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The Importance of Cognitive Fit in Mobile Information Systems

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Abstract:

This study extends the range where cognitive fit theory (CFT) has been tested. We replicate on a mobile device the original Vessey and Galletta [1991] study to see if the theory holds in the same way, and we find approximately the same results. However, when we extend the experiment to include common additional tasks to find its relative importance, we find CFT to not be nearly as important as other human-computer interaction concepts like crowding and text entry. The experiments conducted are explained, and the importance of this research in future context is also discussed.

Keywords: cognitive fit, mobile is, user interface

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I. INTRODUCTION

Wireless and mobile applications have an ever-increasing impact on organizations and individuals, but mobile information services have mainly been text-based. The availability of relevant hardware and software has now made it possible to also use other data representation forms like graphs, images or even video in mobile phones and PDA devices. As mobile communications are shifting from voice and text messages to images and video clips, it is more important than ever to understand the effect of data representations to Information Quality (IQ) and information system success in general.

Mobile information systems are in a very similar development phase today as personal computer applications were 15 years ago. In the late '80s and early '90s, presentation of data in the form of graphs became a viable alternative to tabular formats on desktop devices. Multiple studies were carried out at that time to compare the quality of decision making with graphs and tables. The results however were inconsistent. In some studies graphs performed better than tables, while others found tables superior to graphs. There was no common understanding of the phenomena until Vessey [1991] developed a theory of cognitive fit (CFT) to explain under which circumstances one representation outperforms the other. CFT proposes that the correspondence between task and information presentation format leads to superior task performance for individual users.

In this paper we analyze the effects of data presentation on decision quality and performance in mobile information systems. Our study is based on the concept of cognitive fit. First, to test if CFT holds true in mobile devices with small displays, we repeat the classical cognitive fit study of information acquisition that was originally carried out by Vessey and Galletta in 1991, but this time the end users are completing the tasks with mobile phones.

Next, we analyze the relative importance of cognitive fit in mobile information systems with more complex tasks. Earlier studies have shown that experiments with too-simple tasks have failed to reveal the real effects of user interface characteristics like small-screen size on performance [Chae and Kim 2004], [Han and Kwankh 1994]. To overcome this limitation our second test using the Stock Broker Game (SBG) includes navigation, representation interpretation, selection, and text entry.

The structure of the paper is as follows: In Section II we give a short review on the theory of cognitive fit and report the results of the classical cognitive fit experiment carried out with mobile phones; in Section III we describe the SBG experiment mentioned above to test the importance of cognitive fit and other user interface characteristics in mobile information systems; the results are discussed in Section IV; and the final conclusions are provided in Section V.

II. COGNITIVE FIT AND MOBILE INFORMATION SYSTEMS

Theory of Cognitive Fit

According to information processing theory a person solving a problem seeks ways to reduce the problem solving effort, since he or she is a limited information processor [Newell and Simon 1972]. The method used to reduce the effort by matching the problem or task to its data representation is known as cognitive fit [Vessey 1991].

Cognitive fit views problem solving as an outcome of the relationship between problem representation and problem-solving task (see Figure 1). Information in the problem representation and the problem-solving task itself produce the mental representation that further produces the problem solution [Vessey and Galletta 1991]. The mental representation is the way the problem is represented in human working memory. When a data format fits for its use (representation and task are matching), more effective and efficient problem-solving performance is achieved. It can also be suggested that cognitive fit means higher representational information quality as described in information success models [DeLone and McLean 1992, 2002] and thus has a positive effect on user satisfaction, creates benefits for the users, and increases user's intention to use the system.

Cognitive fit has been studied in many disciplines and areas after the original Vessey and Galletta study. For example, Hubona et al. [1998] carried out a laboratory experiment to assess computer-assisted problem-solving performance when language-conveyed representations of spatial information were matched with the language perspective of the task. They used two different descriptions (route and survey) and two inference task types (also route and survey) and they discovered that the route description resulted in lower error rates but higher reaction time than survey descriptions regardless of the task type.

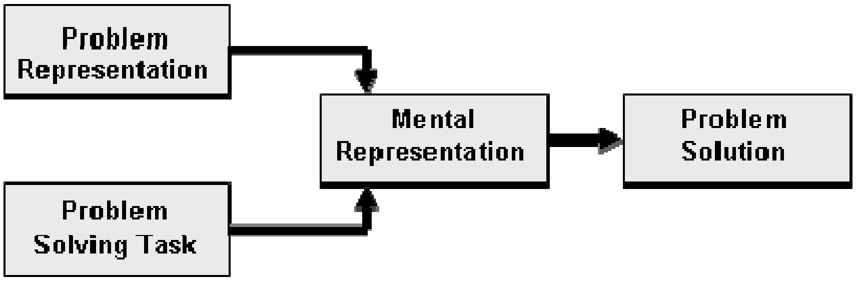


Figure 1. General Problem-Solving Model

Dennis and Carte [1998] extended cognitive fit theory to geographic tasks performed using either map-based presentations or tabular presentations. They found that decision makers using a map-based presentation made faster and more accurate decisions when working on a geographic task in which there were adjacency relationships among the geographic areas. Map-based presentations also gave faster decisions when working on a geographic task in which there were no relationships among the geographic areas, but this time the results were less accurate.

Cognitive fit has also been applied to programming languages [Sinha and Vessey 1992], intelligent agents [Galletta et al. 2003], and online shopping [Hong et al. 2005], but according to our research, the theory has never been used with mobile devices and mobile information systems.

Cognitive Fit on Mobile Devices

One of the key characteristics of a mobile device is a small display size. The effects of screen size have been studied from multiple view points including reading speed [Duchnicky and Kolers 1983], comprehension rate [Dillon et al. 1990], information retrieval methods [Jones et al. 1999], and information and menu structures [Chae and Kim 2004]. Although researchers have been interested in the question of information presentation on a small screen they have not combined problem representation with problem-solving task and mental representation as suggested by the theory of cognitive fit.

The starting point of our study is to find out if the cognitive fit holds true also in mobile devices with small displays. To do that we analyze the fitness of two different data formats (tables and graphs) displayed on the small screen of a mobile device. Although our context is new our approach is not, as similar questions were asked in the early 1990s in different environments as mentioned earlier.

In our first experiment, the original Vessey-Galletta study is repeated but the tasks are this time conducted with mobile phones. The experiment requires the participants to respond to problems regarding deposits and withdrawals of bank accounts over a 12-month period. Using the same task setting gives us the possibility to compare our results with others', and the aim of the first experiment is to test the proposition that cognitive fit theory also holds true when mobile devices with small displays are used, i.e., that the device is not so small that the users are not able to benefit from problem representation as they would with a more readable display.

Table 1. Question Task Matrix

	Symbolic representation (Data in tables)	Spatial representation (Data in graphs)
Symbolic task	Cognitive Fit	No fit
Spatial task	No fit	Cognitive Fit

Experiment 1—Vessey Galletta Test

The original Vessey and Galletta test used a 2 x 2 matrix shown in Table 1. Two data representations (line graphs and tables) were used together with two types of tasks: symbolic and spatial. Symbolic tasks involve extracting precise data values from the shown information, and tables are considered more suitable for this kind of tasks. Spatial tasks require subjects to make associations such as comparison of trends and, according to the cognitive fit theory, better solved with graphs (spatial representations).

Based on the two task types, the proposition that cognitive fit applies in mobile information systems can be written in the form of the following four null hypotheses.

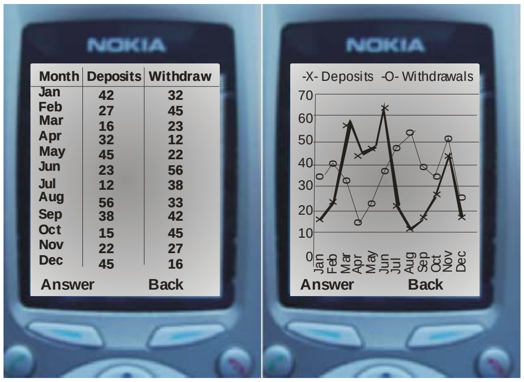
$H1_0$: Cognitive fit does not increase efficiency of mobile information systems in symbolic tasks.

$H2_0$: Cognitive fit does not increase efficiency of mobile information systems in spatial tasks.

$H3_0$: Cognitive fit does not increase accuracy of mobile information systems in symbolic tasks.

$H4_0$: Cognitive fit does not increase accuracy of mobile information systems in spatial tasks.

To test the hypotheses, Vessey and Galletta’s original experiment is repeated with mobile phones. The devices used in this test are Nokia 3650 phones and the experiment is carried out in a controlled laboratory environment. Figure 2 and Table 2 present examples of the spatial and symbolic questions and representations used in our test. All the questions can be found in Appendix 1. Both tasks and the representations were made to be as similar as possible with the original ones.



Month	Deposits	Withdraw
Jan	42	32
Feb	27	45
Mar	16	23
Apr	32	12
May	45	22
Jun	23	56
Jul	12	38
Aug	56	33
Sep	38	42
Oct	15	45
Nov	22	27
Dec	45	16

Figure 2. Symbolic and spatial data representations

Table 2. Examples of Symbolic and Spatial Questions	
Symbolic Task	*Please provide the amount of withdrawals in April.*
Spatial Task	*In which month is the difference between deposits and withdrawals greatest?*

Eighty-two volunteer undergraduate students participated in the experiment. All participants answered 20 questions (10 spatial and 10 symbolic). The data representation was in 10 cases a table and in 10 cases a graph giving us five questions for each cell of Table 1. We coded a Java/MIDP based test program for mobile devices and the program randomized the order of the questions to avoid any kind of learning effect.

Our software collected the two performance measures used in the original study: time and accuracy. Time measurement started when the user, after reading the question, moved to the page containing either a table or a line graph. Time was stopped as soon as the user entered the answer and accepted it. The accuracy points were calculated by subtracting 0.1 points from the correct accuracy score of 1 for each unit difference from correct value. Hence, if the correct response was 40, a subject response of 43 scored 0.7 points.

The means and standard deviations for time and accuracy for the five questions in each category are shown in Table 3. To be able to compare our results against the earlier study, the results of Vessey and Galletta are shown in Table 4.

In their original study, Vessey and Galletta compared the result against the following proposition:

> *More effective and efficient problem solving results when the problem representation matches the task to be accomplished.*

The outcome of their study was that the proposition is fully supported for symbolic tasks and partially for spatial tasks. If we compare data collected from our mobile phone test against the original proposition, we get the same results. Symbolic tasks were solved faster and with fewer errors when there was a match between task and the representation. In spatial tasks, problems were solved faster with cognitive fit but there was no statistically significant difference in accuracy. Interestingly, more errors were made with spatial tasks both in this study and in the original study when the cognitive fit existed.

Table 3. Descriptive Statistics of Experiment 1 (N=82)

	Symbolic representation (Table)		Spatial representation (Line graph)	
	Time (sec)	Score (max. 5)	Time (sec)	Score (max. 5)
Symbolic task average (stdev)	37.40 (22.48)	4.88 (0.32)	72.67 (31.57)	4.53 (0.53)
Spatial task average (stdev)	115.31 (68.12)	4.52 (0.49)	89.72 (41.88)	4.41 (0.65)

Table 4. Descriptive Statistics of the Original Vessey and Galletta Study (Task-Representation Condition)

	Symbolic representation		Spatial representation	
	Time (sec)	Score (max. 5)	Time (sec)	Score (max. 5)
Symbolic task average (stdev)	71.67 (22.48)	4.97 (0.08)	138.13 (35.99)	4.01 (0.35)
Spatial task average (stdev)	105.40 (31.96)	4.48 (0.84)	80.93 (44.26)	3.31 (1.15)

(64 users of 128 carried out test in task-representation condition and in each cell there were 16 participants)

Table 5 shows observed significance levels of the efficiency and accuracy hypotheses. Based on the results we can make the same conclusion as Vessey and Galletta did with their data. The theory of cognitive fit is fully supported for symbolic tasks and partially for spatial tasks. Our results indicate that the theory of cognitive fit applies also in mobile information systems where devices with small displays are used.

Table 5. Results of the Hypotheses Tests (N = 82)

		t value	Observed significance level	Hypothesis rejected?
$H1_0$	Cognitive fit does not increase efficiency in symbolic tasks.	8.24	> 0.99	yes
$H2_0$	Cognitive fit does not increase efficiency in spatial tasks.	2.90	> 0.99	yes
$H3_0$	Cognitive fit does not increase accuracy in symbolic tasks.	5.12	> 0.99	yes
$H4_0$	Cognitive fit does not increase accuracy in spatial tasks.	-1.22	0.78	no

III. RELATIVE IMPORTANCE OF COGNITIVE FIT

Limitations of Mobile User Interfaces

Most current mobile Internet devices suffer from small screens, low bandwidth and cumbersome input facilities. These characteristics have a direct effect on usability of the mobile information systems [Chan et al. 2002]. From the user-interface point of view two main questions arise: how information should be presented and how users interact with the device [Buchanan et al. 2001]. Cognitive fit theory gives us a framework for studying information representation but we must add also the interaction issues into the analysis.

Scholars have focused on two main topics in mobile interaction research: mobile text entry and mobile navigation. The key motivation of mobile text entry research has been in solving the limitations associated to mobile environment. As the physical restrictions prevent the use of input methods typical in desktop computers, large numbers of different input mechanisms have been introduced. In a typical text entry study efficiency, accuracy and preference of alternative text entry methods have been compared against each other (see e.g. [Koivisto 2007] for more details). As the main interest has been in selecting the best input method, the effect of cumbersome text entry to overall performance has received less attention.

Earlier studies investigating the effects of small displays have indicated that reduced screen size is closely related to user behavior including navigation, searching and browsing [Dillon et al. 1990; Duchnicky and Kolers 1983]. With small displays the need for navigation by the user is increased. To overcome this problem special attention should be paid to structure of the navigation. The two dimensions of the hierarchical navigation structure are the depth and the breadth of the menu [Henneman and Rouse 1984]. The depth is typically defined as number of levels and the breadth as number of options in each level. There are some studies on optimal navigation structures (e.g. [Lee and MacGregor 1985; Parush and Yuviler-Gavish 2004; Roske-Hofstrand and Papp 1986]), but the results are still somewhat inconsistent.

Experiment 2—Stock Broker game

Our aim is to analyze the user interface related characteristics in a broader context by combining the information representation, navigation and text entry under the same framework. Instead of analyzing each of these separately we combine them together in order to identify the relative importance of each of them to the general performance of the mobile information system.

To be able to analyze the relative importance of cognitive fit in mobile information systems, our second test is a more complicated experiment in which users are playing the Stock Broker Game (SBG). SBG is played with a HTML browser running on a mobile phone (Nokia 3650), and the connection to the server is implemented with Bluetooth. The aim of the game is to carry out as many brokerage tasks as possible in a limited time. Each task includes three subtasks that are shown in Figure 3.

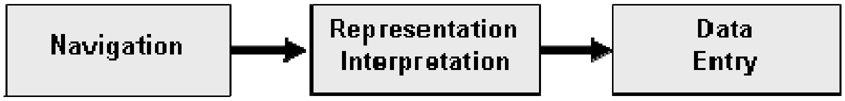


Figure 3. SBG Subtasks

Each task begins with a task description that includes the name of a company. In the navigation phase, data on or about the company should be found from the system. There are 20 companies altogether, but only the first 10 names or lines of the menu fit on the display of the mobile phone. Because the amount of information exceeds the available space, the last 10 names can be accessed only by scrolling down the menu. The presence of more options in a single menu than a user can process immediately is called *crowding* [Chae and Kim 2004].

After selecting the right company from the menu, the information about the stock value history of the company is shown either in table or graph format. Because we use both spatial and symbolic tasks, there are cases with and without cognitive fit in both representation types. When the player has made a decision to buy, sell, or keep stocks, he or she is then ready to enter the answer with the mobile phone's keyboard. If the decision is to keep, the player just selects that option from the menu and does not give any number of stocks. If the decision is either to buy or sell, the player must also enter how many stocks he or she is trading.

A week after our first experiment the same student group participated in our second test. Due to timing problems 75 out of 82 students participated in this experiment. Now the participants were divided into two groups. The first group (n = 37) played the game using only tables and the second one (n = 38) using only graphs. All participants had 10 minutes to do as many tasks as possible. The examples of spatial and symbolic tasks are shown in Table 6. The full list of questions can be found in Appendix 2.

Table 6. Examples of Questions in SBG

Spatial Task	*If the price of Amer Group is today higher than yesterday, sell 300 stocks. Otherwise, buy 400 stocks.*
Symbolic Task	*If the price of Amer Group is now 300, buy 350 stocks. Otherwise, do nothing.*

When participants played the game, our software automatically registered the answers of the players, time used, and points earned for each question separately. Based on that information, the efficiency and accuracy of every task were analyzed. Each player was informed of his or her success after each task by showing the total number of points earned. Because we wanted the players to pay attention both to accuracy and efficiency, points were not gained only with a correct answer but a faster correct decision gave more points than a slower one. The rules of the game were explained to the players before they started the game, and they carried out two test tasks before the game started. After the game, users evaluated the usability of the system with a System Usability Scale (SUS) questionnaire [Brooke 1996]. See Appendix 3 for details.

The results of the second test were studied at two levels. First, we analyzed performance and preference differences between the two groups using different representations. Second, we wanted to understand the importance of different subtasks in the performance of mobile information systems. As described previously, each task in the game included navigation, data interpretation, and data entry. Cognitive fit affects only the data interpretation phase, but task performance is moderated by other user interface characteristics like menu structures and input methods. The navigation and text entry phases increase the cognitive load on the user and may have an impact on performance of the mobile information systems. To be able to understand the relative importance of cognitive fit on overall performance, we created the following three null hypotheses.

$H5_0$: Crowding does not have an effect on user performance.

$H6_0$: Cognitive fit does not have an effect on user performance.

$H7_0$: Amount of input or data entry fields has no effect on user performance.

To test the hypotheses we analyzed the data according to the matrix shown in Table 7.

Table 7. Hypotheses Testing Matrix

Hypothesis	Condition A	Condition B
$H5_0$: Crowding	Cases where the right selection is seen immediately without scrolling	Cases where the right selection is not shown unless the user scrolls down
$H6_0$: Cognitive fit	Cases where cognitive fit exists when tasks and representation match	Cases where cognitive fit does not exists when task and representation do not match
$H7_0$: Amount of input	Cases with only one radio button input field	Cases with one radio button and one text entry field

The means and standard deviations for efficiency, accuracy, and preference metrics (time per question, error rate, and SUS score, respectively) of the two groups are shown in Table 8.

Table 8. Results of the Two Groups Playing SBG

Task type	Group1: Symbolic representation (Data in tables) N= 37			Group2: Spatial representation (Data in graphs) N = 38		
	Time	Error rate	SUS	Time	Error rate	SUS
All tasks	48.23 (11.12)	0.085 (0.083)	69.75 (13.87)	48.38 (10.60)	0.077 (0.071)	70.24 (13.06)
Symbolic tasks	49.43 (14.44)	0.071 (0.119)		52.19 (14.42)	0.037 (0.079)	
Spatial tasks	46.87 (10.35)	0.099 (0.135)		44.15 (8.37)	0.119 (0.113)	

The results indicate that there was no overall performance or preference difference between tables and graphs. Users spent an almost identical average time per question in both formats (about 48 sec) and the error rates were also very similar (about 8 percent). The preference ratings of the two representations were also very similar. If we analyze performance from a cognitive fit perspective, we can see that tasks with cognitive fit were performed nominally, but not statistically significantly, faster.

After finding equal efficiency, accuracy, and preference ratings with the two representation types, we analyzed the data at the subtask level. The results shown in Table 9 suggest that both crowding and additional text entry increased the average time spent on the task, so $H5_0$ and $H7_0$ can be rejected. This result is not surprising, but high observed significance levels suggest that menu and input structures are critical to mobile information system performance. Cognitive fit seems to have positive effects on the performance, but with the low observed significance level, $H6_0$ cannot be rejected. Failing to reject the null hypothesis however does not mean that we have shown that cognitive fit does not have any effect on the performance, but this study was unable to reject the null.

Table 9. Results of the Hypotheses Tests (N = 75)

		N	Average Time	St dev	t-value	Observed significance level	Hypothesis rejected
$H5_0$	Without crowding With crowding	75 75	42.31 55.13	9.18 15.73	6.10	> 0.99	yes
$H6_0$	Without cog fit With cog fit	75 75	49.56 46.75	12.78 11.98	1.39	0.84	no
$H7_0$	Without text entry With text entry	75 74 *	33.42 51.63	8.40 11.91	10.82	> 0.99	yes

*N in condition with text entry is 74 because one participant did not reach the first text entry task in limited time.

We also analyzed the impact of crowding, cognitive fit, and text entry on error rates but none of them had statistically significant effects. It was surprising that text entry did not increase significantly the number of errors. The reason for this was that only a very small number of errors took place during text entry, and the main source of errors was an incorrect interpretation of the data. Only 11 percent (eight cases) of the errors took place during navigation or text entry, and 89 percent (68 cases) can be classified as interpretation errors.

IV. DISCUSSION

Findings of the Study

In this paper we carried out two laboratory experiments regarding cognitive fit on mobile devices. The first experiment was identical to the original Vessey and Galletta [1991] study and the outcome of our study was very similar to the original. In both contexts, cognitive fit increased efficiency regardless of the task type and accuracy for symbolic tasks. Accuracy of the spatial tasks was increased neither in the reference study nor in ours. As the test results were almost identical, it can be said that the theory of cognitive fit holds true similarly with mobile and stationary information systems.

In their original study, Vessey and Galletta suggested that the research of cognitive fit should be extended to encompass more complex problem solving tasks. Other scholars have also pointed out that experiments with basic tasks have failed to reveal the real effects of user interface characteristics on performance [Chae and Kim 2004; Han and Kwankh 1994]. We followed these recommendations in our second experiment which included more complicated tasks. Our analysis in the second experiment did not reveal any efficiency, accuracy, or preference difference between the two representation types (tables and graph). Based on that, it can be stated that neither of the representation types was superior and the success of a mobile information system is a far more complicated issue than finding an attractive data representation format.

Our subtask level analyses revealed that the need to scroll in the navigation phase and the number of fields in the text entry phase had a significant effect on task time. On the other hand, the cognitive fit of data and task representations did not have a similar effect. We consider that these findings are important characteristics of mobile information systems. Chae and Kim [2003] have pointed out that users´ disappointing experiences with the mobile Internet result from the limitations that distinguish mobile devices from conventional desktop PCs. From the users´ point of view, the main differences between the PC and mobile devices are input methods and screen sizes. One of the key challenges of mobile device and system manufacturers is to identify an optimal input method for their devices [Koivisto and Urbaczewski 2005], and although many limitations of mobile devices will disappear in future generations, the display sizes will remain relatively small due to the need for portability.

Small screens do not only cause problems in data representation, but also in navigation. Scholars have discovered that navigation problems can be even more serious than the representation problems. Han and Kwanhk [1993] discovered that searching through menus on smaller displays is much slower than on conventional displays. Small screen size prevents the usage of sophisticated menu structures typical to stationary information systems and forces line-based navigation. Acton et al. [2004] made similar conclusions and highlighted the importance of maximization of the available screen area on small screen devices especially in menu design.

Our experiments support the findings of previous studies. The small screen size caused challenges even in very simple navigation tasks. The need for scrolling to the right menu selection caused by crowding was enough to seriously affect system performance. After users found the right path to the information, it was noted higher representation quality in the form of cognitive fit did not have a significant effect on efficiency or accuracy.

Limitations of the Study

It is important to note the main limitations of the study. First, our tasks were carried out in a laboratory environment thereby potentially reducing external validity. One of the key elements of mobile information systems is mobility. Mobile services are used in various contexts, offering users freedom of place and often of time. Our experiments did not allow users to carry out their tasks freely, but they completed tasks in a fixed place at a predefined time. On the other hand, laboratory experiments have their well-known strengths like minimal effects of external factors as well as more accurate and precise measuring possibilities. We make no claims here in regards to mobility, but rather only on the information systems designed for mobile use.

A second limitation of our study was that only one type of device was used. Today there is a large variety of mobile devices available, and it is quite possible that devices with different input methods and screen sizes might have produced different results. However, small screens and challenging input methods are typical to all mobile devices and are the main user interface difference between mobile and stationary information systems. As a result of this, we believe our findings can at least be generalized across mobile devices of the type and class of our device. Future research should be done to compare other types of devices and input methods.

A third limitation is that the study only included students from a single university. Using only student subjects can be criticized, but in this case it should also be remembered that young people and students are the most frequent users of mobile services. While students are not a random sample of the entire universe of mobile users, they are heavy users and they can give us valuable information about the future.

V. CONCLUSIONS

The successful introduction of mobile information systems requires more than fast networks and devices with more colorful displays. Information system success is a result of multiple factors including quality, use, satisfaction, and benefit dimensions [DeLone and McLean 2002]. No single aspect can guarantee success as success is based on an optimal combination of different elements. In a mobile context, the system quality aspects related to the limitations of the user interface seem to be key challenges for system developers. Navigational challenges caused by both small displays and text entry difficulties caused by cumbersome input methods need further developments and innovations.

The importance of representational data quality in mobile information systems can be analyzed from a cognitive fit standpoint. If the data representation suits the task (e.g. cognitive fit exists), the representation fits for the intended use. The significance of representational quality to information system success varies from one system to another. Our analysis indicates in mobile information systems, the relative importance of representational information quality is minor to the shortcomings of system quality from user interface characteristics. However, we need to strongly state that this idea requires further study.

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APPENDIX 1. LIST OF QUESTIONS IN EXPERIMENT 1

The following questions were shown to the users in random order and all users answered to all questions.

In which month is the difference between deposits and withdrawals greatest?
In which month is the difference between deposits and withdrawals smallest?
In which month are withdrawals increased most compared to the previous month?
In which month are withdrawals decreased most compared to the previous month?
In which month ended the longest period of growth in withdrawals?
In which month started the longest period of growth in withdrawals?
In which month are deposits decreased most compared to the previous month?
In which month are deposits increased most compared to the previous month?
In which month had deposits of the smallest value?
In which month had deposits of the greatest value?

Please provide the amount of withdrawals in February.
Please provide the amount of deposits in February.
In which month were deposits below 20,000 dollars?
In which month were withdrawals below 10,000 dollars?
In which month were deposits 40,000 dollars?
In which month were withdrawals 48,000 dollars?
Please provide the amount of deposits in November.
Please provide the amount of withdrawals in November.
In which month were withdrawals between 60,000 and 65,000 dollars?
In which month were deposits between 60,000 and 65,000 dollars?

APPENDIX 2: LIST OF QUESTIONS IN EXPERIMENT 2

Questions were shown to all users in same order (starting from question 1) and each user answered as many questions as he or she could in limited time (10 minutes).

Question 1:
If the buy value of Nokia is more than 12.15, buy 200 stocks; otherwise do nothing.

Question 2:
If the sell value of Outokumpu has risen from yesterday, sell 100 stocks; otherwise buy 300 stocks.

Question 3:
Check the buy value of Viking Line. If it is over 24.00, buy 350 stocks. If not, sell 100 stocks.

Question 4:
The news told that the sell value of Atria has risen from yesterday. If this is true, sell 500 stocks; if not then do nothing.

Question 5:
Buying the stocks of Comptel Corp seems interesting. If the buy value is less than 2.10, buy 150 stocks; if the value is higher, do nothing.

Question 6 :
The rumors say that Huhtamäki is going down. If the sell value has lowered from what it was 2 days ago, sell 600 stocks. In other case do nothing.

Question 7 :
There is need for some extra cash. If the sell value of Elisa is over 13.35, sell 300 stocks. Otherwise wait for a better value and do nothing now.

Question 8 :
The newspaper told that Olvi has done well lately. If the rising of the sell value still continues, sell 100 stocks. If it has stopped, buy 100.

Question 9 :
I wonder if the stocks of Kesko should be sold. If the sell value is more than 20.50, sell 200 stocks. In other case, do nothing.

Question 10 :
Finnair has done some wrong investments. If the sell value has come down at least three days, sell 400 stocks. If it has not, buy 100.

Question 11 :
The buy value of TietoEnator seems pretty high. I just wonder what was the price four days ago? If it was less than 25.90, buy 700 stocks. If the value is more than 26.00, do nothing.

Question 12 :
I checked the buy value of M-real last time two days ago, and then it was going down. If that has continued, sell 750 stocks. If the value has risen, buy 200.

Question 13 :
The buy value of Martela Oyj has risen rapidly. There is a possibility it is only temporary. If the sell value of the stock is over 6.60, buy 300 stocks; in other case, sell 200.

Question 14 :
It might be a good time to buy stocks of insurance companies. If the buy value of Pohjola Group has risen for at least three days, buy 900 stocks; if not, then do nothing.

Question 15 :
The stocks of Basware Corp have not done well enough. If the sell value of yesterday is more than 8.20, sell 400 pieces. If it is less, do nothing.

Question 16 :
What is it with Sysopen Plc? Their sell value has gone down again. If this has been going on since four days ago, sell 500 stocks. In other case, do nothing.

Question 17 :
The buy value of Kemira Oyj has gone down. If the value is still over 15.60, buy 150 stocks. If it is lower, sell 300 stocks.

Question 18 :
There are rumors, that Sanoma WSOY is going to launch a new Internet service. It is possible that other people already know this. If the buy value is higher than four days ago, do nothing. If same or lower, then buy 400 stocks.

Question 19 :

The current sell value of Vaisala Corp is quite high. If the sell value was at least 20.20 2 days ago, sell 250 stocks. If the value is less, buy 250 stocks.

Question 20 :

It is time for your final task. If the buy value of F-Secure has lowered for at least three days, buy 550 stocks. If it has not, then do nothing.

APPENDIX 3: LIST OF QUESTIONS IN SUS QUESTIONNAIRE

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1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system were well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

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