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Mobile customer segmentation based on smartphone measurement

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ABSTRACT

While customer segmentation for mobile services is typically based on demographics and reported use, smartphone measurement software enables to add directly observed user behavior. This explorative paper develops customer segmentation on relevant metrics from the perspective of network operators, handset manufacturers, and application developers. We analyze the results of a smartphone measurement project among 129 users using latent class analysis. The data are subsequently related to demographics and psychographics, to enable lifestyles. We find that several service clusters can be defined from the perspectives of the usage of the network (i.e. voice, SMS and data) and the usage of content services (i.e. URLs and applications). We demonstrate that such clusters can be related to demographic as well as psychographic segments. The results provide fine grained insights in market segments as well as new hypotheses about mobile behavior that are open for further testing. While being exploratory in nature, the study demonstrates the relevance of customer segmentation on smartphone measurement data.

1. Introduction

Smartphones have a profound effect on lifestyles as they change the way that people live, work and learn (Ling, 2012). Smartphones come with modern design including touch screen and bigger screen size. With technological convergence, integration of voice, texting, video, gaming, mobile internet and GPS and the increasing capacity of mobile networks, smartphones are able to provide advanced functionality to their users such as seamless communication, social networking, information, multimedia entertainment, m-commerce, personal productivity tools, and much more.

However, the smartphone revolution also poses challenges to the actors in the mobile ecosystem as usage patterns are far from stable. Evolving technologies are enabling novel value-adding services, Internet players are pushing aside communication services from network operators and applications are just as easily hyped as marked outdated. As a result, network operators, application developers and handset manufacturers need to understand and respond to the dynamic change in behavior of users. An important marketing approach to do so is market segmentation, i.e. dividing the addressable market into segments that have a consistent demographic, psychographic or usage pattern.

Typically, such market segmentation is based on reported use figures as well as static demographic indicators. Operators and developers do collect actual usage numbers but typically only on their own service offerings. However, smartphones enable a novel way of data collection across any device, network and application by having a background application on the handset log the activities of users. This paper reports on an explorative study that aims to elicit customer segmentation

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based on data collected through smartphone measurement software. Specifically, we will construct customer segments on observed behavior metrics that are relevant from the different perspectives of network operator, application developer and handset provider. We will subsequently relate these behavioral segmentations to demographic and psychographic segmentations, i.e. lifestyle groups.

First we will discuss segmentation literature and prior research in the mobile domain. Next, we will present our research approach and results based on latent class analysis. The paper will conclude with a discussion, limitations, implications and future research.

2. Literature review

The concept of market segmentation is introduced by Smith (1956). "Market segmentation involves viewing a heterogeneous market as a number of smaller homogeneous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction on their varying wants (p. 6)". Smith suggests three criteria to be fulfilled in segmentation: (1) homogeneity (i.e., communality of needs within group), (2) distinction (i.e., uniqueness between groups) and (3) reaction (i.e., similarity of response towards marketing strategy, product, offer or services within group). Kotler (2003a) claims that market segmentation allows creating a more fine-tuned product or service offering and price appropriately for a target segment. He also claims that marketers can provide better distribution and communication channels to the segment.

Three major segmentation dimensions are commonly used: demographic, psychographic and behavioral (Kotler, 2003b). Demographic variables are the most popular dimensions and include age, family size, family life cycle, gender, income, occupation, education, religion, race, generation, nationality, and social class. The purpose of psychographics is to obtain a better understanding of the consumers as a person by measuring psychological dimensions, way of living, interests and opinions (Ziff, 1971). The most widely used approach to measure lifestyle is by using activities, interests, and opinions (AIO) rating statements (Plummer, 1974; Wells and Tigert, 1977). A widely-used tool for lifestyle segmentation is the VALS scheme (Rokeach, 1973) that blends research of values, hierarchy of needs and sociology in its operation. Behavioral segmentation focuses on the actual behavior of users, including occasions, benefits, user status, usage rate, loyalty status, readiness and attitude toward products.

All three segmentation techniques have been used in research on mobile acceptance and usage behavior, see Table 1 for an overview. Most researchers take behavioral segmentation as a starting point. Behavioral data can be gathered through self-reports which is done by Uronen (2008), Jansen (2007), Falaki et al. (2010b), Sohn and Kim (2008), and Aarnio et al. (2002). Lin (2007) gathered mobile usage data through call detail records collected by an operator. Hashemi (2010), Falaki et al. (2010b), Okazaki (2006), Mazzoni et al. (2007), Gilbert and Kendall (2003), and Siddiqui et al. (2009) did not use the actual usage of handset or mobile service usage but the intention to use or perceived benefits. While most papers focus on mobile services in general, some of them segment users according to the type of services they prefer.

In addition to behavioral segmentation, most studies use demographic segmentation as well. According to Walsh et al. (2010) younger users are most likely to be highly involved with their mobile phones. Plaza et al. (2011) find that elderly people apply mobile phones merely to communicate with relatives, as memory and daily life aids, as enjoyment and self-actualization, and as tools to feel safe and secure. In terms of gender, Castells et al. (2004) find that female users not only appropriate mobile phone as a fashion item but, more importantly, also as a key channel to maintain intimate personal relationships, as opposed to men who tend to use mobile phone for instrumental purposes (Castells et al., 2004).

Psychological segmentation for market researchers in our finding is not as popular as demographic and behavioral segmentation, exceptions being Hashemi (2010), Mazzoni et al. (2007), Sell et al. (2010), Siddiqui et al. (2009) and Tao (2008). Mazzoni et al. (2007) combine psychographic segmentation with demographic and behavioral segmentation and find that lifestyle groups have different motivations and product attributes. Bouwman et al. (2008) present a psychographic segmentation based on sociological factor in which how people deal with their social life, and psychological factor of the person (introvert or extrovert). Four segments are found which consist of unique needs, demands, motivations, requirement on products or services or communication. Additionally, De Reuver and Bouwman (2010) find that those four lifestyle segments moderate the effect of context-use of mobile phone towards mobile user behavior intention to use product and services.

Which behavioral variables to use for segmentation depend on the perspective of the actor. For mobile operators, Seth et al. (2008) analyze different service quality attributes and show that responsiveness is the most important dimension followed by reliability, customer perceived network quality, assurance, convenience, empathy and tangibles. Haque et al. (2007) suggest that price, service quality, product quality & availability, and promotional offer play a main role in choosing a telecommunication service provider. Moreover, Park and Lee (2011) find that mobile users prefer to have instant connectivity, wherever they are, and equal or higher data speed than fixed internet. They also added that alternative network access technology such as WiFi which now can be supported by most of current smartphones, possess treat to the usage of cellular network as consumer still prefer to access internet free of charge with data speed that equals or are higher than cellular network.

For application developers, how users make choices from the vast amount of applications depends on the type of application they use such as information, entertainment or social life. In the US, users are spending more time to use mobile applications rather than web browsing (Newark-French, 2011). Furthermore, gaming and social networking application are mostly used by consumers throughout the day.

Table 1
Summary of research in mobile market segmentation, order on basis of year of publication.

Sources	Dimensions of segmentation	Core attributes	Mobile services
Aarnio et al. (2002)	Demographic and behavioral	• Demographic (age, gender, and level of education) • Behavioral (used channel for mobile services and used mobile and internet services)	Mobile services usage of finnish market
Gilbert and Kendall (2003)	Demographic and behavioral	• Demographic (age, gender and level of education) • Behavioral (intention to use mobile WAP services, and other specific services)	Mobile data services in Malaysia and Singapore
Okazaki (2006)	Demographic and behavioral	• Demographic (age, gender marital status, occupation, monthly allowance, household structure) • Behavioral data (attitude e.g. content and source credibility, informativeness, entertainment, irritation, general liking and willingness to access)	Mobile internet services
Jansen (2007)	Demographic and behavioral	• Demographic (age, gender, phone type, subscription type) • Behavioral data (number of call, average call duration, average SMS, destination number, etc.)	Voice call and SMS usage
Lin (2007)	Behavioral	Usage data taken from mobile call detail records, including its ARPU, voice call duration, GPRS traffic volume, etc.	Mobile call, SMS and internet usage
Mazzoni et al. (2007)	Demographic, psychographic and behavioral	• Demographic (gender, age, social status, education, and occupation) • Psychographic (socio-graphic, value and interest) • Behavioral (mobile phone attribute e.g. price, aesthetic, technologic capabilities, use motivations e.g. relationships, affiliation, security, information and entertainment)	Mobile services in Italian mobile telecommunication market
Sohn and Kim (2008)	Demographic and Behavioral	• Demographic (age) • Behavioral data (usage rate, loyalty points used, activity, payment history)	Mobile additional services (caller id, auto recording system, data and information services, new and weather)
Uronen (2008)	behavioral	Mobile handset usage (heavy half segmentation), benefit sought (benefit segmentation) and personal occasion (person-situation segmentation)	Browsing, SMS, music & radio, mms, calendar, voice calls, camera
Tao (2008)	Demographic and psychographic	• Demographic (age, gender, level of education, income, occupation) • Psychographic (lifestyle variables such as knowledge-, recreation-, high living quality-, favorite information-, price sensitivity-, and fashion-oriented	Mobile tv content on public transportation
Siddiqui et al. (2009)	Psychographic and behavioral	• Psychographic (personality strait such as extraversion, agreeableness, conscientiousness, neuroticism, openness to experience being related to consumption style) • Behavioral (mobile phone intention to use)	Mobile usage of student of university of management and technology, lahore, Pakistan
Hashemi (2010)	Psychographic and behavioral	• Psychographic non-metric variables (yuppies, socially concerned, traditionalist and career makers) • Behavioral metric variables (I will use, I will not use, I will probably use)	MMS, email, news weather, internet surfing, e-shopping, e-banking, internet chat (messaging), mobile TV, etc.
Falaki et al. (2010b)	Behavioral	User interactions, application use, network traffic, and smartphone energy drain	Mobile phone
Sell et al. (2010)	Demographic and psychographic	• Demographic (gender, age, level of education, income and socio-economic group) • Psychographic (lifestyle categorization resulting 4 groups of people: skillful, efficient, trendy, basic and social)	Mobile services

3. Method

Log data is collected using smartphone measurement software, i.e. a measurement application runs on the background of the mobile phone, and transmits log files on user activities regularly to the server. Only a few studies that apply smartphone measurement have been published over the past few years (Eagle & Pentland, 2006; Falaki et al., 2010; Raento, Oulasvirta, & Eagle, 2009; Verkasalo & Hämmäinen, 2007;). Given the technical and privacy-related challenges of smartphone measurement, the present study is intended to be exploratory and to elicit the opportunities of smartphone measurement.

Privacy of participants is guaranteed by conforming to both Finnish and Dutch regulation, and data were processed after anonimization. Potential participants for the study received an extensive description of the purpose and procedure of the study. Participation is based on informed consent, as required by regulation. Furthermore tasks like data-collection and data-analysis were separated. Combination of handset measurement data with survey data was done based on unique identifiers. Data analysis was done by the researchers who also coordinated all the processes, but didn't have access to personal data.

Respondents were selected from a pool of 20,000 households that regularly take part in survey research. This pool is randomly recruited through random digit dialing using landline phones as well as through automatically generated mobile phone numbers. 20% of the members of the pool drop out per year, and new members are added continuously in order to replace them. The pool is continuously monitored on participation and response rates. Typically, members are approached once per month to participate in a study, for which they principally do not receive compensation.

From this overall pool, a random sample was drawn consisting of 3125 persons, who were invited to participate in the study using a computer assisted self-completion interviewing tool. Of those 3125 persons, 2053 responded to the invitation. Of these 2053 persons, 31% were not eligible as they do not possess a smartphone. This leaves a group of 1414 potential, eligible participants to the study.

Of the 1414 potential participants, 64% refused to participate in our study, mainly because of: reasons unrelated to the study including lack of time or being on holiday (183 respondents), privacy concerns (163), not being allowed to install applications because using a company phone (70), not knowing how to install software (28), concerns on the effect of the measurement software on the performance of the phone (16). Ultimately, 324 respondents agreed to participate in the study.

Of those 324 respondents, 140 did not download or install the measurement application. Out of the 184 panelists that did install the application, 55 removed it during the course of the study because of privacy concerns (11%), error messages (25%) or power drainage of the phone (22%). For the final sample, we retain 129 users that had the measurement application running for at least 14 days. It should be noted that 50 of those 129 users removed the application before the end of the 28-day time frame. Therefore, all aggregate metrics resulting from the log data have been weighted to the total number of days that panellists had the measurement software running on their device.

We compare the 129 participants to the 1414 eligible smartphone owners that chose not to participate in the study. We find that participants do not differ significantly from non-participants regarding age, gender, working status, family income, geographical region and education level. For example, both participants and non-participants are about 45 years old and typically male (55%). Participation also does not differ between different mobile operators. The only background variable that differs between the two groups is the device. The final sample contains significantly more Samsungs and HTCs, and significantly less Nokias. It should be noted that especially Nokia owners dropped out of the study as the Symbian version of the measurement application contained several bugs. Windows mobile users were not eligible to participate as the measurement application did not work for that operating system. Blackberries are somewhat underrepresented in the final sample as they are used more often as a business phone, and often are not allowed to download software.

Each panelist filled out two additional questionnaires. Psychographic categories of panelists are identified before the survey took place. They classified mobile users based on view, motivations, and attitude toward mobile services (Bouwman et al., 2008).

A massive amount of log data was generated in the study. For example, our 129 participants launched mobile applications 130,000 times over the 28-day period. Aggregate metrics were computed by calculating the average number of voice calls, SMS messages, MBs sent and received, applications installed, applications used and URLs browsed per day.

4. Results

4.1. Descriptive results

From descriptive analysis we can see how the panelists' usage behavior varies among each other. Some panelists only use voice call services but no data usage and the other way around. In terms of type of day usage for voice, messaging data, we found that most of the panelists use their data during weekday rather than during the weekend. Data consumption is higher in WLAN connections than cell connections, as most WLAN connections have higher speed and lower costs. In term of URL pages requested, websites with a high utility are used most, followed by infotainment, social networking sites, messaging and process. For utility types of URLs, search engines are commonly used by all panelists. For infotainment URLs, most panelists search for news and information, weather information and also sports or other type of entertainment news.

For application usage, messaging is the most used application followed by social networking, utility and telephony. Panelists use their smartphone to send messages and chat with their colleagues and relatives by using add-on messaging application such as whatsapp, yahoo messenger, blackberry messenger, etc. The second mostly used application is social networking, i.e. Facebook, Twitter, Hyves, etc. are also popular.

4.2. Latent class analysis

We use latent class analysis (LCA) (McCutcheon, 1987), which assumes that each observation is a member of one and only one of K latent, i.e., unobservable classes, with K being a finite, natural number. In market segmentation, LCA uncovers unobserved heterogeneity in a population and aims to find substantively meaningful groups of people that are similar in their responses to measured variables based on probability (Nylund et al., 2007). We used Latent Gold 4.5 software, which uses expectation-maximization and Newton–Raphson through an iterative process to calculate maximum-likelihood estimates (Vermunt and Magidson, 2005).

In the context of the present research a clustering approach based on a latent class model has three advantages. First of all, the clustering approach allows us to identify and explore meaningful qualitative differences between various user patterns. For example, it would be plausible to assume that there are user patterns which only make use of certain services, while other user patterns show low or high overall usage for various services. Secondly, by deriving qualitatively different behavioral clusters the relations between the behavioral indicators, on the one hand, and the demographic characteristics and psychographic segments, on the other, can also be better understood. It would be plausible to assume that each behavioral cluster is linked in a different way to the demographic variables and the psychographic segments. Such non-linear relationships cannot be revealed if the behavior indicators are directly linked to the demographic characteristics and/or the psychographic segments. And third, the latent class analysis also has a statistical advantage, since it can effectively deal with the erratic nature of the log data distributions (which are far from normal or even symmetrical). The LC model assumes that these (non-normal) distributions can be decomposed into several normal distributions (each with a distinct mean and variance). In effect, in the next step, the resulting nominal variable (i.e. the latent class variable) can be related (in a non-parametric way) to the demographic variables and the psychographic segments without violating any statistical assumptions (linearity, normality, etc.).

When running LCA for variables relevant from operator perspective, BIC indicates that a six cluster solution shows the best fit (Nylund et al., 2007), see Table 2.

After selecting the best fit model, we analyze the characteristic of each cluster based on the variance of observed variables, see Table 3.

The analysis leads to the following clusters:

– Basic service users are: panelists with medium usage on voice and SMS, and low usage on data services for both WLAN and cell connection. Both female and male users with age around 45–54 years old. They are highly educated with full-time job and above average income level.
– Basic service users with cellular data are: panelists with medium to high usage of voice and SMS that mainly use data services through cell connection. Typically these are both female and male users with age around 35–44 years old. They are medium educated with full-time job and above average income level.
– WLAN-only users are: panelists with low usage on voice, SMS and data through cell connection but medium usage for data services through WLAN connection. Mostly these are female users with age around 55–64 years old. They are medium to high educated with full-time job and above average income level.
– Medium overall users are: panelists with high usage of voice telephony and medium usage of SMS and data. Most of them are male users around 35–44 years old. They are highly educated with full-time job and most of them have above average income level.
– Data-only users are: panelists with low usage of voice and SMS but high usage for data services on both cellular and WLAN connections. Mostly are female users with age around 18–24 years old. They are medium educated with full-time job and most of them have above average income level.
– High overall users are: panelists with high usage for all mobile services (voice, SMS and data). These are mostly female users around 25–34 years old. They are highly educated with some of them have full-time job. Most of them have around average income level.

Table 2
Model fit: operator perspective.

Cluster	LL	BIC (LL)	AIC (LL)	CAIC (LL)	Npar	Class. Err.	Entropy
5	−4821.4	9856.6	9730.8	9900.6	44	0.123	0.779
6	**−4796.2**	**9849.9**	**9698.4**	**9902.9**	**53**	**0.113**	**0.810**
7	−4778.9	9859.0	9681.7	9921.0	62	0.118	0.815
8	−4761.4	9867.9	9664.9	9938.9	71	0.106	0.834

Table 3
Cluster results: operator perspective.

Indicators	Value	Basic service users	Basic service users with cellular data	WLAN-only users	Medium overall users	Data-only users	High overall users
Average number of calls per day	Mean	1.88	2.64	0.72	5.03	0.95	3.82
Average SMS messages per day	Mean	1.29	5.11	0.36	2.24	1.29	12.17
Average data on WLAN (MB) per day	Mean	1.02	1.42	5.15	6.28	25.76	21.85
Average data on cell (MB) per day	Mean	0.47	4.88	1.75	1.93	10.18	11.75
Cluster size (%)		28.55	19.94	18.56	14.53	14.01	4.42

Next, we will describe the clusters from an application developer perspective. Six clusters result from only three observed variables, see Table 4.

Table 5 displays the resulting six clusters:

- Application ignorant users are: panelists who request a low number of URLs, make limited use of built-in and installed applications. These are mostly female users with age around 55–64 years. They are highly educated with full-time jobs and above average income level.
- Basic application users are: panelists who consult a limited number of URLs and make limited use of installed applications but run a medium number of applications. Mostly these are female users with age around 45–54 years old. They are highly educated with full-time jobs and above average income level.
- Average app users are: panelists who consult a medium number of URL pages, have a moderate usage of downloaded and installed applications. Most are male users around 35–44 years old. They are medium to high educated with full-time job and above average income level.
- Information seekers are: panelists who request a high number of URL pages but have a low usage of applications. Most are male around 45–64 years old. They are medium to highly educated with full-time job and most of them have above average income level.

Table 4
Model fit: application developer perspective.

Cluster	LL	BIC (LL)	AIC (LL)	CAIC (LL)	Npar	Class.Err.	Entropy
5	−955.877	2076.987	1979.7534	2110.987	34	0.1348	0.7656
6	**−936.165**	**2071.5828**	**1954.3305**	**2112.5828**	**41**	**0.1242**	**0.7996**
7	−924.443	2082.1576	1944.8866	2130.1576	48	0.1106	0.8299
8	−911.733	2090.7555	1933.4658	2145.7555	55	0.0984	0.8474

Table 5
Cluster results: application developer perspective.

Indicators	Value	App ignorant users	Basic app users	Average app users	Information seekers	App savvy users	High utility users
Average number of URLs visited per day	Mean	1.41	0.11	4.47	13.39	13.34	40.55
Average number of Applications run per day	Mean	13.93	27.80	33.36	17.56	55.63	43.94
Average number of applications installed per day	Mean	0.30	0.01	0.73	0.17	1.11	0.31
Cluster Size (%)		26.43	24.85	16.54	12.40	11.26	8.52

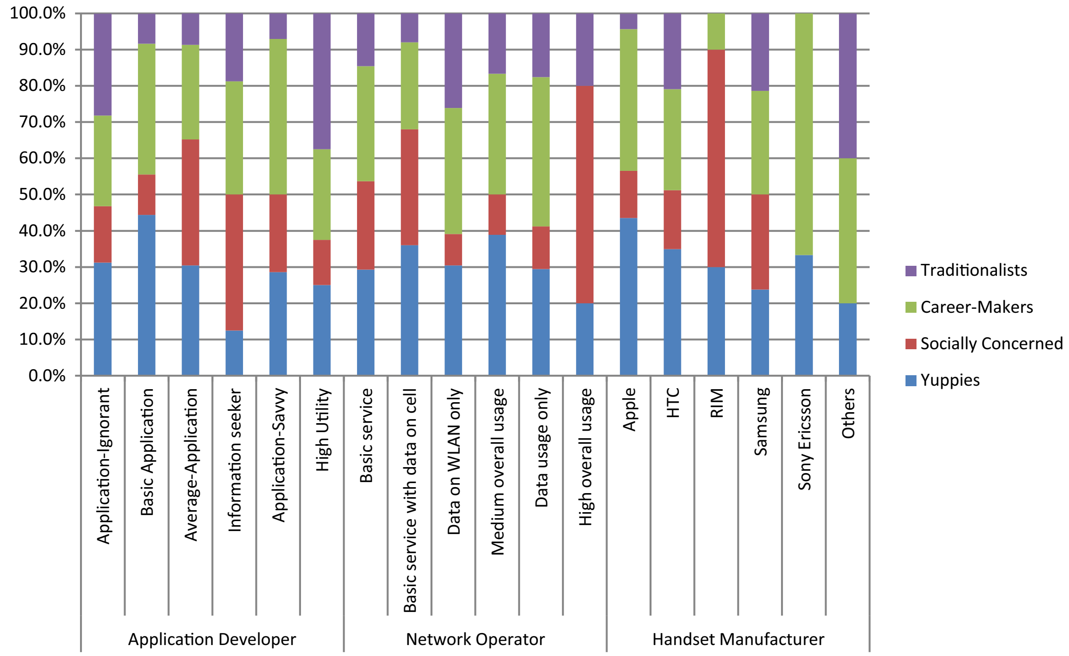

Fig. 1. Psychographic characteristic of each segment.

– App savvy users are: panelists with a high usage for URL pages, and extensive use of applications. Most are female users with age around 18–24 and 45–54 years old. They are medium educated with full-time job and most of them have above average income level.
– High utility users are: panelists with high usage of URL pages and extensive usage of downloaded applications run but low usage of installed applications. Both male and female users with age around 35–44 years old typically belong to this category. They are low to medium educated with full-time job and around average income level.

4.3. Relating the clusters to psychographics

Next, we will relate the clusters to lifestyle characteristics of the panelists, see Fig. 1. Yuppies are users of Apple and HTC handsets, and can be found in the clusters ''Basic Application'' cluster, ''Basic service with data on cell'' and ''Medium overall usage''. Socially concerned type of users can be found in clusters ''Average Application'' and ''Information seeker'' and ''High Overall usage'' cluster. Career-makers mostly can be found in clusters ''Application-Savvy'', ''Medium overall usage'', ''Data on WLAN only'' and ''Data usage only'', making use of Sony Ericsson and Other type of handsets. Traditionalists can be found in clusters ''High Utility'' and ''Data on WLAN only''.

By understanding the profile of each segments through demographic and psychographic attributes of member of segments, any actors in mobile ecosystem (i.e. handset manufacturer, application developer and network operator) may easily recognized their target users or target markets and can adapt on how to approach these type of users by taking into consideration those attributes for each segment. Moreover based on these cluster making use of distinctions between psychographic, types of handset, operator related clusters and application developers clusters we can formulate fine grained hypotheses that are open for future testing. For instance it might be hypothesized that Apple users are only making use of basic operator services in combination with data subscriptions in order to access basic applications.

5. Conclusion and discussion

This study is a first to segment the mobile service market using log data collected through smartphone measurement. This paper illustrates the potential of combining behavioral segmentation based on log data with psychographic and demographic segmentation based on survey data. While behavioral segments in existing segmentation studies are solely based on survey data, we have analyzed observed usage levels using log data obtained throughsmartphone measurement. We have related the resulting usage clusters to lifestyle characteristics and handset ownership as collected via survey data. In this way we have illustrated in an explorative way how behavioral and psychographic segmentation can be combined. By understanding the behavior of panelists, we can see how people actually use their smartphone and we are able to identify possible consumer segments based on that behavior.

The present study should, however, be considered as explorative. The sample size is rather limited, which increases the risk that outliers distort the findings. Repeating the study with a new and larger set of users would, as in any exploratory study, create more confidence in the findings. Although we set out to have a much larger sample, and invited more than a thousand smartphone owners, 90% refused to participate or left the study earlier due to privacy concerns, lack of self-efficacy and technical problems. Partly, this can be improved in subsequent studies by improving technical functionality of the application. The sample size is not per se representative for the wider population of smartphone owners as their perceived use of mobile applications was found to be higher than for non-participants. Still, there are no significant demographic differences between participants and non-participants. However, on a detailed level of analysis requirements for representativeness become far more relevant in order to be able to present reliable results. Another limitation is that the measurement software did not work flawlessly on all smartphones. *While the problems with Symbian phones were severe, only a small part of the population actually has a Symbian phone. We encountered issues with logging specific services on Blackberry and iPhone but were still able to log the vast majority of the applications on these brands.* Another important issue is that several services can also be accessed through the browser of the smartphone, i.e. they need not necessarily be accessed using a dedicated application. Exploring the URLs browsed in more detail and aggregating them somehow with the applications being used is a next step in our research. Specific limitations also include the measurement of WLAN versus cellular data usage: this may depend on the pricing model of a user (i.e. pay per data packet versus flat fee) or the type of device (i.e. some devices actively search for WLAN networks to connect while others do not). A big difference in mobile phone use to be further explored is whether smartphones are used for work or private purposes. Another limitation is that the resulted segments from LCA are model based. This means that the result could be different if the model used is differently. In the end the results only demonstrate if the data fit the model. Testing the model with other data is therefore highly relevant. While smartphone measurement is thus far from straightforward and we encountered several limitations in the present study, we do argue that relevant insights can be gained by applying segmentation analysis on smartphone measurement data, and they offer opportunities to formulate fine grained hypotheses for further research.

Besides the segmentation approach as discussed in this paper, log data from smartphone measurement can be utilized in several other promising fashions. For instance, log data can be used to discover discrepancies with data gathered from self-reports in surveys or diary studies. Besides exploring these discrepancies to cross-test and refine self-report measurement scales (see De Reuver et al., 2012), these discrepancies can possibly lead to latent need extraction by confronting the users with them. Log data could also applied in design projects, for instance in order to test prototypes in a living lab environment. Log data could then identify the intensity of use but also provide more insight into the context of use as well as help identify which users stop using a certain application after a try-out period.

A suggestion for further research would be to complement the psychographic and demographic segmentation as applied in this paper with other segmentation dimensions. One example could be to segment the users according to expected or desired quality of service and to link that to the segments of intensity of use. Applying such segmentation dimensions would help to test theories, for instance on quality of service experience, through actually observed usage data rather than self-reports.

As the aim of the present paper was to illustrate the potential of behavioral segmentation through log data, we did not strive for maximum granularity in the data. How to elicit context characteristics from smartphone measurement data is a research issue in its own right and far from straightforward, see for example Karikoski and Soikkeli (2011). We suggest combining work on context elicitation methods with our segmentation approach.

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