced by the penetration of open mobile software platforms, is changing the way how end-users use mobile phones. The key hypotheses of the thesis include:

1. A long-tail of mobile applications is emerging, and the application demand is distributed over an increasing number of applications
2. The mobile application market is more fragmented than earlier, there is more variety both in supply and demand
3. Niche products can achieve high usage among the few who adopt them

The research problem of this study is to find out whether empirical metrics of smartphone usage over time reflect these hypotheses. New empirical modeling approaches are developed in solving the problem [24].

The article first introduces the concept of long-tail, and then proceeds to a summary of the current state of the mobile industry, particularly with regards to smartphones and add-on applications. After that, the research setting and dataset of this study are explained, and then rigorous analysis practices are applied in studying the distribution of add-on application usage activity. Finally, the article summarizes the main findings of analysis.

II. BACKGROUND

A. Long-tail

The long-tail phenomenon is first introduced by Anderson (see [1] and [2]). Anderson realizes that many businesses of today (e.g., Amazon) generate significant revenue by selling a high number of items in small quantities. Despite the market including a small number of dominating titles that sell in huge numbers, the digital age provides cost-efficient distribution and storing mechanisms to economically sell practically an infinite number of items, each potentially selling only a handful of copies. However, all together these low-selling items represent a significant amount of total volume.

Statistically the concept of the long-tail has been known for ages. Many distributions, such as power law and Pareto distributions, experience a long-tail. Statistically the long-tail means a low-frequency part of the distribution following a high-frequency part. This low-frequency part of the distribution asymptotically tails off. Many business cases account for this phenomenon, as it relates to many things from sales volume to productivity of employees. For example, McKinsey is using its 80/20 rule typically in communicating various business-related findings [8].

What Anderson [1] [2] and Shirky [18] contribute to the existing literature, is the suggestions that the digital economy makes both storing and distribution of products (e.g., content, applications, software, products) cheaper, thus making it economically viable to provide much more heterogenic portfolios of products available for sale. In other words, the supply of products (in terms of number and variety of items) goes up. Given the heterogenic preferences of people, there will be a creation of markets for niche products, selling only few copies. These niche products contrast with the bestseller hits that dominate the rankings. However, due to the changing economies of supply and demand, the relative total volume and value of these niche products (making up the long-tail) is much higher than in traditional markets.

In addition to Anderson and Shirky, Ken McCarthy [15] points out the impact of the Internet (and openness) and the potential emergence of the long tail phenomenon. The assumption is that all people have individual preferences, and there is (some) demand for a high number of products, given they can be economically provided for sale. For example, digital online stores, such as Amazon, boost the size of the market and variance of products sold, creating consumer surplus by simply changing the mode of product delivery [3]. In a later article [2] it is also suggested that demand side dynamics, such as search engines and recommendation engines, help customers to find niche products and to induce the long tail effect. The long tail has been discussed under many topics, from competition [12] to user-driven innovation [10], and from science fiction novels [9] to contrary effects of the Internet [7].

B. Mobile software platforms

This paper follows the definition of Webodia [25] for a *mobile operating system*, which is defined as an operating system for mobile devices, meaning essentially a *software platform* on top of which applications can run. Software platform is used as a synonym to operating system in this paper, highlighting the platform functionality of operating systems.

The key contribution of a mobile software platform is its programmability: in addition to default programs embedded in the system also new applications can be installed and used. The PC industry is known for its modular technical design, in which openness and the role of operating systems as platforms is critical. The emergence of mobile operating systems, such as Symbian, Windows Mobile, Apple iPhone and Google Android (forthcoming) are transforming the mobile industry towards more PC like evolution. Symbian is a market leader of platforms at Q4/2008 (65% market share), followed by Windows Mobile (12%) and RIM (11%). Symbian is mainly being boosted by Nokia (see Table 1) with its massive sales volume of converged devices.

TABLE 1 - SALES OF CONVERGED MOBILE DEVICES Q4/2007 [6]

Vendor	Q4 2007 shipments	% share	Q4 2006 shipments	% share	Growth Q4'07/Q4'06
Total	**35,522,360**	**100.0%**	**20,667,200**	**100.0%**	**71.9%**
Nokia	18,802,480	52.9%	11,114,630	53.8%	69.2%
RIM	4,046,860	11.4%	1,829,260	8.9%	121.2%
Apple	2,320,840	6.5%	-	0.0%	NA
Motorola	2,301,260	6.5%	1,463,090	7.1%	57.3%
Others	8,050,920	22.7%	6,260,220	30.3%	28.6%

Smartphones are here defined as pocket-sized computer devices that provide at least cellular circuit and packet switched connectivity, and run a mobile operating system. Smartphones can also be called as multimedia computers [17] or converged devices [5]. Smartphones access wireless networks through various radio-access technologies, such as WiFi, 3G and EDGE. Processing power and memory capacity of smartphones support advanced services, from games to office applications. Smartphones effectively combine traditional offline functions, such as personal information management or office applications, with online services such as person-to-person communications or Internet browsing. [11] Effectively mobile phones are migrating from communication devices towards computers. According to [11], today's smartphones hold the highest potential in becoming multi-purpose devices supporting everything from communications to digital wallets and from personal data assistants to authentication/authorization devices

Mobile software platforms are the key cornerstone in the transformation of the mobile industry [22]. As the user-driven innovation, open APIs, and connectivity to the Internet are the key factors of this evolution, smartphones together with open mobile software platforms serve as catalysts of the evolution. This paper assumes that the open mobile software platforms are creating new supply of services and applications. Independent and numerous developers all over the world can build new applications, and for example players of Internet and computer industries can easily port their existing solutions to mobile phones. Along with the increasing supply also increasing demand should realize, as the potential demand can better be fulfilled. The emerging variety of available mobile applications is defined here as the *mobile application market*. The mobile application market is created partially by the increasing number of applications shipping with new devices, but more importantly because of the programmability of devices and availability of add-on applications.

The creation of the mobile application market could have two profound effects on the usage of applications:

- First, it can shift demand to low-frequency and niche applications.
- Second, it can create new demand by providing solutions that did not exist earlier.

The purpose of the empirical part of the paper is to collect and analyze data particularly with regards to the first implied effect. The second effect is more difficult to study, as the size and length of the panel studies used for data collection in this study are different, and therefore the absolute number of identified applications does not necessarily communicate the absolute domain of demand. In addition, the micro-level analysis perspective of this study is suitable particularly for relative comparisons (the first implied effect above).

III. ANALYSIS

A. Research setting

A handset-based end-user research method is used in the empirical analysis of this paper [20]. This research method is developed over the years to study the behavior of mobile end-users using smartphones. The research method includes a handset-based client, that observes usage-level events (e.g., application sessions), and transmits this data to centralized research servers at predefined intervals. In addition, various web-based surveys can be deployed through the research platform.

The handset-based end-user research is structured as panel studies, which typically include a few hundred consumers from each geographical market for a period of 1-2 months. The advantages of the platform are the combination of subjective survey and objective usage-level data, observations of real end-user behavior, and accuracy as well as variety of data points available. The shortcomings include the effort of arranging panel studies, and adverse selection of panelists (only early-adopters can be studied because of the requirement of owning a smartphone).

The dataset of this study include three panel studies, arranged in a similar manner in three consequent years in Finland 2005-2007 (for the reports of the studies, see [14]; [21] and [23]). Only panelists with a self-purchased device are included in the dataset. This is because handset bundling in Finland is bringing smartphones to more mass-market oriented people, which can be hypothesized to form a different type of market (in terms of tech-savvy nature) from smartphone self-purchasers [22] [19]. 500, 369 and 276 Finnish early-adopter consumers (equipped with Symbian smartphones) are studied in years 2005, 2006 and 2007, respectively. In the analysis of the data, each application usage session of the panelists is identified, and analyzed with standardized data mining methods. For each application several metrics are calculated, ranging from number of trial users to number of active users, and from average time spent per day to average number of weekly application activations. All in all, 359 744, 251 749 and 138 636 application activations are observed in the panels of 2005, 2006 and 2007, respectively.

B. Usage of mobile applications

Usage-level data (applications usage) is available from three years. In addition, a special add-on application survey is conducted during the smartphone panel study of 2007. Panelists are asked several questions regarding add-on application installation and usage. Appendix A provides the results of the questionnaire. All in all, 84% of panelists have installed add-on applications to the device, and 35% claim to install applications frequently. The most typical way to install applications is to download from the Internet with computer (70% of those who installed applications), and to install then the application from computer to mobile phone via USB (66%). 57% of those who have installed applications, have downloaded applications directly with a mobile phone. The Internet is the best source of information when looking for applications (85% of those who have installed applications browse the Internet with computer when looking for information). 42% of those who installed applications have heard of new applications from friends or family. The most typical reason for not installing more applications is the lack of interesting applications in the market (62% of those who have installed applications blame this). 31% blame the prices, but only less than 20% blame the difficulty of installation or search. 76% of panelists have a positive attitude for an advertising-based delivery of content and applications. Handset vendors and operators are still considered as the most important actors among the producers of applications (31%, 26%, 10% and 6% consider vendors, operators, Internet companies and media companies as very important actors in mobile service delivery, respectively). See Appendix A for details.

The usage-based dataset of three years is first processed with standardized data mining processes. The raw data consists of accurate traces of each application usage session of each panelist over the panel period, and the data is available from all of the three annual panel studies. Voice calls are not studied here, and the focus is solely on smartphone applications. In the data mining process, average activation times per day and average usage frequencies (share of days when used) are calculated for each application and for each user. This data is further linked to separate application mapping files (see [20]) that map each application into a distinct functional category. Based on the data also the number of users for each application is calculated. Table 2 illustrates some of the key descriptive statistics of the dataset. All in all, the number of panelists without a bundled subscription (the requirement for the panelist to be included in the dataset) is not that high for the newest panel than earlier. However, significant amount of data is collected each year. The average usage activity (in activations per day) and distribution of application activations among the different types of applications do not experience significant changes. PIM (*personal information management*) corresponds to the use of phonebook, calendar and other daily applications.

TABLE 2 - DESCRIPTIVE STATISTICS OF APPLICATION GROUPS

Means	**Group A**			**Group B**			**Group C**		
	Usage Frequency	Usage Intensity	User Rate	Usage Frequency	Usage Intensity	User Rate	Usage Frequency	Usage Intensity	User Rate
2005	22 %	0,55	77 %	5 %	0,09	22 %	7 %	0,14	3 %
2006	25 %	0,61	81 %	6 %	0,11	23 %	7 %	0,20	3 %
2007	26 %	0,65	79 %	7 %	0,13	25 %	6 %	0,12	4 %

This article studies the patterns of application usage and the structure of realized demand. Regarding the use of applications, Figure 2 plots the share of panelists who have at least once tried applications. All the applications are plotted in descending order of number of users (x-axis as the percentile). The figure communicates the diversity of applications that are used by end-users. All in all, 820, 752 and 404 different applications are observed for the years 2005, 2006 and 2007. The number of distinct applications is decreasing over time, because in the most recent panels the amount of usage data collected is lower than earlier.

It is notable that the more recent panels experience wider use of mobile applications. In other words, for example the 10% percentiles of user rates (in share of panelists) are 3%, 5% and 10% for 2005, 2006 and 2007. The share of panelists, therefore, adopting rare applications (outside of top 5%), is higher in newer panels. In other words, an increasing number of mobile applications are achieving high penetration rates among early-adopters.

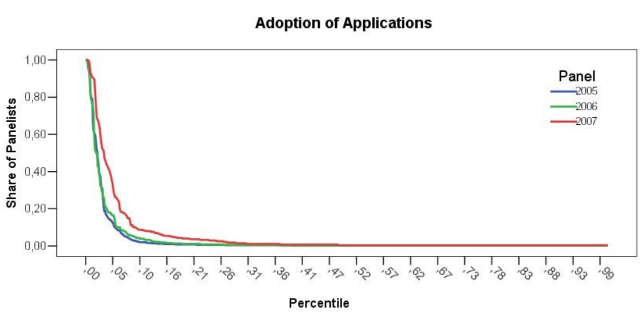

FIGURE 2 - ADOPTION OF MOBILE APPLICATIONS

Next, more accurate usage-level profiles of applications are studied. Usage frequencies are plotted across user rates for all applications that have at least 1% user rate (meaning that at least 1% of all panelists have used that particular application). Usage frequencies communicate the average frequency of usage in percents (the share of all panel days when the application is used), and user rates communicate the share of all panelists who have tried the application. Figure 3 plots the exemplary results for the applications observed in the panel of 2007.

It is interesting to differentiate between three main types of applications. The widely adopted applications (group A; having a user rate higher than 50%; all embedded applications), less widely adopted applications (group B; having a user rate between 10% and 50%; almost totally embedded application that do not achieve high success), and niche applications (group C; having a user rate lower than 10%; almost totally 3rd party applications).

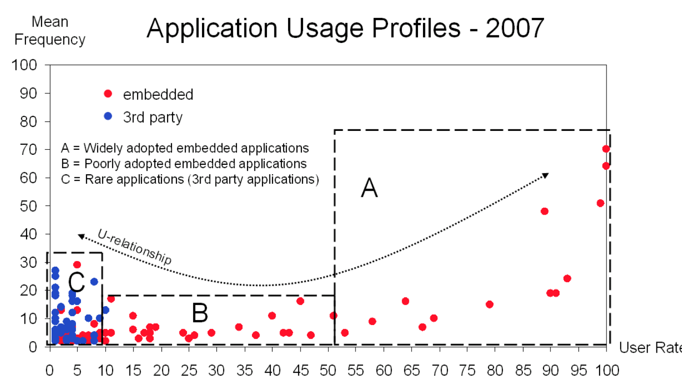

FIGURE 3 - THE U-RELATIONSHIP BETWEEN MEAN FREQUENCIES AND USER RATES

Though it can be expected that only few applications make it to the group A, it is interesting that many of the embedded applications in today's smartphones (for example embedded calculators and notes applications) do not achieve the 50% user rate, and are instead categorized into less widely adopted applications. The most significant observation is the high number of applications existing in the group C, meaning that a long-tail of applications exist - including many niche applications that do not achieve a high user rate.

Panel	Panelists	Different Applications Observed	Total Amount of Panelist-Days	Mean Number of Application Activations per Day per User	Share of Browsing	Share of Multimedia	Share of Messaging	Share of PIM
2005	500	820	32 749	10,90	2 %	11 %	26 %	45 %
2006	369	752	24 630	10,11	3 %	12 %	26 %	44 %
2007	276	404	14 431	9,85	4 %	12 %	27 %	43 %

Many of the applications in group C receive high mean usage frequencies, meaning that those few panelists, who use them, use them actively. This means that though these niche applications receive a low number of users, these niche applications can still generate a lot of value to the end-user, assuming that high usage frequency corresponds to high perceived value. This inverted relationship between user rates and mean usage frequencies is here called as the U-relationship between the number of users and usage activity. This U-relationship holds irrespective of the panel (see Figure 4).

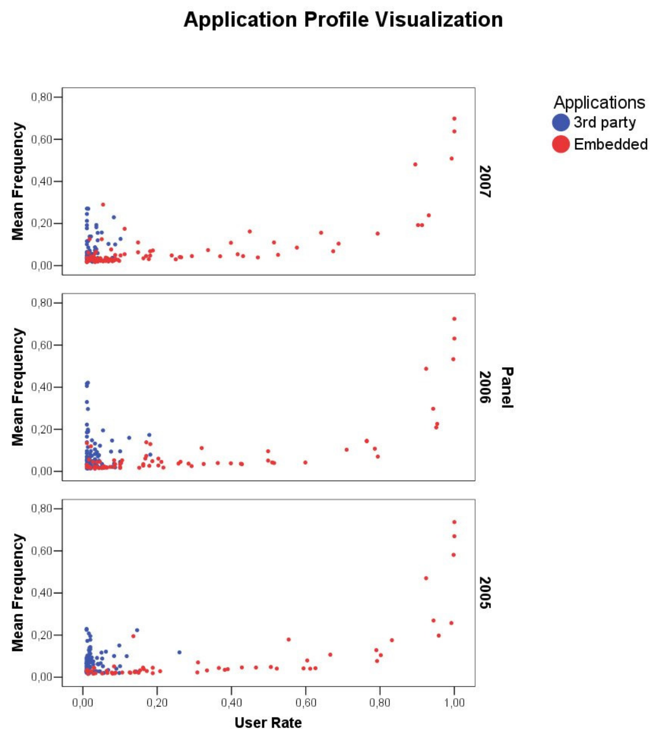

FIGURE 4 - ADOPTION OF MOBILE APPLICATIONS

Table 3 highlights the identified patterns in each of the application groups. Usage intensity is calculated as the average number of activations per day per user. Expectedly the usage intensities and frequencies are highest in the group A of applications. However, there are no significant differences between applications of group B and C. In the panels of 2006 and 2005 the mean usage frequencies and intensities are higher for the applications in the group C than in the group B. The number of applications that achieve high usage frequencies (>20%) is higher in the category C than in the category B, this holding in all panels. However, the number of applications is also higher in the category C, which forces the arithmetic means quite low.

The descriptive analysis of this chapter reflects the diversity of application usage. In addition, it emphasizes the U-relationship between application usage frequency and number of users. In other words, the study suggests that though the application might be a niche item in terms of number of users, the realized usage activity might still be quite high. This gives support regarding the hypothesis of the existence of the long-tail of mobile application usage.

C. Long-tail of mobile applications

The hypothesis of this paper is that the usage of mobile applications is more heterogenic today than earlier. In other words, the distribution of total application usage should be flatter than earlier, due to increasing usage activity of add-on applications. Figure 5 plots the total amount of usage (daily usage intensities) over the users of the applications. The applications are sorted in the descending order of total usage (in number of launches per day).

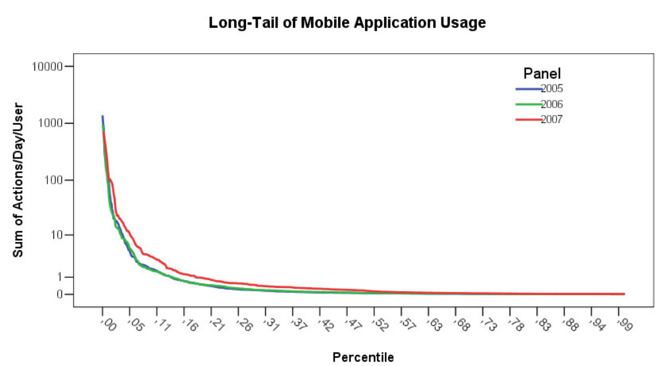

FIGURE 5 - TOTAL AMOUNT OF MOBILE APPLICATION USAGE (LOGISTIC SCALE)

The figure reveals that the end of the usage distribution is very flat (the logistic scale is used for the purposes of illustration). Demand exists for a number of applications. Additionally the hypothesis of the study can be confirmed true, as the distribution of application usage for 2007 is flatter than in 2006 or 2005. In other words, the value of the tail of the distribution is higher in 2007 than earlier, though absolute numbers are used in the figure (and fewer panelists are included in the dataset of 2007 than in 2006 or 2005).

Table 4 presents the analysis for each panel study. Generally, the top applications catch a significant share of total application usage. This is not surprising. However, the share taken by these top applications is decreasing over time. In 2005 the top 3% of applications (ranked based on total usage activity) represent 92.18% of total usage, in 2006 only 89.64% and in 2007 85.76%. The estimation of the total volume of usage in the long-tail part of the distribution (the bottom 80% of applications) reveals that in 2007 application usage patterns are more heterogenic than in 2006 or 2005, mainly because of increasing usage activity of add-on, niche applications. The total share of usage in the bottom 80% of the distribution is 0.89% in 2005, 1.39% in 2006 and 2.10% in 2007.

TABLE 4 - LONG-TAIL STATISTICS OF MOBILE APPLICATION USAGE

	2005	2006	2007
Cumulative volume of top 1% of titles	79,35 %	75,95 %	65,64 %
Cumulative volume of top 3% of titles	92,18 %	89,64 %	85,76 %
Cumulative volume of top 5% of titles	95,51 %	93,82 %	90,87 %
Cumulative volume of top 10% of titles	97,76 %	96,82 %	95,38 %
Cumulative volume of top 20% of titles	99,11 %	98,61 %	97,90 %
Total volume of the bottom 80% of titles	0,89 %	1,39 %	2,10 %
Rule	4.8%/95.2%	5.6%/94.4%	6.9%/93.1%

Figure 6 illustrates graphically the cumulative usage of mobile applications. As can be seen, in 2007 the cumulative distribution line is beneath the lines of 2006 and 2005, indicating that a relatively higher number of applications are responsible of the total demand for mobile applications.

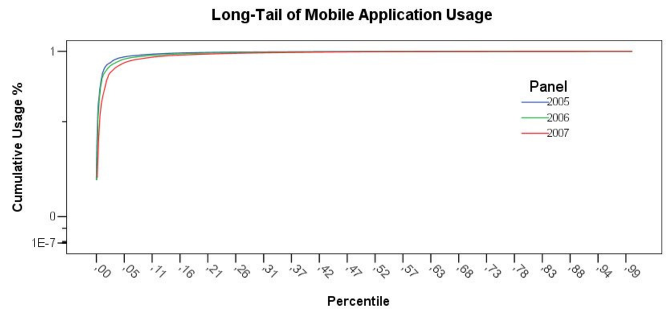

FIGURE 6 - CUMULATIVE USAGE OF MOBILE APPLICATIONS (LOGISTIC SCALE)

The statistics above support the hypothesis, that the long-tail of the mobile application market is not insignificant. In fact, it has been growing in volume over the years. In general, instead of the typical 20%/80%, a modified rule of 6.9%/93.1% holds in the panel study of 2007, for example. Top 6.9% of applications, ranked by total usage activity, are responsible for 93.1% of total smartphone usage observed in the panel study of 2007. The analysis confirms that average usage activities of niche applications have risen, and the bottom part of the distribution represents more of the usage in 2007 than in 2006 or 2005. It is not possible to analyze the absolute size (length) of the long-tail in this study, as the panel studies are of different length and size (which affects the likelihood of observing applications). This relative comparison, however, confirms that the balance in usage between default platform and niche add-on applications is shrinking.

Figure 7 explores the usage patterns of mobile applications. Though the total number of usage sessions in the panel is not that high for the bottom 80% of applications (deriving from the rules of ranking), the mean absolute usage activity (sessions per day per user) is still quite high for many applications, as can be seen in Figure 7. The usage activity in sessions (application activation and consequent usage) per day per application user can be considered as a proxy for the value of the service, as it reflects the extent of application usage among those who have really adopted the application. Also alternative metrics for usage activity exist, such as absolute face time per day per user, but different applications experience high variety in this variable due to their inherent nature (consider e.g., music players against calendars). Therefore usage sessions were chosen as the key metric in this article. Although the total panel-wide usage is not always so extensive, the value of the application to an individual user might be high. This corresponds to the finding of a U-relationship between the number of users and mean usage frequencies. In essence, the value of niche applications can be significant to the ones who adopt them, and this leads to the long-tail phenomenon.

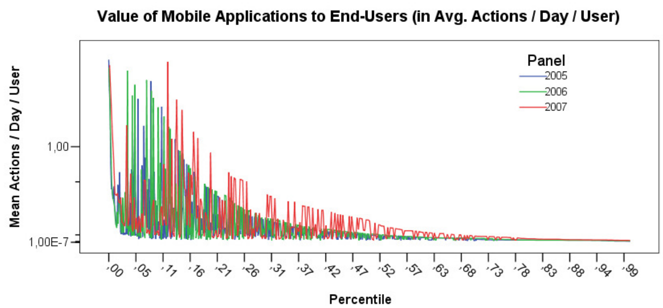

FIGURE 7 - VALUE OF MOBILE APPLICATIONS TO END-USERS (LOGISTIC SCALE)

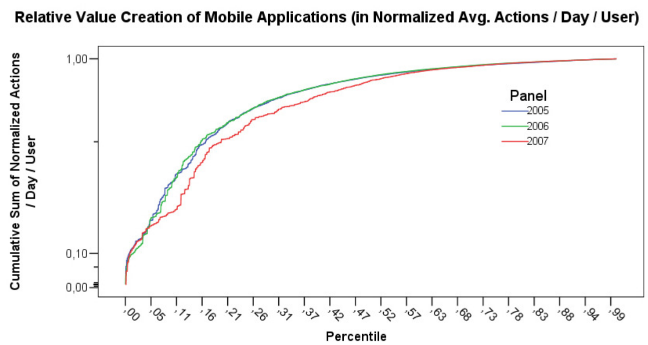

FIGURE 8 - CUMULATIVE RELATIVE VALUE OF MOBILE APPLICATIONS TO END-USERS (LOGISTIC SCALE)

Figure 8 reflects the value-creation of mobile applications. An average number of usage sessions per application per day per user are normalized against the total number of sessions observed in the panel, and then the cumulative sum of these values (assuming that observed usage sessions per day per user reflect the value of applications) are plotted against percentiles. The figure illustrates that the value creation of mobile applications is not that steep in 2007 as in 2006 or 2005. This suggests that the value of mobile application usage increasingly derives from niche applications, the finding that is done already earlier in this paper with the U-relationship of application user rate and usage frequency, and with the long-tail analysis of Table 4.

CONCLUSION

According to a survey study conducted in 2007, 84% of panelists have installed add-on applications to their mobile devices, and 35% claim to install applications frequently. 76% of panelists have a positive attitude for an advertising-based delivery of content and applications. Handset vendors and operators are still considered as the most important actors among the producers of applications (31%, 26%, 10% and 6% considered vendors, operators, Internet companies and media companies as very important actors in mobile service delivery, respectively).

The study covering real empirical usage-level data from three consequent years 2005-2007 in Finland reveals that a U-relationship exists between the number of users and average usage frequency of applications. In other words, the most widely adopted applications also experience high-frequency usage from end-users, meaning that they are valuable to end-users. The middle group of applications, including applications that are used by many panelists because they are typically embedded in smartphones, do not experience very active usage on average. However, the niche applications, receiving only a handful of panelists, experience very active usage inside their narrow user domains, increasingly so over time. These niche applications therefore generate significant value to the particular end-users who adopt them.

The further analysis of usage-level data reveals that indeed the demand for mobile applications is more heterogenic in the newest panel study than earlier panels. In other words, though the top 5% of applications typically represent 91-96% of all application usage, the bottom 80% of applications (the long-tail part) already represent 2.10% of total observed application usage in 2007, whereas this tail was only 1.39% in 2006 and 0.89% in 2005. This change is due to the increasing usage activity of add-on applications. In the newest dataset from 2007, 6.9% of top applications represent 93.1% of total smartphone usage.

The article finds that indeed the mobile application market is fragmenting, and end-users increasingly derive value from niche applications. This holds albeit still the top applications represent a significant volume of total smartphone usage. Value plots of the paper are based on the assumption that the observed usage activity per panelist reflects the value of the application to end-users. Based on this value analysis, it seems that the value is created increasingly in the long-tail of the application market. In this regards the mobile industry is moving towards the PC and Internet industries, where wide consumer choice is prevailing. The implication of this research is that there is a clear business case for developers who are targeting a selected group of subscribers, and not selling in high numbers. The value of the application (and therefore willingness to pay) might be very high for the selected, niche, subscriber segment.

Though the relative plots of application usage patterns confirm the hypothesis regarding the existence and relative size of the long-tail of the mobile application market, the absolute growth of mobile application market cannot be studied with the obtained data. This mainly results from the fact that that the size of the panel studies differs from each other and the length of the studies is different. Future research should attempt to collect data that is easier to control and compare against other available datasets. In addition, a more macro-level instead of a micro-level study setting (meaning more representative, bigger panels) should be established in order to follow the trends on the market. Future research should attempt to understand if the findings are a result of shifting demand or advancing technology.

References

[1] Anderson, C. (2004). The Long Tail. *Wired*, volume 12, number 10 (October), at http://www.wired.com/wired/archive/12.10/tail.html, Referred 4.7.2008.

[2] Anderson, C. (2006). *The Long Tail*. London: Random House.

[3] Brynjolfsson, E. & Hu, JY. & Smith, MD. (2003). Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers. MIT Sloan Working Paper No. 4305-03.

[4] Brynjolfsson, E. & Hu, JY. & Smith, MD. (2006). From Niches to Riches: Anatomy of the Long Tail. *Sloan Management Review, Vol. 47, No. 4, pp. 67-71, Summer 2006.*

[5] Canalys. (2007). 64 million smartphones shipped worldwide in 2006. Press release, February 12, 2007. http://www.canalys.com/pr/2007/r2007024.htm. Referred 12.3.2008.

[6] Canalys. (2008). Mobile device market 2007. Available at: http://www.canalys.com/pr/2008/r2008021.htm. Referred 20.7.2008.

[7] Elbers, A. (2005). Should You Invest in the Long Tail*? Harvard Business Review, July, 2008.*

[8] Ethan, R. (1999). The McKinsey Way: Using the Techniques of the World's Top Strategic Consultants to Help You and Your Business. McGraw-Hill Professional.

[9] Gibson, W. (2003). *Pattern Recognition*. G.P. Putnam's Sons, February 2003.

[10] Hippel, E. (2006). *Democratizing Innovation*. MIT Press, Cambridge, MA.

[11] Iftode, L. & Borcea, C. & Ravi, N. & Kang, P. & Zhou, P. (2004). Proceedings of the 10th International Workshop on Future Trends in Distributed Computing Systems, FTDCS 2004.

[12] Jackson, D. (2005). Competition and the Long Tail. Seeking Alpha, March 15, 2005. http://seekingalpha.com/article/1175-competition-and-the-long-tail. Referred 3.8.2008.

[13] Kilkki, K. (2007). A practical model for analyzing long tails. *First Monday, volume 12, number 5 (May 2007).* http://firstmonday.org/issues/issue12_5/kilkki/index.html. Referred 2.7.2007.

[14] Kivi A. (2006). Mobile Internet Usage Measurements: Case Finland. Master’s Thesis Series. Networking Laboratory. Department of Electrical and Telecommunications Engineering. Helsinki University of Technology, Espoo, Finland, May 2006.

[15] McCarthy, K. (1994). Presentation: "The first conference on web commercialization". Available at http://video.google.com/videoplay?docid=-5046297730700144952. Ken McCarthy, Mark Graham, Marc Andreessen, San Francisco: November, 1994. Referred 1.7.2008.

[16] Medford, C. (2008). Apple, Nokia Battle for Mobile Startups. Red Herring, 10 July, 2008. http://www.redherring.com/Home/24459. Referred 12.7.2008.

[17] Nokia. (2006). Sharing discoveries - Nokia Nseries delivers the latest in mobile multimedia. Nokia Press Release, September 26, 2006. http://www.nokia.com/A4136002?newsid=1077763. Referred 12.3.2007.

[18] Shirky, C. (2003). Power Laws, Weblogs, and Inequality. Writings About the Internet. http://shirky.com/writings/powerlaw_weblog.html. Referred on 1.7.2008.

[19] Tallberg, M. & Hämmäinen, H. & Töyli, J. & Kamppari, S. & Kivi, A. (2007). Impacts of handset bundling on mobile data usage: The case of Finland. *Telecommunications Policy, vol. 31, pp. 648-659, 2007.*

[20] Verkasalo, H. & Hämmäinen, H. (2007). A Handset-Based Platform for Measuring Mobile Service Usage. *INFO: The Journal of Policy, Regulation and Strategy. Vol 9 No 1, 2007.*

[21] Verkasalo, H. (2007). Handset-Based Measurement of Smartphone Service Evolution in Finland. Journal of Targeting, Measurement and Analysis in Marketing; Special Issue; December 2007.

[22] Verkasalo, H. (2008a). Framework for the Strategic Analysis of the Mobile Internet Business. Presented in EuroCPR 2008, in Seville, Spain, March 30 - April 1, 2008.

[23] Verkasalo, H. (2008b). Summary of the Annual Finnish Smartphone Study 2007. ComNet / Helsinki University of Technology.

[24] Verkasalo, H. (2009). Open Mobile Platforms: Modeling the Long-Tail of Application Usage. Presented at ICIW 2009. The Fourth International Conference on Internet and Web Applications and Service. May 24-28, 2009, Venice/Mestre, Italy.

[25] Webodia. (2008). Mobile operating system. Accessible: http://www.webopedia.com/TERM/M/mobile_operating_system.html. Referred 13.7.2008.

Appendix A - Add-on application survey results

N: 606 Data: Finnish smartphone panel study 2007

Have you installed applications to the phone?

Yes, frequently	35 %
Yes, a couple of times	49 %
No	16 %

I used the following methods in installing applications to the phone? (multiple answers)
(from those who installed applications)

Downloaded from the Internet with computer	70 %
Transmitted via USB	66 %
Downloaded from the Internet with phone	57 %
Transmitted via Bluetooth	48 %
Device application market (Download!)	23 %
Operator provided	18 %
From friends, workmates, or family	18 %

How did you learn about the applications that you installed? (multiple answers)
(from those who installed applications)

Browser the Internet with computer	85 %
From friends, workmates, or family	42 %
Browser the Internet with phone	29 %
Device application market (Download!)	23 %
From operator	21 %

Why haven't you installed more applications to the phone? (multiple answers)
(from those who installed applications)

I have not found more interesting applications	62 %
Add-on applications are expensive	31 %
I did not know, what other kinds of applications are available	28 %
I am afraid of viruses	18 %
Finding of applications is difficult	18 %
Installation is difficult	10 %
Other reason	7 %

Would you be willing to receive advertising, if you got free applications and content in exchange?

Yes	24 %
Maybe	53 %
No	24 %

I consider the following actors important in the delivery of mobile services…

	Consider very important	Consider important
Mobile phone vendors (e.g., Nokia)	31 %	79 %
Telecom operators	26 %	75 %
Internet companies (e.g., Google)	10 %	45 %
Media companies (e.g., MTV3)	6 %	33 %