User perception on Location Based Services: the more you know, the less you are willing to pay?

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Abstract— **This paper describes the results of an electronic user survey with *118* volunteer participants, conducted between December *2012* and January *2014* and focusing on users' perception on Location Based Services (LBS) and their use of mobile devices in the context of personal navigation and navigation-related applications. The users are first classified into several user classes according to their Objective and Subjective Knowledge in the field of wireless positioning. Then, the user preferences with respect to various LBS aspects, such as cost and feature preferences, are analyzed per user class. In addition, the user classes are compared according to Mann-Whitney-Wilcoxon and Fligner-Policello statistical tests in order to find out if their differences in the LBS preferences are statistically significant. The main finding is that the users belonging to the classes with higher objective knowledge in the field of wireless localization techniques and technologies are generally less willing to pay for enhanced localization approaches and for location based services on their mobile phones than the users with lower technical knowledge.**

Keywords- Fligner-Policello (FP) test, Mann-Whitney-Wilcoxon (MWW) test, Location Based Services (LBS); LBS billing; localization technologies; user survey.

I. PURPOSE OF THE STUDY AND NOVELTY

Location Based Services are ones of the most sought after sources of revenues in the future mobile devices [1]. One step towards designing better LBS and inventing new position–based applications would be to understand how different classes of users appreciate different categories of services and which are the relationships between users' characteristics and their preferences and needs in terms of LBS. Finding quantitative indicators to classify users is a problem of high relevance in today's mobile industry and related research, because this would allow the service providers to offer better services to the mobile customers [2]. In addition, the problem of mapping the quantized user classes into LBS designer targets and constraints is still an open problem. It is the Authors' view that being able to quantize the user preferences based on some measurable parameters, such as the users' knowledge with respect to wireless positioning technologies, is one important ingredient towards the paradigm of cognitive positioning applications and services, meaning those applications and services which are aware of the context and of the environment and are designed and personalized accordingly. The users' perceived preferences regarding LBS have been previously investigated in [3], [4], [5], [6], [10].

Our approach is different from [3] and [4] as follows: no user classification has been attempted in [3] and the volunteer participants in the survey of [3] were all university master-level students (while in our current studies we have broader age coverage and a broader educational background, as described later in Section II). The methodology in [3] and [4] is also different from the methodology in here (e.g., electronic surveying tool in here versus paper surveying in [3], [4], no student bonus point incentive and no open-ended questions in here compared to [3], [4], wider population background in here, and generally a more focused approach in this study, aiming at finding the relationship between user classes and their LBS preferences). Also the sample size is larger in this case (*118* answers in here, compared to *58* in [4], and *109* in [3]).

The studies in [5] focus on LBS information delivery mechanisms with privacy considerations as focal point. It is shown in there that certain user privacy concerns can be overridden through certain LBS benefits, appropriate information disclosure, and a fair distribution of outcomes among users. Our study focuses on a different aspect, namely the users' knowledge on wireless positioning technologies and LBS. The studies from [6] and [10] focused on end-user acceptability and adoption of various ICT services, with LBS included in the studies. There was no user classification in there. Also no user surveys were used in [10], while in [6] the pilot surveys concentrated on the reliability indexes about users' willingness to adopt LBS for emergency management. Additional studies related to users' adoption of LBS can be found in [11] and [12], but they focus on users' privacy concerns.

Our paper addresses the following *research question*: does the amount of technical knowledge related to wireless positioning technologies influence the users' preferences in terms of LBS costs, billing types, mobile device features and desired level of detail in having the position displayed on own mobile device? An *additional research question* addressed here

978-1-4799-5123-9/14/$31.00 ©2014 IEEE

is: to what extent the differences in user preferences are significant?

Based on Authors' literature searches, we find that such study is unique in the current review literature and it may provide a small building brick for the bridge of cognitive positioning paradigm of tomorrow, illustrated in Figure 1. The application (APP) and physical (PHY) layers from Figure 1 are typically completely disjoint, and the APP layer builds upon the PHY layer, meaning that according to the achievable accuracy level coming from the used positioning technology, certain LBS are enabled. For example, three of the major positioning technologies nowadays are the Global Navigation Satellite Systems (GNSS) [7], cellular-based positioning [8], and WiFi-based positioning [9]. While the first offers the best positioning accuracy we can achieve in outdoor, the latter two are gaining more and more interest in both outdoor urban and indoor scenarios. According to Authors' opinion, hybridization solutions between different technologies are the answer to the future seamless outdoor-to-indoor localization.

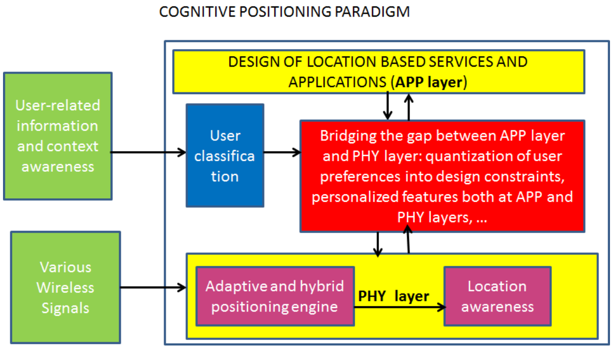

Figure 1. Illustration of the cognitive positioning paradigm.

In a cognitive approach, as illustrated in Figure 1, additional user-related and context awareness information can be inserted into the positioning chain, in order to enhance both the provided LBS and the positioning solution desired by a particular class of users. Thus, there will be a bi-directional flow of information between the APP and PHY layers, in such a way that the overall provided solution (both in terms of technical and commercial features) is best customized to the users' needs and preferences.

It is thus the goal of the paper to investigate whether users could be divided into user such classes which have significance in terms of users' preferences at APP and PHY layers.

II. METHODOLOGY

Our survey was organized as an electronic survey with *37* questions using Webropol 2.0 survey software. The average time to complete the survey was estimated to be *35* minutes. More than *1000* persons were invited to complete the survey, through LinkedIn groups, research mailing lists, friends' contacts, and through direct student and teacher contacts in three European universities: Tampere University of Technology, Finland, Universitat Autonoma de Barcelona, Spain and University Politehnica of Bucharest, Romania. The survey was open for more than one year. *118* persons answered the survey questions, with a gender distribution of 14% female respondents and 86% male respondents. Since most of the respondents were from technical university programs, the big difference in the gender balance could be attributed to general gender imbalance present in such programs. The respondents (denoted as 'users' in what follows, since the focus was on the LBS usage and preferences) came from *17* different countries, as illustrated in Figure 2. Unsurprisingly, the top three countries in the list of participants are those from the three universities involved in the data collection. One respondent kept his or her country of residence private, this being the reason for the N/A value in the list. The survey was first opened in December 2012 and the current results are analyzed with the data arriving into the system until January 2014. The users' answers were stored anonymously and the users gave their consent to the sub-sequent conglomerate analysis of their answers.

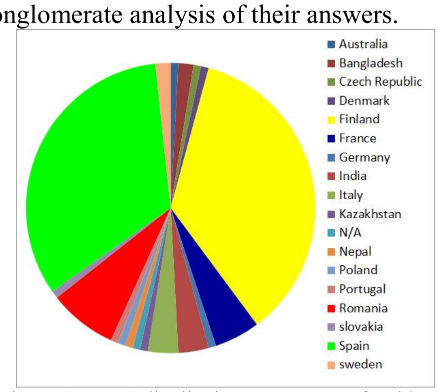

Figure 2. Users' distribution per country of residence

The age variation of the respondents per age groups is illustrated in Figure 3 (we did not ask for the exact age in order to minimize the privacy invasion regarding the users). The majority of the users were between 21 and 30 years old (about 75% of the users).

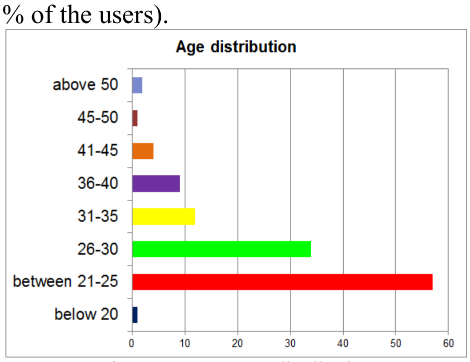

Figure 3. Users' age distribution

Figure 4. Users' occupation distribution

Figure 4 shows the employment status of the users and Figure 5 shows the last completed degree ('other' in Figure 5 may signify a non-technical degree or a degree less than the bachelor degree).

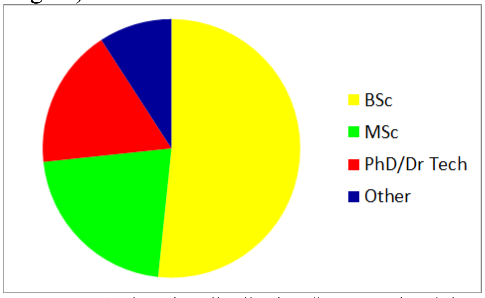

Figure 5. Users' education distribution (last completed degree)

III. USER CLASSIFICATION

The knowledge-based classification was done according to two set of background questions. In the first set of questions, the users were asked to evaluate, on a Likert scale from 1 (None) till 5 (Excellent), their level of familiarity with the technical features of the following systems used in navigation: GPS, Galileo, GLONASS, COMPASS, EGNOS, WLAN, WCDMA, LTE, UWB, Bluetooth and DTV. The answers to these questions were quantized into the parameter of ***Subjective Knowledge***, which was normalized to 1 (corresponding to an 'Excellent' self-assessed knowledge about all these systems). Basically, the subjective knowledge refers to the users' own perception of their technical knowledge in the field of wireless positioning. The second set of questions contained *15* multiple-choice assertions, with one possible correct answer among three choices (True, False and Don't Know). All those questions pertained to the localization technologies mentioned in the first set of questions. For example, the assertion "*There are currently 5 IOV Galileo satellites on sky*" had the correct answer 'False' (counted as a 'hit'), and the other two options were counted as a 'miss'. The parameter ***Objective Knowledge*** was quantized as the number of total hits divided by the total number of assertions (here *15*). Thus, this objective knowledge refers to the users' technical knowledge in the field of wireless positioning as perceived by an external observer with good technical expertise in the field. After these two parameters normalized to *1* have been computed, the **thresholds** between 'low' and 'high' have been set to the mid interval **0.5**. The division into users' classes has been done according to Table 1 (the nomenclature is self-defined following basic intuition, in the absence of other studies pertinent to such classification). The number of users identified in each class is seen in brackets in each class, together with the percentage of female users.

Table 1. User classification according to their Objective and Subjective Knowledge (in brackets there is the number of users in each class and the female percentage in that class)

		Objective Knowledge	
		High	*Low*
Sub-jective Knowl.	*High*	Proficient(20/5%)	Overconfident(12/ 0 %)
	Low	Modest(18/27.7%)	Novice(68/16.1%)

IV. USER PREFERENCES REGARDING LBS

Following the classification in Section III, several user preferences were analyzed per user class and they are presented in what follows. Table 2 shows how much a user is willing to pay extra (compared to the currently owned device) for a mobile device with various location capabilities: i) basic or cellular-only (few hundred meters accuracy), ii) GPS-based positioning capability (meter accuracy outdoors, no coverage indoors, long latency at start-up), iii) Assisted-GPS positioning capability (meter accuracy outdoors, limited coverage indoors, fast position computation at start-up) and iv) Hybrid high-accuracy positioning (combination of GPS, WLAN , cellular, meter accuracy both indoors and outdoors and 3D positioning) . The answers were mapped into a 1 to 6 scale as follows: 1) less than 10 EUR extra, 2) between 10 and 30 EUR extra, 3) between 30 and 50 EUR extra, 4) between 50 and 80 EUR extra, 5) between 80 and 100 EUR extra, 6) between 100 and 150 EUR extra (the users were asked to choose the interval which is closest to their maximum estimate). The mean and standard deviation values per user class are shown in Table 2 with the maximum mean value among user classes emphasized in bold-faced figures for each location capability level. Unsurprisingly, all users are willing to pay more for more advanced localization features on their mobile device, and the low Objective Knowledge users seem in favor to pay few tens of EUR extra (on average) on their mobile device in order to acquire better accuracy in the location solution. The Overconfident user class seems the class most prone to pay more for advanced location technologies.

Table 2. User Preferences in terms of device price, computed on a scale from *0* (minimum price) to *5* (maximum price)

	High Objective Knowledge		***Low Objective Knowledge***	
Mean / std	***High Subjective Knowledge (Proficient users)***	***Lower Subjective Knowledge (Modest users)***	***Higher Subjective Knowledge (Over-confident users)***	***Lower Subjective Knowledge (Novice users)***
i) For basic location capability (cellular)	1.2 / 0.41	0.88 / 0.32	1.25 / 0.96	**1.41** / 0.95
ii) For GPS location capability	1.55 / 0.75	1.94 / 0.80	**2.00** / 1.65	1.73 / 1.15
iii) For A-GPS location capability	2.05 / 0.99	2.33 / 1.41	**2.41** / 1.56	2.00 / 1.29
iv) For advanced hybrid location	2.4 / 1.31	2.5 / 1.61	**3.25** / 1.60	2.58 / 1.53

Another addressed question was about the users' willingness to pay for various location-based services, divided into 10 LBS classes: i) an emergency alert service informing the user of any present or forecast disturbances (e.g. floods, crisis, fire, earthquake) in the neighborhood of user location, ii) an LBS-based advertising service (e.g., giving a list with all nearby shops having a desired item and a list of their prices/specifications), iii) a public transport routing service (e.g., showing several routes between points A and B via public transport, what are the fees to get from point A to point B, and what is the status of the traffic: fluent/congested), iv) a pollution-level indicator service (e.g., showing what is the air and water quality of the town/district the user is in and which are the health risks associated with that quality level), v) a personalized health-advice service (e.g., based on user medical history and physical activity levels, the user will get daily recommendations about the healthy level of exercise/physical activity to achieve and indications about nearby places where he/she can perform physical activity), vi) a social networking service (e.g., based on user pre-defined hobbies and interests, she/he will get on demand sms alerts with coordinates of other people with similar hobbies/interests that have subscribed to this service), vii) a LBS service about the location of user's children, close family or friends, assuming that they gave the consent to be located/tracked, viii) Checking automatically or automatic payment for a museums, trains, theater shows, etc, based on user mobile device with location capabilities (this would decrease the queues and waiting times), ix) automatic geo-tagging of photos taken with mobile device, x) Facebook-'check-in' application (to be able to 'check-in' automatically at the user location).

Table 3. User Preferences in terms of monthly fee per LBS, computed on a scale from *0* (minimum price) to *5* (maximum price).

	High Objective Knowledge		***Low Objective Knowledge***	
Mean / std	***High Subjective Knowledge (Proficient users)***	***Low Subjective Knowledge (Modest users)***	***High Subjective Knowledge (Overconfident users)***	***Low Subjective Knowledge (Novice users)***
Emergency	0.95 / 0.75	0.72 / 0.82	0.91 / 0.99	**1.05** / 1.20
Advertising	0.50 / 0.68	0.44 / 0.92	**1.25** / 0.86	0.89 / 1.06
Public transport	1.25 / 1.06	1.05 / 0.80	**2.08** / 1.08	1.54 / 1.08
Pollution level info	0.80 / 1.05	0.38 / 0.60	**1.25** / 1.35	0.67 / 1.07
Health	1.15 / 1.34	0.61 / 1.03	**1.58** / 1.50	1.16 / 1.15
Social networking	0.65 / 0.98	0.16 / 0.38	**1.50** / 1.38	0.82 / 1.00
Family tracking	1.15 / 1.22	0.72 / 0.89	**1.91** / 1.24	1.22 / 1.19
Automatic payments	**1.45** / 0.94	1.16 / 0.92	1.41 / 1.50	1.14 / 1.08
Geo-tagging	0.65 / 0.81	0.44 / 0.70	**0.91** / 1.16	0.58 / 0.85
Facebook automatic check-in	0.20 / 0.52	0.33 / 0.59	**1.50** / 1.44	0.51 / 0.92

The answers were quantized on levels from 0 to 5 according to the maximum monthly fee the users were willing to pay for such applications, as follows: 0) 0 EUR, 1) between 0 and 1 EUR, 2) between 1 and 2 EUR, 3) between 2 and 5 EUR, 4) between 5 and 10 EUR, 5) between 10 and 20 EUR. The results (mean and standard deviation) are shown in Table 3. Again, the users from the low objective knowledge class, and especially those belonging to the Overconfident user class, are willing to pay more for most of the LBS enumerated as examples. The only difference is regarding the automatic payments, where proficient users seem to be willing to pay more, but as shown later in Section V the differences in this particular case are not significant. Top two LBS applications in terms of willingness to pay monthly fees for them are those related to *automatic payments* and *public transport* information for the Proficient and Modest users (high Objective Knowledge classes). For the Overconfident and the Novice users, the most appealing LBs are the *public transport*-related and the *family tracking*-related LBS. The monthly average fees that the users are willing to pay for one particular LBS are moderate (between *1* and *2* EUR per month).

Table 4. How much the users are willing to pay per LBS (numbers given in EUR this time)

	High Objective Knowledge		***Low Objective Knowledge***	
Mean/std values [EUR]	***High Subjective Knowledge (Proficient users)***	***Low Subjective Knowledge (Modest users)***	***High Subjective Knowledge (Overconfident users)***	***Low Subjective Knowledge (Novice users)***
Overall average monthly fee for a package of several LBS services	4.25 / 3.46	9.33 / 8.99	**15.08** / 17.47	8.14 / 7.48
Maximum monthly fee for a particular/desired LBS	2 /1.11	1 / 0.89	**5** / 0.99	2 / 1.12

Table 4 shows also how much the users would be willing to pay per month for a bundle of LBS services (e.g., when all the ten above-mentioned LBS would be offered jointly) and how much they would be willing to pay per month for their top LBS application. The values in Table 4 are given in EUR and they match with the previous conclusion: that Overconfident users seem more willing to pay more for LBS than the other three classes of users and that the Proficient users seem the ones less willing to pay large sums for LBS compared to other user classes.

We have looked so far at several user preference related to costs. Table 5 shows also the desired level of detail for the display of the location solution on the mobile screen, assuming that such levels were technically possible.

Table 5. Desired level of detail in the accuracy of the location solution

	High Objective Knowledge		***Low Objective Knowledge***	
Preferences regarding the level of detail Mean/std values	***High Subjective Knowledge (Proficient users)***	***Low Subjective Knowledge (Modest users)***	***High Subjective Knowledge (Overconfident users)***	***Low Subjective Knowledge (Novice users)***
Outdoors, rural	**2.05** / 0.82	1.72 / 0. 66	1.33 / 0.65	1.64 / 0.74
Outdoors, urban	**2.40** / 0.82	2.33 / 0.59	2.25 / 0.45	2.01 / 0.61
Indoors	2.25 / 1.06	2.50 / 0.70	**2.83** / 0.93	2.35 / 0.95

Three scenarios were considered as case studies: outdoor rural, outdoor urban and indoors, and the desired level of accuracy was quantized from level 0 (10 m accuracy) to level 3 (1 cm accuracy). Level 1 corresponds to (1 m accuracy) and level 2 corresponds to 10 cm accuracy. Proficient users have realistic expectations about the level of detail in various environments, despite the fact that the question was emphasizing the point of '*if it were technically possible*'. On average, sub-meter accuracy is desired (most mean values are around level 2, meaning 10 cm accuracy). All user classes except the

Proficient users seem to want increased accuracy when moving from outdoor rural towards indoor urban scenarios. The Proficient users however prefer on average a slightly better accuracy in outdoor urban scenarios compared to indoor scenarios. This might be explained by the fact that Proficient users might have disregarded the assumption from the question about the feasibility of the solution, and they might have based their answers on their own knowledge on the state-of-art techniques for positioning.

Finally, Table 6 illustrates the top three preferences and the least appreciated feature in terms of mobile device features for a mobile device with location capabilities. The users' choices were among the following nine: 1) high accuracy of the location estimate; 2) low cost of the mobile device; 3) small size of the mobile device; 4) light weight of the mobile device; 5) small delay in starting an application; 6) user-friendly interface; 7) mobile device overall design; 8) large screen size, and 9) continuous location capability. Low objective knowledge users have identical preferences, while the Proficient users seem to favor the small delays over the lower cost of the mobile device.

Table 6. Top and bottom preferences regarding a mobile device with localization capabilities.

	High Objective Knowledge		*Low Objective Knowledge*	
Preferences	***High Subjective Knowledge (Proficient users)***	***Low Subjective Knowledge (Modest users)***	***High Subjective Knowledge (Overconfident users)***	***Low Subjective Knowledge (Novice users)***
Top three features on a mobile with location capabilities	High location accuracy, Small delays, user-friendly interface	Small delays, high location accuracy, low cost of mobile device	High location accuracy, user-friendly interface, low cost of mobile device	High location accuracy, user-friendly interface, low cost of mobile device
Least appreciated feature	Large screen size	Small size of the mobile device	Device design	Device design

V. CLASS SIMILARITY ANALYSIS

The question addressed in this section is the one about the statistical significance of the findings in our previous section. For this purpose we compared the 38 users belonging to the high objective knowledge class with the 80 users belonging to the low objective knowledge class. There are several statistical tests available to compare populations of unequal sizes, depending on the underlying assumptions on the population distributions and variances. In the absence of prior knowledge of the population distribution parameters, we selected two of the most encountered statistical tests to perform the analysis:

- The **Fligner-Policello (FP)** test which does not assume either normality or equal variances of the populations to be compared [13].
- The **Mann-Whitney-Wilcoxon (MWW)** test (its Der Waerden version) which assumes equal variances of the populations [14].

Both of these tests compare two hypotheses, denoted via H_0 and H_a, at a certain significance level α:

- H_0 is the hypothesis that the two user classes have similar preferences
- H_a is the hypothesis that the difference between groups is statistically significant.

Both test compute the so called p-value at a certain α (here taken as 0.05 or 5% significance level), and the p-value carries the following information: a large p-value indicates that there is likely to be little (or no) population-related difference between the preferences; the smaller the p-value is, the more likely it is that the preferences of the two groups are statistically different. The thresholds to decide whether p-value is small enough are test dependent, and in our cases they are equal to *0.025* for FP test and *0.05* for WMM test. The results for the different user preference criteria analyzed in section IV are shown in Table 7.

Table 7. Statistical analysis (FP and MWW tests) about classes' dissimilarities when comparing the higher objective knowledge user class with lower objective knowledge user class

Analyzed feature	*FP p-value (threshold 0.025)*	*MWW p-value (threshold 0.05)*	*H_a accepted (i.e., significantly dissimilar preferences)*
Device price for basic cellular-only location capability	0.023	0.05	**Yes**
Device price for GPS location capability	0.21	0.50	No
Device price for A-GNSS location capability	0.20	0.47	No
Device price for advanced hybrid location capability	0.25	0.36	No
Monthly fee for emergency	0.36	0.42	No
Monthly fee for advertising	0.003	0.01	**Yes**
Monthly fee for public transport	0.008	0.02	**Yes**
Monthly fee for pollution info	0.37	0.33	No
Monthly fee for health	0.05	0.11	No
Monthly fee for social networking	0.002	0.009	**Yes**
Monthly fee for family tracking	0.05	0.11	No
Monthly fee for automatic payments	0.16	0.33	No
Monthly fee for geo-tagging	0.38	0.37	No
Monthly fee for automatic Facebook check-in	0.022	0.02	**Yes**
Overall average monthly fee for a package of several LBS services	0.03	0.09	No*
Maximum monthly fee for a particular/desired LBS	0.05	0.16	No
Detail level for rural outdoor	0.01	0.03	**Yes**
Detail level for urban outdoor	0.009	0.01	**Yes**
Detail level for indoor	0.41	0.71	No

*Very close to the thresholds

Clearly both tests point out towards the same conclusion: when p-value is smaller than the threshold, it means that the two user classes have statistically significant differences in their preferences on LBS. Column 2 and 3 show the computed p values via the two tests and the last column shows whether the two considered user classes (high Objective Knowledge versus low Objective Knowledge) have statistically dissimilar preferences (the Yes cases are emphasized in boldfaced letters).

The analysis of the results in Table 7 shows that in most of the cases the differences in user preferences may not be necessarily significant, but there are at least one third of the cases where the two populations do have statistically significant differences in preferences. These statistically significant differences are especially evident for the device costs when only basic positioning capability is available (high Objective Knowledge users are not willing to pay for what they know to be already state-of-the-art in mobile devices) and for some LBS, such as advertising, public transportation, social networking and automatic check-ins.

From such analysis, it is easy to interpolate, although it may be not perfectly accurate, that the more a user knows about underlying location technologies and techniques, the less he or she is willing to pay for Location Based Services in general, at least when having to make a choice between existing pool of LBS services and applications. It could also mean that LBS designers targeting proficient users or users with higher knowledge in the field of wireless localization need to put an additional effort to create added value to such users and to find out which personalized services may be best appealing to a specific user class.

Regarding device-related preferences for mobiles with location capabilities the two user classes have significantly dissimilar preferences regarding the delay in starting the positioning engine and the interface user-friendliness. In addition, the users belonging to the higher objective knowledge class appreciate significantly more the existence of a GPS chipset on their mobile device.

VI. Conclusions

From this analysis we can conclude that users' preferences are indeed **influenced** by users' background and that the technical knowledge regarding location technologies is an important quantitative factor which may differentiate between classes of users. The significance study showed that preferences regarding more of one third of the analyzed features are dissimilar between the different user classes. Interesting enough, the users with more technical knowledge seem willing to pay less for various Location Based Services and localization enhancement features. The different users classes have similar demands in terms of location accuracy (or detail level) in indoors scenarios, and higher objective knowledge class users prefer a fine level of detail (sub-meter to cm level accuracy) also in outdoor scenarios. We remark also that knowledge is not static. Instead, it emerges over time (e.g. someone who knows nothing about positioning, a month later may know more). So, taking the user's degree of knowledge into account when designing a service should be done in a flexible way, in the sense that the design should evolve over time to follow the changes in users' knowledge.

The next step would be to see whether different user classifications (such as according to their privacy level in mobile applications, according to gender and employment status, or according to the usage level of mobile devices) have any significant influence on users' preferences regarding LBS and how these preferences can be best quantized in terms of designer's parameters and constraints both at application and at physical layer levels.

Acknowledgment

The Authors express their warm thanks to the Academy of Finland (project 256175 "Cognitive Approaches for Location in Mobile Environments") for its financial support for this research work. The Authors would also like to express their warm thanks to all the volunteers who participated to our survey.

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