Segmentation Bases in the Mobile Services Market: 
Attitudes In, Demographics Out

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Abstract
In this paper we present two different segmentations based on the same consumer data; done utilizing the same segmentation method, but with different segmentation bases. We compare these two analyses with regard to their potential to increase our understanding of the elusive mobile services consumer markets, in a situation where few consumers are actual users of mobile services (besides calls and SMS) outside the early adopter category. Our findings are that using socio-demographic segmentation bases yields modest useful information, whereas using attitudes as segmentation base is more informative. In the future, attention should be paid to understanding attitude selection better to yield even more relevant segmentations in the mobile services market, and to discovering whether combinations of different segmentation bases might be the most powerful base to do segmentation upon.

1. Introduction
The mobile services market has experienced a rapid expansion in the last two-three years, due to changes in distribution models for mobile applications and a paradigm shift in mobile interfaces brought on first by the iOS and followed by others (e.g. Android). The market for mobile services is growing as mobile applications become more reachable to a larger number of consumers due to the proliferation of smart phones among market segments outside the early adopter category. Researchers and practitioners do not, however, yet have a grasp of how to target development and marketing of mobile services, as we are dealing with a market in rapid development. Our best understanding is of the early adopter /technological enthusiast category of consumers, as much of the research effort has been focused on these users. In this paper we aim to continue our efforts towards understanding the mobile services market as a whole; not only the easily reachable early adopters, through the means of consumer segmentation. We base our research on a survey based on a random sample of 1.300 Finnish consumers aged 16-65 years, conducted in 2009.

Consumer segmentation methods have traditionally been used to understand which categories of consumers can be extracted from a set of data, e.g. CRM data. Essentially, segmentation is used to group consumers into categories of consumers who share some similar attributes; the general idea for our purposes being that consumers belonging to any of these categories might share similar wants and likes regarding products and services. Consumer segmentation can be conducted as e.g. a product specific, company specific or market specific process. In our analysis we focus on the Finnish mobile services market as a whole. The additional twist making this segmentation situation especially demanding is, that even though the mobile services market has experienced expansion, there is still a majority of Finnish consumers who have no or very little experience of mobile services beyond the ubiquitous SMS.

Consequently, we are in the situation where there is no possibility to collect data on actual user behavior regarding mobile services markets for a majority of the Finnish consumers. There are methods for collecting usage data directly from users’ mobile phones; such methods have been used by e.g. [1, 2]. This data collection method is reliable and free from respondent bias, but regarding non-users even this method is not informative. We must, therefore, base our segmentation on what we do know about them – i.e. demographic data, general attitudes towards mobile services and some knowledge about future interest to use specific mobile services. For comparison, a telecommunications provider would have access to user data from their customers’ use of mobile phones and mobile services and could use this data for segmentation analyses. With our goals in mind, this
would, however not be more helpful, as we are interested in the market as a whole – also and especially in the majority of consumers who are currently not using mobile services. In our opinion, the future of mobile services is not only for technology enthusiasts, but for more average consumers as well, as mobile technology has already permeated all sections of society and mobile services are likely to do the same. Technology enthusiasts are often described as innovators and drivers’ of technology adoption in society. The majority of consumers might actually be practically unmoved by the behavior of these innovators, and unlikely to follow their path towards adoption. They might, however, find their own paths and have their own motivations yet undiscovered by mobile service developers and designers.

The paper is organized as follows: Section 2 discusses choice of segmentation bases and introduces previous research on the topic. Section 3 we present the methodology for the study and in section 4 we present the results. Finally, in section 5 we discuss our findings, their implications and give some indications for future research.

2. Background

A key question in our line of research is how to choose the correct variables for the segmentation problem at hand, as selection of bases is critical with regard to the results and usability of the segmentation [3]. As background we present a discussion on previous research on choosing the most efficient segmentation bases for market segmentation.

Segmentation bases are essentially characteristics or groups of characteristics of consumers, which are used to determine how to assign consumers to different segments. Segmentation bases can be categorized in a number of ways. We find the division first introduced by Frank, Massy and Wind in 1972 and presented in [4] to be useful and illustrative for our purposes. Frank et al divide bases along the axes general/product-specific and observable/unobservable. General bases are such characteristics of consumers or customers which are not dependent on products, services and/or circumstances as opposed to product-specific which can be related to any or all of these. In the data used for this study, demographic and socioeconomic variables fall into the general group, whereas frequency of use of the mobile phone, and being a user or non-user of a mobile service fall into the product-specific group. Observable bases can be directly measured, e.g. behavior and demographic variables, whereas unobservable bases are such that cannot be known without asking the consumer about them – exemplified by values, benefits, preferences, intentions etc.

As a general rule on the effectiveness of different segmentation bases, [4] state that the most effective bases are product-specific unobservable bases, e.g. psychographics, perceptions on product-specific benefits and brand attitudes. In our case, brand attitudes might be a useful add-on, but cannot be the basis we build our segmentation on. Attitudes towards brands of mobile phones or telecommunication providers might provide some clues on e.g. which services a consumer might perceive as trustworthy or of high quality. But a majority of the mobile services which are available on the market are not themselves associated with any widely known brands or have developed strong brand identities of their own (even though known examples of the opposite exist, such as the ubiquitously popular Angry Birds game by Rovio). Perceptions on product-specific benefits are also not directly useful for our purposes, as we are not evaluating one or a few specific products, but a market. More general benefits of using mobile services are, however, of potential usefulness in our research. They hold some promise for explaining why certain consumers seek out a certain kind of product.

Minhas and Jacobs feel there are powerful reasons motivating the use of benefit segmentation [5]. They build their case by stating that benefits are the basic reason behind purchase decisions. According to Minhas and Jacobs, a main reason supporting the use of benefit segmentation is the fact that the benefits a consumer seeks actually have a causal relationship to future behavior. Many other methods of segmentation focus on current behavior or do an “ex post facto analysis of the kinds of people who make up specific segments of a market”. Minhas and Jacobs propose, that researchers should aim to first identify certain kinds of behavior we are interested in and after that find out who are the people in that segment, as opposed to the usual practice of first identifying segments who are similar in some ways and then looking at their behavior. We share this view as highly relevant for our research of the mobile services market. Most Finnish consumers are not users of mobile services, yet we would like to find out what sorts of services would they be interested in. In other words, we have no relevant behavior to observe in the mobile services field, aside from the usual groups of innovators and early adopters. Is there thus any meaning in grouping together consumers, who share similar traits, if, however, they do not share similar interests and behavior regarding mobile services? Should we not rather find out which attitudes are precedents of a certain kind of consumer-behavior? We believe in turning the segmentation process around from the traditional; we need to find out which variables are powerful and explanatory in the mobile services
context, rather than group consumers together based on factors non-related to mobile services and then try to find out whether they have any similar needs and wants related to mobile services. Compared to more traditional markets, we believe this view to be of even more importance in an immature, evolutionary market such as the mobile services market.

Psychographic segmentation can be based on for example social class, lifestyle, attitudes or personality variables [6, 7]. Vyncke [8] reports on the effectiveness of psychographic versus demographic and socioeconomic segmentations in a four-market comparison study. In all the markets analyzed in the study, it was clear that the psychographic segmentation bases (in this case lifestyle variables) performed better than demographic and socioeconomic variables. Some of the demographic and socioeconomic variables did hold greater predictive power than others; e.g. sex of the consumer was found to perform much better than social class.

Aspects of personality have been frequently used as bases for segmentation, but Minhas and Jacobs draw attention to the fact, that a majority of studies have shown the possible link between personality and consumer behavior to be so weak that it is of very little practical value. Minhas and Jacobs also criticize social class segmentation, due to it being usually performed in a too general fashion and ignoring the possibility of an individual having conflicting rankings on different social class variables, such as a high income but low education. Tonks [9] also voices his concern for using social class as a variable, due to it having many possible interpretations and dimensions.

Lifestyle is currently understood as the ways in which people live and choose to spend their time and money [8]. In lifestyle segmentation, the variables used are often unrelated to the market being studied. For instance, a lifestyle segmentation might include variables on consumers’ hobbies, fashion sense and travel habits. This renders lifestyle segmentation as less useful on its own when applied to a specific product or market, but potentially highly useful when combined with variables which are specific to the area under study [4]. Wedel and Kamakura point out also other potential difficulties in lifestyle segmentation which warrant future studies to firmer establish how to use lifestyles in identifying homogeneous segments. For instance, consumers’ values have proven to be relatively stable, but the link between values and behavior has not been firmly proven.

Finally, Wedel and Kamakura point out, that the effectiveness of any bases used are, however, dependent on the dilemma at hand and its specific features and how well the bases are matched to them. Tonks makes the point that choice of variables is always subjective and researchers should be aware of the dangers of familiarity, inertia or “common sense agreement” leading to potentially poor selection of variables.

As a conclusion of this discussion, we see that the choice of variables is by no means a simple or self-evident task in any segmentation situation. Furthermore, in our research the choice is complicated by the impossibility of obtaining certain kinds of data, such as e.g. data on actual usage for a majority of the potential users. In this paper we seek to evaluate two choices of segmentation variables in our specific segmentation problem; we have chosen to contrast a traditional choice of demographic and socioeconomic bases with attitudinal variables. Our decision to choose demographic and socioeconomic variables as one of the bases was motivated through some traditionally held ‘truths’ in the field of information systems adoption and acceptance, where it is often seen that e.g. young, male consumers are the most eager adopters and users of new technology. We were curious to see whether we can extract some meaningful segmentation information from our data through categorizing the consumers in our data through demographic and socio-economic variables. At the same time, we had a sense that we might uncover some interesting information about the users who receive little love and attention in the information systems field; e.g. elderly women, persons with low income, pensioners etc.

Our second choice of variables, which we wanted to compare the demographic and socio-economic variables against, was motivated e.g. by the above discussion on previous literature, where lifestyle and psychographic variables are frequently mentioned to be more useful than demographic variables in many cases. We chose to compare the socio-demographic segmentation to attitude-based segmentation. Heterogeneity among consumer attitudes, along with consumer preferences and perceived benefits, is one of the main reasons for conducting segmentation in the first place, but rarely used as basis for market segmentation [10]. Also, using attitudes or benefits as segmentation bases can potentially explain consumer behavior, whereas socio-demographic segmentation can only describe behavior but not explain it [10]. Therefore, it is also not possible to predict consumer behavior based on socio-demographic segmentation, whereas attitude-based segmentation can potentially give us clues regarding consumers’ future behavior. The attitudes we chose for our analysis are market-specific gauging the respondents’ attitudes towards mobile services and mobile device use. Market-specific variables seemed also intuitively to be an advantageous choice.
Segmentation analyses of mobile phone markets have been reported e.g. by [11] and [12], but there is little previous research on segmentation of mobile services markets.

3. Methodology

The empirical data was collected in 2009 via a self-administered questionnaire that was mailed to a sample of Finnish consumers. The sample was selected from the electronic sampling frame provided by the Finnish Population Register Centre, based on a stratified sampling procedure. To select the sample we used a simple random sampling method, and the frame we used offered a complete representation of the target population, which was defined as the Finnish population between the ages of 16 and 64, whose mother tongue was either Finnish or Swedish and who resided in mainland Finland. The sample size was 1,300. To encourage respondents to complete and return the questionnaire, they were offered a chance to win a top-of-the-line mobile phone. The number of completed, valid responses was 429 (response rate 33 %).

We chose to perform K-means cluster analysis on our data, as it is generally agreed upon to be almost a standard for segmentation in market research, although other approaches have emerged and hold promise, such as neural networks and fuzzy clustering [4, 7], for examples see e.g. [13] and [14]. The segmentation is carried out as a post hoc analysis, i.e. we have not described and defined the segments beforehand, but rather wish to extract meaningful segments from the data. The number of segments was chosen to be five for both segmentation analyses, as this number had been identified as suitable in previous analyses [15, 16].

For the second segmentation we chose eighteen attitude variables which had previously been identified through factor analysis as belonging to five separate groups with some explanatory power regarding consumer behavior with regard to mobile services [15, 16].

Variables used for cluster analysis based on attitudes (attitudes graded on 5-point Likert scale where 5 = Completely agree and 1 = Completely disagree; 3 = Do not agree nor disagree):

1. I want my mobile phone to be the newest model
2. I use my mobile phone only for calls
3. I want to be among the first ones to try new mobile services
4. I need my mobile phone only for calls and SMS
5. My mobile phone needs to be of newest model
6. I do not take into use new technologies or appliances before it is absolutely necessary because of my private life or my work
7. My social life would suffer without my mobile phone
8. I use my mobile phone to keep in touch with friends and family
9. I have the know-how and skills to use mobile services
10. I know how to make use of mobile services
11. It is easy for me to learn how to use mobile services
12. It is effortless for me to learn how to use mobile services
13. I think using mobile services seems easy

Variables used for cluster analysis based on demographic data:

1. Age
2. Gender
3. Highest level of education completed
   a. Elementary school
   b. Middle school
   c. Secondary school
   d. Vocational school
   e. College
   f. Polytechnic
   g. University
4. Yearly income
   a. Up to 10,000 €
   b. 10,001 - 20,000 €
   c. 20,001 – 30,000 €
   d. 30,001 - 40,000 €
   e. 40,001 – 50,000 €
   f. More than 50,000 €
5. Socio-economic group
   a. Manager
   b. Entrepreneur
   c. Upper-level administrative
   d. Lower-level administrative
   e. Employee / Worker
   f. Student
   g. Pensioner
14. Through mobile services I can get the knowledge I need whenever and wherever
15. With mobile services I can do my tasks whenever and wherever
16. Using mobile services make me more efficient
17. With mobile services I can coordinate tasks whenever and wherever
18. It is important for me to have a trendy mobile phone

Table 1 – Segments derived through K-means clustering from the segmentation with socio-demographic bases

<table>
<thead>
<tr>
<th>Segment</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>D5</th>
</tr>
</thead>
<tbody>
<tr>
<td># of cases</td>
<td>84</td>
<td>113</td>
<td>46</td>
<td>66</td>
<td>78</td>
</tr>
<tr>
<td>Age (mean)</td>
<td>46.3 years</td>
<td>44.6 years</td>
<td>22.8 years</td>
<td>45.9 years</td>
<td>58 years</td>
</tr>
<tr>
<td>Gender</td>
<td>100% males</td>
<td>100% females</td>
<td>57% females</td>
<td>77% females</td>
<td>62% females</td>
</tr>
<tr>
<td>Education (mean*)</td>
<td>3.68</td>
<td>5.25</td>
<td>3.8</td>
<td>6.15</td>
<td>2.87</td>
</tr>
<tr>
<td>Income (mean**)</td>
<td>3.54</td>
<td>3.33</td>
<td>1.17</td>
<td>5.41</td>
<td>2.22</td>
</tr>
<tr>
<td>Socio-ec group</td>
<td>57% manual workers</td>
<td>49% manual workers, 24% lower level admin</td>
<td>63% students</td>
<td>52% upper-level admin</td>
<td>53% pensioners</td>
</tr>
</tbody>
</table>

*) Range 1-7, high number representing high level of education
**) Range 0-6, higher number representing higher income

As a final step in our analysis, we needed to evaluate the usefulness of these two different segmentations. We started out by checking to what degree the different segments make use of different mobile services. For this analysis, we chose the top five mobile services used in our sample, that is SMS, m-email, search services, checking time tables and navigation services. Our assumption was that in order for a segmentation to be efficient in the mobile services market, there should be significant differences in mobile service usage between the different segments. In order to measure for significant differences in usage between the different segments, we ran one-way ANOVA with the mobile services as dependent variables. The mobile services usage was measured through a five-point Likert scale representing the frequency of using a specific service (5 = Daily, 4 = Weekly, 3 = A few times per month, 2 = I have tried, 1 = I have never used). In order to test for homogeneity of variance, we ran Levene’s test for equality of variances. As Levene’s test was significant for four of the five services (all except search services), we also ran Welch and Brown-Forsythe statistics to overcome the differences in variance between the segments. For post-hoc testing we used the Games-Howell statistic, which does not assume equal population variances.

4. Results

Using socio-demographic segmentation bases resulted in five distinct segments of consumers (see Table 1). The segments have distinctive socio-demographic profiles. Segment D1 (Demographic 1) is an all-male segment with a majority of manual workers (“male workers”). Segment D2 is an all-female segment, also with a majority of manual workers but a higher education level than D1 (“female workers”). Segment D3 is comprised mainly of students, with a low mean income and a mean age of 22.8 years (“students”). Segment D4 is predominantly female, with a high level of education, high income and a majority in upper-level administrative positions (“accomplished females”). Segment D5 is predominantly made up of pensioners, with the highest mean age of the five segments, a low education level and low income (“pensioners”).
In segment D4, the usage of all measured services is the highest among the demographic segments. The lowest level of use is found in D1 for SMS, D5 for m-email, D3 for search services, D3 for time tables and D2 for navigation services.

Table 2: Segments derived through K-means clustering from the segmentation with attitude bases

<table>
<thead>
<tr>
<th></th>
<th>Segment A1</th>
<th>Segment A2</th>
<th>Segment A3</th>
<th>Segment A4</th>
<th>Segment A5</th>
</tr>
</thead>
<tbody>
<tr>
<td># of cases</td>
<td>95</td>
<td>68</td>
<td>105</td>
<td>70</td>
<td>65</td>
</tr>
<tr>
<td>Age (mean)</td>
<td>44.3 years</td>
<td>49.8 years</td>
<td>42.3 years</td>
<td>39.8 years</td>
<td>51.3 years</td>
</tr>
<tr>
<td>Gender</td>
<td>55% females</td>
<td>54% males</td>
<td>70% females</td>
<td>69% males</td>
<td>52% females</td>
</tr>
<tr>
<td>Education (mean*)</td>
<td>4.76</td>
<td>3.35</td>
<td>4.81</td>
<td>4.84</td>
<td>3.88</td>
</tr>
<tr>
<td>Income (mean**)</td>
<td>3.09</td>
<td>2.95</td>
<td>3.32</td>
<td>4.01</td>
<td>3.22</td>
</tr>
<tr>
<td>Socio-ec group</td>
<td>31% manual workers, 15% lower level admin</td>
<td>35% manual workers, 27% pensioners</td>
<td>31% manual workers, 18% lower level admin</td>
<td>31% manual workers, 26% upper level admin</td>
<td>38% manual workers, 14% pensioners</td>
</tr>
</tbody>
</table>

*) Range 1-7, high number representing high level of education

**) Range 0-6, higher number representing higher income

Looking at the results from the analyses of variance, we find that there are statistically significant differences in usage. As the assumption of homogeneity of variances was violated for all services except search, the Brown-Forsythe F-ratio is reported:

1. SMS: $F(4, 255.03) = 5.63, p < .001$ (Levene’s $F(4, 370) = 11.13, p < .001$)
2. M-email: $F(4, 303.61) = 17.65, p < .001$ (Levene’s $F(4, 366) = 7.22, p < .001$)
3. Search: $F(4, 333.92) = 10.2, p < .001$ (Levene’s $F(4, 368) = 1.72, p = .145$)
4. Time tables: $F(4, 272.17) = 12.82, p < .001$ (Levene’s $F(4, 366) = 13.82, p < .001$)
5. Navigation: $F(4, 290.37) = 5.14, p < 0.01$ (Levene’s $F(4, 364) = 7.26, p < .001$)

Looking at the results from our post hoc tests (Games-Howell) we find, however, that actually only one of the segments is significantly different from the others with regard to usage of mobile services. The usage profile of segment D4 (who could be called “accomplished females”) is distinct from most other segments on all measured mobile services, but none of the other segments are distinct. Based on the Games-Howell test we find:

a) SMS: Segment D4 ($M = 4.85, SD = 0.361$) is different from segments D1 ($M = 4.22, SD = 1.018$) and D5 ($M = 4.23, SD = 1.173$) at the 0.01 level of significance. Segment D4 is different from D2 ($M = 4.58, SD = .897$) at the 0.05 level of significance. There is no significant difference between D4 and D3 ($M = 4.54, SD = 1.048$). There are no other significant differences.

b) M-email: D4 ($M = 3.43, SD = 1.658$) is different from all other segments at the 0.01 level of significance. There were no significant differences between D1 ($M = 1.94, SD = 1.314$), D2 ($M = 1.92, SD = 1.251$), D3 ($M = 1.87, SD = 1.185$) or D5 ($M = 1.81, SD = 1.254$).

c) Search: D4 ($M = 3.65, SD = 1.353$) is different from all other segments at the 0.01 level of significance. There were no significant differences between D1 ($M = 2.56, SD = 1.241$), D2 ($M = 2.52, SD = 1.327$), D3 ($M = 2.46, SD = 1.149$) or D5 ($M = 2.53, SD = 1.442$).

d) Time tables: D4 ($M = 2.62, SD = 1.476$) is different from all other segments at the 0.01
level of significance. There were no significant differences between D1 (M = 1.65, SD = 0.988), D2 (M = 1.49, SD = 0.923), D3 (M = 1.47, SD = 0.757) or D5 (M = 1.71, SD = 1.218).

c) Navigation: D4 (M = 2.22, SD = 1.364) is different from segments D2 (M = 1.48, SD = 0.913) and D5 (M = 1.59, SD = 1.116) at the 0.05 level of significance. There were no other significant differences (D3 (M = 1.58, SD = 1.055), D1 (M = 1.86, SD = 1.106).

The “accomplished female” segment (D4) has a distinct profile of usage of mobile services, where it is noteworthy that the D4 segment surpasses the other segments regarding level of usage of all tested services. The differences are greatest regarding m-email, search services and checking time tables. What is especially striking is that there are no significant differences on any of the services between any of the other segments; all of the significant differences involve segment D4.

In summary, the socio-demographic segments are distinct in demographic profile, as was expected, but only one of the segments is significantly different from the others regarding usage of mobile services.

The attitude-based segmentation yielded five segments, which are not as distinct socio-demographically as the segments derived through demographic clustering (see Table 2). None of the segments are as easily described demographically as for example the demographic D3, “students” or D5, “pensioners”. In all of the segments, manual workers are represented by approximately a third of the members. There are differences in age, gender, education and income, but yet all values fall within a rather small range.

When looking at the attitudes on which the segmentation is based, clearer differences naturally emerge (see Table 3). For example, the members of segment A1 have high confidence in their abilities to learn and use mobile services. The consumers in segment A2 are the most conservative in regard to mobile services and least interested in trying out new technologies and devices. The segment A3 places the greatest value on the social aspects of mobile services. Segment A4 could be described as the consumers most interested, most enthusiastic, most skilful and generally with a positive attitude towards mobile services and their own abilities to use them. Segment A5 saw mobile devices and services to be least essential for their social lives and overall very conservative regarding mobile services. They did however place value on the efficiency benefits that can be found when using mobile services.

Comparing the attitude-based segments, the highest level of usage on all five of the services is found in segment A4. The lowest level of usage is found in A2, except for SMS which is least in use in segment A5.

Again, looking at the analyses of variance we find that there are significant differences in the use of mobile services between the segments. As the assumption of homogeneity of variances was violated for all services except search services, the Brown-Forsythe F-ratio is reported:

1. SMS: F(4, 219.83) = 11.66, p < .001 (Levene’s F(4, 394) = 24.46, p < .001)
2. M-email: F(4, 334.00) = 37.93, p < .001 (Levene’s F(4, 393) = 14.64, p < .001)
3. Search: F(4, 358.40) = 11.55, p < .001 (Levene’s F(4, 393) = .346, p = .847)
4. Time tables: F(4, 306.67) = 16.81, p < .001 (Levene’s F(4, 393) = 13.52, p < .001)
5. Navigation: F(4, 307.36) = 19.03, p < 0.01 (Levene’s F(4, 392) = 16.59, p < .001)

On closer examination with the Games-Howell statistical test we find:

a) SMS: There are significant differences between segments A1 and A4, A1 and A5, A2 and A4, A3 and A5, A4 and A5. The differences are significant on the 0.05-level.

b) M-email: There are significant differences between segments A1 and A3, A1 and A4, A2 and A3, A2 and A4, A4 and A5. The differences are significant on the 0.05 level.

c) Search: There are significant differences between segments A1 and A3, A1 and A4, A2 and A3, A2 and A4, A3 and A5, A4 and A5. The differences are significant on the 0.05 level.

d) Time tables: There are significant differences between segments A1 and A3, A1 and A4, A2 and A3, A3 and A4, A4 and A5. The differences are significant on the 0.05 level.

e) Navigation: There are significant differences between segments A1 and A4, A2 and A3, A2 and A4, A3 and A4, A4 and A5. The differences are significant on the 0.05 level.

In other words, out of fifty possible pair-wise comparisons, twenty-six (52%) were significantly different statistically. In the same analysis conducted with the demographic clusters, seventeen out of fifty (34%) possible pair-wise comparisons were significantly different statistically (all involving segment D4).
Table 3: Mean-scores and standard deviations for attitudes in attitude-based segmentation, by segments

<table>
<thead>
<tr>
<th>Attitude</th>
<th>Segm</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>A1</td>
<td>96</td>
<td>1,50</td>
<td>.768</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>68</td>
<td>1,57</td>
<td>.869</td>
</tr>
<tr>
<td></td>
<td>A3</td>
<td>105</td>
<td>2,12</td>
<td>.937</td>
</tr>
<tr>
<td></td>
<td>A4</td>
<td>70</td>
<td>3,80</td>
<td>.754</td>
</tr>
<tr>
<td></td>
<td>A5</td>
<td>65</td>
<td>1,74</td>
<td>.853</td>
</tr>
<tr>
<td>2.</td>
<td>A1</td>
<td>96</td>
<td>2,95</td>
<td>1,387</td>
</tr>
<tr>
<td></td>
<td>A2</td>
<td>68</td>
<td>3,53</td>
<td>1,440</td>
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<td></td>
<td>A3</td>
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<td>1,118</td>
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<td></td>
<td>A4</td>
<td>70</td>
<td>1,50</td>
<td>.830</td>
</tr>
<tr>
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5. Discussion

Certain important questions and considerations arise from the above results.

As stated by [17], we can in the light of our analysis agree that different bases for a segmentation analysis will give rise to very different segments. As evident from looking at the demographic descriptives, the segments from the socio-demographic segmentation are not at all the same as those found through attitude-based segmentation. If they would...
have been the same, or reasonably similar, it is obvious that the socio-demographic segmentation would be the most beneficial and effective to use due to easy accessibility and measurability. Demographic segmentation is easy to use and easy to understand, and thus a common choice even when not appropriate or efficient in a given market [18]. When looking at the attitude-based segmentation, the demographic information regarding the different segments appears to be completely redundant or non-informative. The segments are distinct regarding their attitudes, but are not clearly distinguishable regarding their age structure, education, income etc. Yet the segments exhibit different usage of mobile services. This seems to challenge commonly held beliefs about factors such as gender and age influencing usage of technology (e.g. [19]).

But how can we reach consumer segments found through attitudinal clustering? The beauty of demographic segmentation lies in the convenience of reaching such segments. Segmentation is not worth much, if it cannot be acted upon. One possibility to reach attitude segments would be to look into for example the routines and structures of their everyday lives, which might give us clues how to define and describe the different segments.

When looking at the way the socio-demographic segments use different mobile services, we could say that this segmentation is mostly unsuccessful in producing meaningful results, as there are no significant differences between the segments regarding usage of mobile services. There is only one exception, which is segment D4 identified in the socio-demographic segmentation. This segment is distinct regarding both demographic profile and usage of mobile services, and could be useful for research and marketing. This segment is comprised mostly of highly educated female consumers with a relatively high mean income and could be interesting to investigate in more detail, as they scored relatively highly on the usage of all measured mobile services.

As mentioned above, demographic segmentation has previously been identified as less powerful than for example using lifestyle variables [8] or product-specific bases [4]. We were still surprised to see the socio-demographic segmentation yield such poor results in the mobile services market. It would be interesting to see whether it would be more powerful when investigating a specific sub-set of mobile services (for example navigation services), as the mobile services market on the whole is broad, consisting of a very wide range of mobile services answering to very different user needs and wants.

Attitude-based segmentation seems to yield better results in the mobile services market. This result could likely be further improved through developing the choice of attitude variables. We will also continue our research to improve the segmentation by combining attitudes with other bases, for example perceived benefits. The research presented in this paper constitutes ground to build on, but there is a lot of work to be done in order to identify the proper bases for segmentation in the mobile services market. At this stage we can with a reasonable amount of confidence say that a purely socio-demographic segmentation is not likely to be particularly efficient or useful in this market at this stage.

In future work different ways of evaluating the segmentation should be looked at. Aside from general guidelines for evaluating a segmentation (e.g. [20] [21]), several other aspects could be used to measure whether a segmentation analysis is efficient and practically possible to employ [17, 20]. We have the possibility of utilizing e.g. i) intended future use of mobile services, ii) usage of other services than only the top five, iii) perceived benefits from using mobile services, and iv) contexts of use. Combining this information with the results of the segmentations would raise our understanding of the desires and needs of the separate segments and improve the applicability of the segmentation. Also putting the segmentation to practical use should be investigated; how can the derived segments be used in a design or marketing process and how will we make sure that we have actionable segmentation information [22]. As mobile services are a highly international phenomena, also international aspects of segmentation would be beneficial to understand (see e.g. [23]). But first things first: in order to be able to predict the future use of mobile services, it is necessary to segment the market. Even more importantly; being able to choose the proper segmenting bases enables us to understand what kind of services should be developed in order for them to be successful in the mobile services market.

6. References


