Support for Real-Time Decision-Making in Mobile Financial Applications

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Abstract

Mobile users making real-time decisions based on current information need confidence about their context been taken into consideration in producing recommendations. This chapter reviews current use of mobile technologies for decision support. Specifically, it describes a framework for assessing the impact of mobility in decision-making. The framework uses dynamic context representation of data quality to represent uncertainties in the mobile computing environment. This framework can be used for developing visual interactive displays for communicating to the user relevant changes in data quality when working in mobile environment. As an illustration, this chapter proposes a real-time decision support procedure that aims at providing on-the-spot assistance to the mobile consumer when choosing the best payment option to efficiently manage the user's budget. The proposed procedure is based on multi-attribute decision analysis, scenario reasoning and a quality of data framework. Feasibility of the approach is demonstrated with a mobile decision support system prototype implementation.

Keywords: mobile decision support, real time decision making, quality of data, financial decision making

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1. Introduction

Use of mobile devices enrich today's world of widespread e-services and extend opportunities for decision support. Users can make real-time decisions based on the most up-to-date data accessed via wireless devices, such as portable computers, mobile phones and personal digital assistants (PDAs). Business transactions, such as online shopping and banking, can be completed in a secure mobile computing environment. Travelers can optimize their trips and organize short-time holidays if customized sightseeing and entertainment recommendations are available from their mobile device (Carlsson et al, 2006; Nielsen, 2004). A movie-goer can select from her PDA a movie that is currently showing in the nearest cinema at her preferred time (Jayaputera et al, 2003). A stock trader can monitor her stock investment from a PDA that provides alerts about interestingly behaving stocks (Kargupta et al, 2001). A TV fan can watch her favorite soap via her mobile phone (Carlsson and Walden, 2007).

Mobile technology is increasingly evolving in conjunction with wireless networking capabilities. Advances in wireless and mobile technology brought into existence phrases such as 'mobile era', 'mobile commerce' and 'mobile workers' (Mennecke and Strader, 2003). Its successful use and implementation in several fields has highlighted the need for growth in this area and its importance for decision support. It created opportunities for meeting users' information needs for "real time" and "on the spot" decision making. In addition, the availability of up-to-date information, coupled with the potential for such tools to time save and increase productivity, are seen to highly-motivate individuals to use of such devices (Carlsson et al, 2005).

While decision support systems have typically been associated with desktop systems and involve considerable processing, the development of new compact and mobile technologies provides new opportunities (Aronson et al, 2005). Work environments which are mobile in nature and can not facilitate desktop based decision support can now be accommodated through the use of mobile technologies. Such technology can also be adapted to current workplaces to address limitations of current systems (Sharaf and Chrysanthis 2002). Since accessing real-time information is essential for good decision making the usefulness of mobile devises for decision support, in our opinion, is hard to overestimate (ref – Julie, may be you'll still find a ref – not come across anything that claims this definitively).

In today's consumer-oriented society, "we are bombarded with advertising showing us that we can have it all now" (Tarica, 2001). Merchants are now targeting mobile consumers' needs through intelligent advertising, in which the consumer receives location-based advertisements via SMS or MMS on his mobile phone, that are tailored to his personal preferences (Panis et al, 2002). Financial institutions now offer online services that can be accessed by the mobile user via web enabled devices such as the PC, Palm Pilot, Web Phone and WebTV (Reis et al, 2003). For the individual consumer, these online transactions include account balance enquiries, funds transfers, account applications, ATM locators, and electronic bill payment. For companies, online banking services include monitoring cash balances across a company's accounts, checking account balances, paying salaries, and checking transaction details (Rogers, 2003). Electronic payments with credit cards are also very common and part of the consumer's daily life (Hartman and Bretzke, 1999). With the introduction of location-based services, online banking and electronic payments, the consumer is left to make hard decisions responding to targeted marketing and advertising, requiring them to try and efficiently manage his/her budget with the real risk of acquiring high levels of debts which are often difficult to control.

In this chapter we review opportunities and challenges of mobile decision support. Mobility introduces additional uncertainties into the decision environment. Firstly, information held in a mobile device is likely to be incomplete or outdated, and may not reliably support the user's needs in critical situations such as healthcare management, national defence or weather forecasting. In another context, availability of e-services to support business transactions varies depending on the number of mobile users requesting services, changing locations of users, or type and size of mobile devices. We proposed a framework for assessing the impact of mobility in decision-making based on multi-attribute indicator for measuring quality of data (QoD) (San Pedro et al, 2003, Burstein et al, 2004). QoD can provide the basis for a DSS for generating alerts about changes in problem and user context. In this chapter we describe the way such indicator can be calculated and used in decision process in mobile environment.

As an illustration, we explore factors that affect users' ability to make financial decisions in a mobile environment. We look at how to enhance the level of decision support that the mobile user can receive from his/her mobile device when making financial decisions. The aim is a real-time decision support procedure that provides on-the-spot assistance to a mobile consumer who wishes to purchase a product or pay for a service today whilst still efficiently managing his/her budget for the month.

In the following section, we consider the concept of mobile, real-time decision support via a mobile device, including various technical architectures for such implementation. Section three illustrates how this concept can be applied to assist in financial decision making. Section four describes a mobile account management problem, followed by a proposed multi-attribute model and prototype implementation for a DSS which dynamic monitors account information.

2. Mobile Decision Support

A high degree of mobility is desirable for most mobile decision making environments, where provision of current information is essential and access to desktop computers is not available. Mobile technology is rapidly developing and encompasses a considerable number of devices, from small PDAs, to laptops and tablet PCs (Derballa and Pousttchi 2004). Mobile devices can be broadly divided into the Laptop

Computer, Handheld (e.g., Palm), Telephone, Hybrid (e.g., 'smart phone' PDA/telephone), Wearable (e.g., jewellery, watches), Vehicle Mounted (in automobiles) and Speciality, with enabling technologies such as GPS and Blue Tooth (Mennecke and Strader, 2002). While all such devices can provide decision support benefits and, in a general sense, be considered mobile, devices in the form of PDAs and Smart Phones are of most relevance and are becoming increasingly popular with general users (Burstein et al, 2004, Carlsson et al, 2005). In this chapter, we illustrate the potential for mobile decision support using a PDA style interface, as this is the device with which the authors have most familiarity with. However, the style of interface is felt to be applicable across all devices.

Mobile technology provides a number of advantages over stationary computing. One of the most notable is real-time information availability (Zhang et al. 2006) and higher flexibility for user interface (Van der Heijden and Junglas, 2006). In conjunction with this are the electronic services that can be provided by mobile devices. Mobile devices and instruments can interact with each other using internet, wireless networks and protocols. In this sense the use of mobile technology can increase productivity and efficiency of mobile users.

The value of mobile devices can also be determined by applying the *Braudel Rule* (Braudel, 1992). The rule suggests that the value of mobile services is determined by whether they change the structure of everyday routines. So for example, the widesread use of one mobile device implies it satisfied Brauden's rule. However, a mobile device that is potentially useful, but has not yet changed the way we live is perceived as having no added value. Carlsson et al (2006) suggest that the value of mobile devices cannot be applied generically, but rather it is specific to the application. – needs wording better, but Braudel's rule is something that Carlsson refers to in most of his papers so think it's important to say something about it..

Mobile technology has benefited various industries both public and private. Its wide range of applications and services include medical information services, tracking and monitoring emergency services (San Pedro at al, 2005; Bukheres et al, 2003; Burstein et al, 2005). By providing cost effective, pervasive access to information, wireless networks and mobile devices are reducing errors and improving access to all information that was once central (Chatterjee, 2003). By changing the way people work in today's dynamic work environment, we have seen the deployment of mobile technology in disciplines ranging from archaeology (Blunn et al, 2007), airport management (Pestana et al, 2005), education (Cabrera et al, 2005), healthcare (Michalowski et al, 2003, Cowie and Godley, 2006, Padmanabhan et al, 2006) and many more. Churchill and Munro (2001) state that changes in technologies led to subsequent changes in the nature of work practices, as a result, "…many work practices that have been traditionally seen as static in fact involve considerable amounts of local mobility" (p.3).

2.1 Technical and computational architecture for mobile decision support

Mobile decision support can be implemented in a number of ways, depending on user requirements, available technological resources, frequency of data access, urgency of data retrieval, etc . As research into such technology is relatively new, optimal architectures for various decision contexts and design configurations and potential future applications are yet to be investigated. In this section we consider how standard component of DSS, ie database (DB), user interface (UI) and analytical model (AM) can be arranged in mobile decision support architecture (Aronson et al, 2005).

Portable devices can act as computational platforms for task specific applications, collecting, storing, processing and providing data. The use of device specific resources or server resources creates a distinction between possible types of DSS that can be provided (Navarro et al. 2006). Mobile decision support can be client-based, server-oriented, proxy-based or distributed across an ad hoc network of similar peer devices (Bukhres et al, 2003). The type of architecture depends on where information is stored and where computations are performed. These varying implementations have their merits and demerits. The usefulness of each depends significantly on the application requirements and underlying technical infrastructure. Systems focused on access to significant amounts of information would be more likely to use a server architecture given the limited processing and information storage capabilities of small portable devices. Alternatively, decision support that may suffice with preliminary processing of information could benefit from coarse granularity processing on a resource-constrained portable device. Independent decision support provides increased system fault tolerance and reduced support requirements. Figure 1 illustrates five possible types of DSS implementation. We illustrate the possible implementations ref

Currently, most popular is the implementation a), where functionality is distributed across client-server environment with user interface (UI) located on the user's portable device, data distributed across both client and server, with user-sensitive data residing on the user device, while massive amounts of data, including historical, are located on a server. In this configuration, analytical model (AM) is also distributed across client server with user device performing elementary computations and delegating more complex and resource-intensive computations to the server.

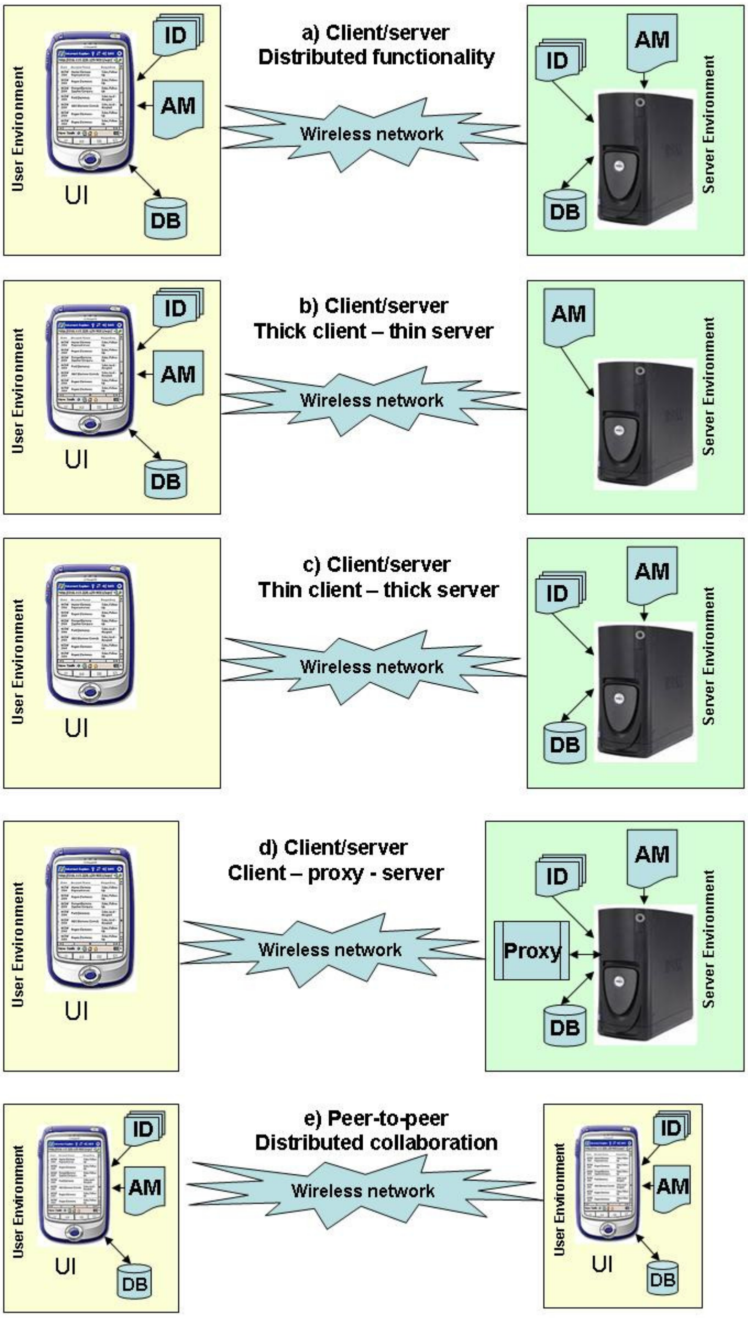


Figure 1 – Mobile decision support architectures
Legend: UI-user interface; ID – input data; AM – analytical model; DB - database

Thick client – thin server and vice versa represent more extreme cases and therefore more rare configurations. Given high likelihood of disconnections in wireless environment, some systems may use the concept of proxy architecture where a proxy process is located on a server side representing a client and, if connectivity is good, then just channelling data and computations between a server and a client.

However, if a client becomes disconnected (eg, driving through a tunnel), then the proxy assumes full functionality of the client and caches data and results until the client reconnects. With proliferation of peer-to-peer computing it is now becoming possible to form ad hoc networks of similar devices, discovered at a time of need, in order to consolidate resources and perform the AM in a distributed computing environment in a cost-efficient manner. These possible architectural implementations enable enough flexibility and scalability for any possible DSS application or scenario.

2.2 Quality Of Data Model

Users need support when facing critical situations and would welcome alerts about reliability of data in such situations, but may be dissatisfied with requests for attention when they are relaxing at home. In recent papers (San Pedro et al 2003; Hodgkin, et al 2004), we proposed a framework for assessing Quality Of Data (QoD) as an indicator of the impact of mobility in decision-making (San Pedro et al, 2003; Burstein et al, 2004, Hodgkin et al, 2004, Cowie and Burstein, 2006) we identified some factors that may be considered in establishing a framework for addressing the issue of data accuracy in mobile decision support. QoD is based on multiple parameters, which measure user-specific, current technology-related and some factors, which can be learned based on past experiences with similar problem situations. By providing a QoD alerting service from the mobile device, the mobile user is warned against making decisions when QoD falls below a predetermined threshold or when QoD becomes critically low. The assumption we make is that a decision-maker should feel more confident with the decision when QoD is high, or be alerted when QoD becomes lower than acceptable.

The QoD model aims at assisting the mobile users in selection of the best option taking into consideration reliability of the data such option was calculated base on. Figure 2 represents a model of QoD comprising attributes that contribute to data quality when supporting personal mobile decision-making (Burstein, et al 2004). These QoD attributes include technology-related, user-related, and historical contexts.

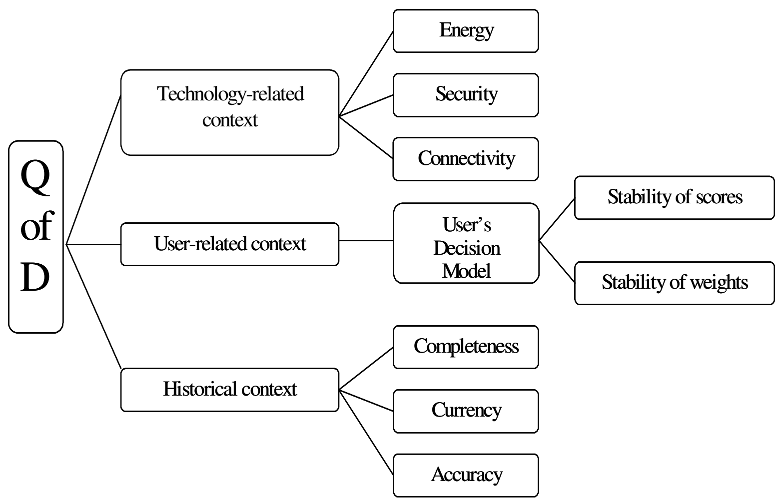


Figure 2. A sample multi-context representation of QoD [adapted from Burstein et al (2004)]

These attributes are further broken down into some QoD metrics relating to energy, security, and connectivity for technology-related contexts, stability of scores and weights for user's decision model relating to user-related contexts, and completeness, currency, and accuracy for historical contexts. Some of these metrics can be calculated by comparing current data with standard data.

In mobile DSS QoD can be calculated incrementally at every stages of decision making process as the mechanism for alerting the user when more data and/or resources are needed before the best option can be selected. For example, following Simon's classical decision making principal phases (Simon, 1960), when describing decision situation, QoD can be used to judge how accurate was the set of data collected at the Intelligence phase; when designing alternative actions, QoD can assist in making sure the user is satisfied with the range of possibilities she is presented with for a choice; when a model is applied for selecting the best alternative, the final output includes a full and explicit representation of the QoD, which was derived as an aggregate of the ones used in the previous stages (see Figure 3).

In the next section we illustrate how real-time decision support can be applied in financial decision context.

3. Real-time financial decision support

The way financial decisions are made is influenced by many factors. Today, there are many options available to consumers when most of financial transactions are made electronically. The "new breed of online consumer who will expect faster delivery, easier transactions, and more factual information" (Martin, 1999) poses a difficult challenge to accounts management. When purchasing an item, there are a number of issues that must be addressed in deciding upon the best payment method.

This situation presents a good example of when real-time decision support could be beneficial (Hartmann and Bretzke, 1999). For example, if one wants to purchase an expensive holiday or pay car service today using cash from her current account, will she still have sufficient funds to cover the direct debits due out of the account next week? If not, are there sufficient funds in the savings account to transfer cash into the current account to cover the direct debits? Would such a transfer of cash incur charges? What if she opts to pay for the holiday on credit card? Is the credit card repayment date sufficiently far in the future that by such a date there will be enough funds to pay it off? Would it be a better option to pay off just the minimum amount due? How will this holiday purchase or car service payment influence our monthly repayments? More importantly, could buying the holiday be done in a way that there is no need to cut down an overall spending?

These are some issues that the mobile consumer might be considering when deciding which payment option is best to minimise transaction fees, minimise credit card debts, and maximise monthly savings. Currently, many such decisions are based on intuition or past experience and there are no analytical tools developed to assist mobile users in these situations. There are a few products on the market that provide different personal finance management solutions. Some of these products are Microsoft Money, SmartMoney, My Money, Quicken and MYOB. These products support and manage operational transactions and permit some analysis of historical data. MYOB, for example is aimed specifically for Australian small-business users. MYOB replaces "the cash register with a point-of-sale system that streamlines store operations and manage sales, stock, GST, staff and customers" (Tsang, 2003). Microsoft Money allows a consumer to view vital financial statistics at a glance, set up regular bill payments as reminders or have them taken from an account automatically, plan and maintain budgets, and see projected cash flow so the user knows how much to spend. However, most of these are not yet customised for access from a mobile device. The only mobile application that comes close to the decision problem described above is Microsoft Money for Pocket PC (http://www.microsoft.com). This mobile version of Microsoft Money, however, provides little decision support as it only allows the user to view the account balances (upon synchronisation with desktop Microsoft Money) and record any new transactions.

3.1 Financial Decision Process in Mobile Environments

The decision support process in a mobile environment is a dynamic process that evolves with different context changes, is characterised by fluctuating uncertainty, and depends on multi-attribute preferences of the individual mobile decision maker. It should link past, current and future states of the mobile environment and needs to be adaptable to user and system constraints (Bukhres et al, 2003). Mobile decision support usually needs the underlying distributed computing infrastructure with wireless and mobile networks as the main components (Ahlund and Zaslavsky, 2002). We describe phases of mobile decision process below and discuss how they are different from non-mobile decision processes.

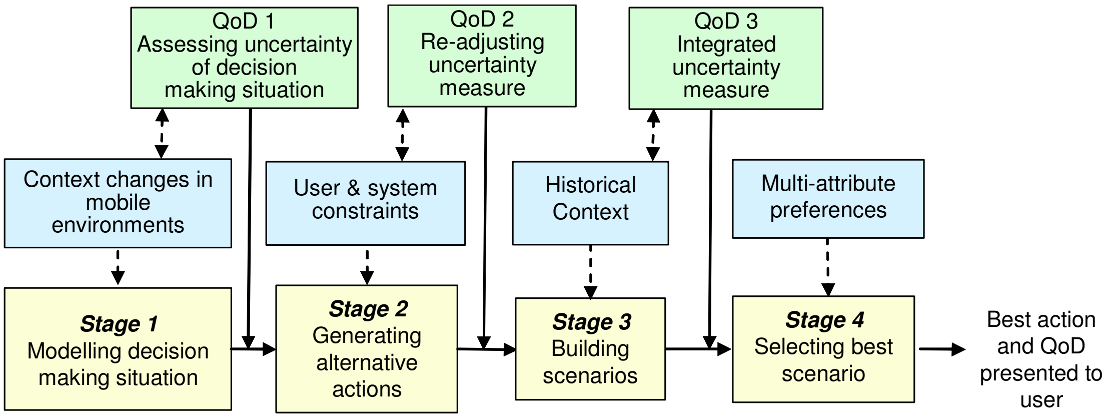


Figure 3: Decision process in mobile environments

Figure 3 depicts this staged process schematically. Initially, the user must recognize the need for making a decision. In addition to addressing the problem at hand, the user must take into account context-specific criteria in assessing whether it is appropriate to use the support system. The next step in the process involves the generation of alternative actions. These are calculated from the available information about transaction history and financial institutions' charges. Again, consideration is paid to context-specific characteristics of the environment as well as the user. The support system utilises historical data, user profiles and expert knowledge to produce scenarios of possible actions. Depending on how much access the system has to the up-to-date transactions history, and the mobile DSS architecture set up, the QoD for decision support will vary and used as a mechanism to ensure enough data is available and the level of its reliability is appropriate to make a acceptable decision. Finally, a multi-attribute description of the problem situation is generated and user preferences evaluated in order to decide upon the best course of action.

In the following sections, we describe the mobile accounts management problem as a dynamic multi-attribute decision making model. We then proceed with a solution procedure using scenario reasoning to assist the mobile user to foresee and analyse the consequences of a choice. Suitable measures of completeness, currency and accuracy of data are also presented as QoD parameters that are related to historical context. Finally, we describe a prototype tool, called iAccountsMgr which demonstrates the feasibility of the proposed procedure to support the mobile consumer in managing financial accounts (Burstein et al, 2004).

4. Mobile accounts management

A mobile accounts management problem refers to a mobile user's problem of selecting the best possible immediate payment option in relation to the associated future gains or losses. Payment options in e-commerce context include payment by EFTPOS (Electronic Funds Transfer at Point of Sale), electronic wallets (Anderson, 1994; Tygar and Yee, 1995), electronic coupons or electronic cash, and of course, more traditional options (for example, paying by cash, lay-by, credit card or cheque). With so many options to choose from, the mobile user can enjoy the convenience of paying for products or services electronically, and charging each to one of multiple bank accounts (savings, credit, cheque accounts). Some online financial services (such as online banking) allow the consumer to view the account balances online, or to record transactions electronically to keep track of his/her transactions and balances. A tool that helps the consumer save money and/or manage their accounts efficiently is regarded as highly attractive to the mobile user Carlsson et al, 2005.

Our approach of supporting the mobile user with QoD is also relevant to the mobile accounts management problem. The reason this indicator can be useful is that the mobile consumer can be better supported in their accounts management when together with the recommendation on the best option to realise future gains, they are informed of the QoD that was used to calculate the choice, or be alerted when QoD is not good enough to justify it.

4.1 Pay by cash, credit or eftpos? A dynamic multi-attribute decision-making problem

In this section, we represent the concept of mobile accounts management, as described above, as a dynamic multi-attribute decision making model. A sample user's model is depicted in Figure 3. In the example, the alternative actions are to pay by (a1) cash, (a2) credit card, (a3) EFTPOS and (a4) EFTPOS and withdraw cash. The available alternatives are determined from user's profile. Thus, for a mobile user, paying by cheque can be one of the payment options but perhaps not the most attractive one. Internet-based transfer using a mobile device will do the job faster and might be a more appropriate option.

The alternatives will be evaluated against multiple attributes. In our example model, the multiple attributes are (c1) cash at hand, (c2) savings1 balance, (c3) savings2 balance, (c4) credit balance, and (c5) overall transaction fees. We assume that for this particular mobile accounts management problem, the mobile user's goal is to minimise transaction fees and credit and maximise savings by the end of the month.

Note that there is some inherent uncertainty in the future state of the multiple accounts if a purchase is made today. Context changes due to user mobility also add some degree of uncertainty into the problem, because they can influence the future evolution of events. Thus, in order to support the mobile user in handling such uncertainty, we will derive scenarios based on one of: the user's strategy, learned strategy, or expert strategy.

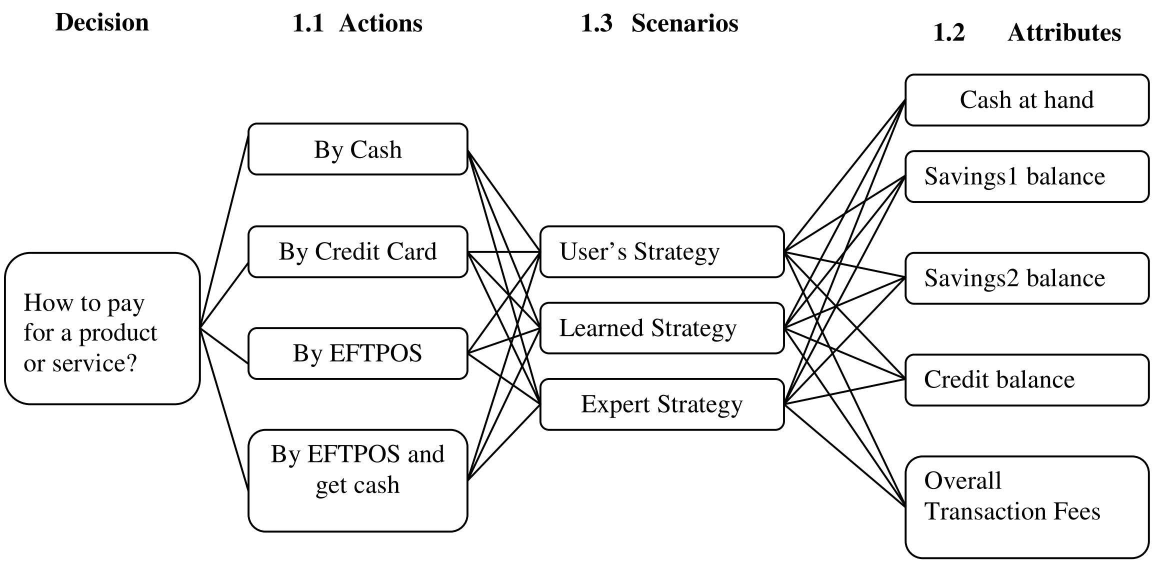


Figure 3: A sample user's model of accounts management problem

4.1.1 Scenarios

A scenario is a sequence of sub-actions and events that may evolve in the future once an action is initiated. We can support the mobile user in his/her choice making, by allowing him/her to look-ahead or to reason in terms of scenarios. For the non-aided mobile decision-maker, the scenario reasoning process can be very complex and confusing due to all the possible consequences of a choice and associated probabilities that need to be considered (Pomerol, 1997). Due to the many constraints in mobile decision making (e.g., limited energy, unstable network connection, limited user interface capability, user mobility), we propose to build only scenarios that are based on the user's predefined instructions, rules derived from recorded transactions or some expert's strategy.

a) User's Strategy

Initially, the mobile user may have a predefined set of rules that he/she wants to impose when selecting best payment options. The example rules can be:

- "If there will be insufficient funds for tomorrow's direct debit payment, then transfer the required amount from Savings2 to Savings1 before midnight."
- "Do not use credit card a week before credit payment is due."
- "Do not use EFTPOS after the second EFTPOS or ATM (Automatic Teller Machine) transaction."

Rules such as these can be stored in a relational database or rule-based system, specific to the mobile user. Other user preferences, such as relative importance of criteria, available payment options, types of transactions, "must-buy" items, "must-avoid" items, target savings balance, etc can be incorporated in the user profile by user registration of preferences. Initially, the user will have to manually input some minimal preferences through registration forms.

A sample set of scenarios for actions a1 – a3 is shown in Table 1 (see Appendix). The problem here is to determine the best payment option to pay for a car service worth $450, if paid by cash, or $500 if paid by credit card or EFTPOS. In this example, based on the user's profile, our particular mobile user has given the instruction to withdraw a minimum of $500 in alternative a4 when building scenarios. Thus, in Table 1, a4 is not a feasible option as there is only $800 available at hand. It is assumed that decisions are set to be made between some critical dates, when balances need to be updated, for example when credit card payment is due, regular credits are made to the accounts or loan interests and other regular payments are due.

Consider **Scenario 1**. Based on the user's predefined strategy for cash payment, $450 is deducted from cash at hand on Day 17 (see Column 4), and all other scheduled payments (including fixed and estimated amounts) until Day 24 will be processed. This sequence of events is initiated by the support system. On the 25th day, the system will initiate a transfer of funds from Savings2 to Savings1 to pay the credit balance of Savings1, pay succeeding estimated expenses and maintain a balance of $500 by the end of the month. Such transfer of funds will incur a transaction fee of $2.50 on the 25th day. In line with the user's predefined strategy, the expected balances at the end of the month will now be 0, 500, 5406, -220, -11.6 for cash, savings1, savings2, credit, and transaction fees, respectively.

Scenario 2 on the other hand, will incur an additional credit of $500, and consequently, the user will reach the credit limit of $3000 before the credit payment due date on Day 25. In order to avoid paying interest on the credit, or a fee for exceeding the credit limit in future payments, the user's strategy is to transfer funds from Savings2 to the credit account. This transaction incurs a fee of $2.50. All other transactions are processed based on estimated expected payments following the user's predefined strategy. Scenario 2 will yield the balances 186, 920, 4750, -220, -9.1 on cash, savings1, savings2, credit, and transaction fees, respectively.

Based on the user's strategy for EFTPOS payment, Scenario 3 will yield (186, 500, 5170, -220, -11.6). If the user has equal weights for the attributes, then taking the weighted sum of the balances will give an optimum of $1135 corresponding to alternative action a1 (see second to the last row, column 2). If the user, on the other hand, has the following criteria weights (0, 0.6, .2, 0, 0.2) then the best payment option will be by credit card with a weighted sum of $1500 (last row, column 3).

b) Learned Strategy

When the user chooses to overrule predefined strategy, scenarios can be identified by implementing soft computing methodologies and intelligent technologies to derive rules from the transaction history. User registration is sometimes not appealing to the user, especially when lots of details need to be manually incorporated into the system. Soft computing and intelligent technologies such as rough sets (Pawlak and Slowinski, 1994), case-based reasoning and bayesian networks (Shiaffino and Amandi, 2000), fuzzy logic (Nasraoui and Petenes, 2003), neural networks (Chen and Chen, 1993; Jennings and Higuchi, 1992) and clustering techniques (Kim and Chan, 2003) may be used to learn about the user's payment strategy in the past. We refer to such strategy as *learned strategy* in Figure 3.

Consider for example the transaction history from the past year. Scheduled direct debit/credit payments with fixed amounts (health insurance, car loan, salary, other income), or variable amounts (e.g., grocery, petrol, gas and electricity bills, phone bill) can be detected from the transaction history (see Column 3 of Table 1). Note that some rules may be deduced by simple sorting of transaction dates or by type of transaction. Variable amounts can be estimated using simple statistical forecasting techniques. Other implicit rules such as the user's decision to not use the credit card a week before credit payment is due; or user's weight preferences (e.g., maximizing Savings2 is more important than minimizing transaction fees); or user's rule-of-thumb when there is insufficient funds to pay an unscheduled, emergency purchase, can be derived using more complex intelligent technologies.

What is interesting in learning about the user's payment strategy based on transaction history is that the system can reproduce how the user made decisions in previous occurrences. Thus, the system can recommend solutions based on the user's context, memory and experience, and potentially can target the user's needs.

c) Expert Strategy

The expert strategy will correspond to a strategy based on expert's advice without considering user's context, but taking into consideration external factors such as credit card interest rates, bank fees, foreign exchange rates, home loan rates, market prices, government policies, end-of-season discount rates and special offers, that directly or indirectly affect the future evolution of events. Such a strategy can be provided by financial advisers and analysts, risk managers, and other experts in the mobile commerce, e-commerce and financial services.

By embedding expert advice, the user can also learn if his/her payment strategy is non-optimal or unsatisfactory and can be advised of better ways to achieve his/her goals. By embedding an expert strategy in the system, we can raise the level of decision support offered by mobile services by providing the user with expert advice based on external factors, or generally based on context changes that are beyond the user's control. For more complex online or mobile financial services, such as portfolio selection (Parkes and Huberman, 2001), building scenarios based on expert strategy can be very useful in supporting the mobile user.

An expert strategy that might be suitable for the proposed mobile accounts management problem is that of comparing a scenario that considers future gains if a purchase is made today against scenarios where the purchase is made tomorrow, or at the end of the season, or even at the end of financial year. Thus, if credit interest rates are expected to increase by tomorrow, or if car service fees will be lower next winter, or fees are at their lowest at the end of financial year, then the mobile user potentially will be better informed of what might happen in the future, and which scenario is likely to best address his/her needs.

4.2 Quality of Data Model for Mobile Account Manager

Due to the inherent uncertainty in using scenarios to select the best option today to realise future gains, mobile decision support can be made more reliable if the user is made aware of the QoD that supports the decision. The QoD model, as described in section 2.2, is based on the assumption that the user will be aware that the recommended solution is based on transaction history for a given period (e.g., 1 year, 6 or 3 months) and he/she will be aware of how complete, accurate and current the data is being used to support his/her choice.

The attributes for QoD metrics relating to energy, security, and connectivity for technology-related contexts, stability of scores and weights for user's decision model and those relating to user-related contexts, as well as completeness, currency, and accuracy of historical contexts are well applicable in mobile financial decision making. In the same way these metrics can be calculated by comparing current data with standard data. For example, completeness of historical data can be considered as a fraction of complete account data available at some particular date when making particular decision. Currency can be calculated based on current time and frequency of transaction updates. In this section we focus how using Historical context attributes can assist mobile decision maker in QoD assessment for better, more accurate decision support.

Historical Context

Using this sample mobile accounts problem, we can come up with suitable measures for completeness, accuracy and currency of data from transaction history.

- *Completeness* – part or fraction of the complete data. In our sample accounts management problem, completeness is a fraction of a complete transaction statement for a given time frame. If purchase is to be made today, and it is the 17th of the month, we can say that the transaction history we have available is 52% complete (because we had a transaction history for 16 out of 31 days of the month). When purchase is to be made on Day 28, four days before the next transaction statement is issued (i.e. 28/31 ~ .90 in a 31-day month), then we can say that the transaction history is about 90% complete. Thus for all the scenarios from Table 1, the transaction history used to support the choice is 52%.

- *Currency* – determines how current today's purchase is relative to the nearest critical date. By critical date, in this case, as was defined above, we mean a date when balances need to be updated, such as credit card payment due date (as in Scenario 1, Table 1), the date when a credit limit will be reached (as in Scenario 2), or a date when transfer of funds is expected to incur a transaction fee (Scenario 3). The data will be more current if the purchase date is close to the nearest critical date. Thus from Table 1, we can say that Scenario 3 is most current, as payment by EFTPOS today will immediately incur a transaction fee. Our currency scores for the three scenarios are calculated based on the following formulae:

$$\text{currency of data \_Scenario1} = \left(1 - \frac{\text{9 days to nearest critical date}}{\text{15 days to end of month}}\right) = 0.40$$

$$\text{currency of data \_Scenario2} = \left(1 - \frac{\text{2 days to nearest critical date}}{\text{15 days to end of month}}\right) = 0.87$$

$$\text{currency of data \_Scenario3} = \left(1 - \frac{\text{1 day to nearest critical date}}{\text{15 days to end of month}}\right) = 0.93$$

- *Accuracy* – number of correct transaction values/total number of transactions until the next update. For our example, in Scenario 1 in Table 1, we have 4 fixed payments out of nine expected transactions until the nearest critical date (the remaining 5 transactions (in bold font) are predicted values). Thus, if payment is by cash, then the data from transaction history is 100* (4/9) % ~ 44% accurate. For scenarios 2 and 3, the data is 100% accurate.

Based on historical context, our QoD can be represented as a weighted sum of completeness, currency, and accuracy. If we assume equal weights, our history-related QoD measure is .45 for Scenario 1, .80 for Scenario 2 and .82 for Scenario 3. Based on our QoD framework, if equal criteria weights are used and alternative a1 is recommended as best option (see Section 3.2) and QoD is only 45%, it is up to the mobile user to accept or reject the recommended solution. A 45% QoD can indicate that the critical date is too far in the future to accurately predict the likely balances at the end of the month.

These measures are used as illustrations only and could be adjusted in other contexts if necessary. In the same way the formulae for calculating the completeness, currency, and accuracy of data can vary depending on the user's preferred definition. What is important is that the user understands how such QoD is calculated in order that it is a meaningful consideration in their decision making. Thus by recommending to the user that the best option is to pay by credit card and that the associated QoD is about 80%, he/she can interpret this as a high quality recommended solution, relative to the transaction date.

User-related and Technology-related Contexts

If the mobile user can be supported online, the user can download a transaction history that is complete, current and accurate. In this case, prediction is likely to be more accurate than when using outdated and incomplete data. However, there is also a need to inform the user of technology-related QoD parameters such as network security, connectivity and mobile device energy to guarantee secure and stable environment to perform online transaction. To date, networked–wide infrastructures for supporting wireless connectivity (Ahlund and Zaslavsky, 2002) and network security (Reis et al, 2003; Ghosh, 1998) have been developed and more are being proposed to handle uncertainties due to unreliable communications and possible disconnections from the network. Our approach here is more on modelling these uncertainties by providing technology-related QoD parameters.

If the mobile user is offline, the completeness, accuracy and currency of the data will be calculated by considering the last time transaction history was downloaded from or synchronised with the user's online banking server. In both cases, when the user is relatively consistent with his/her purchases and payment strategies, or when external factors indirectly influence the user's choice, the scores of alternatives against criteria can be fairly *static* (Hodgkin et al, 2003) for the rest of the month. If the user is inconsistent with his/her purchases, or if the system has not learned enough from user's profile and transaction history, the evaluation scores can be fairly *dynamic*. Equivalently, if external factors can directly impact on future evolution of events, the evaluation scores can also be dynamic. Thus aside from completeness, accuracy and recency of data, we can also consider stability of data as a user-related QoD parameter. We can classify the first three parameters as QoD parameters related to historical context; stability of data as a user-related parameter; and security, connectivity and energy as technology-related QoD parameters. The overall QoD can then be taken as the weighted sum of user-related, history-related and technology-related parameters (Hodgkin et al, 2003, Cowie and Burstein, 2006).

5 Mobile Accounts Manager

In this section we describe how the proposed approach to mobile accounts management can be implemented using mobile devices. We call our prototype mobile decision support tool, iAccountsMgr. Sample user interface designs are shown in Figure 4.

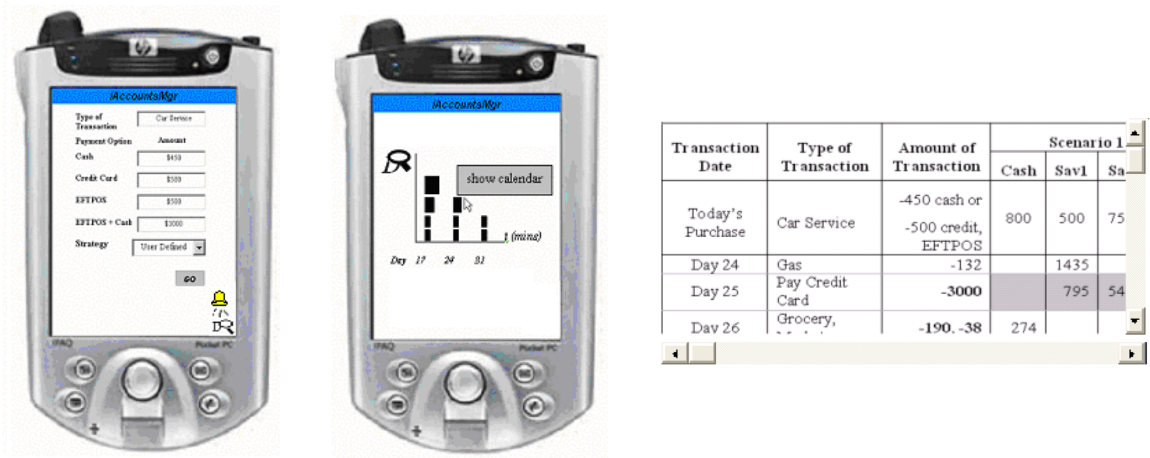
In Figure 4a, the required user inputs are the type of transaction and purchase amounts corresponding to alternative payment options. The user must also identify the strategy (user, learned, or expert) to be used by the system for scenario building. A tap on the GO button will instruct the system to retrieve the multiple accounts of the user based on user's profile, present them as criteria and prompt the user to specify weights using a slide bar. A tap on the GO button in Figure 4b will instruct the system to select the best payment option based on the user's specified weights and chosen strategy. Figure 4c presents the recommended payment option and the expected balances at the end of the month.

4a 4b 4c

Figure 4: Sample user interface for iAccountsMgr

The icon on the lower right of each of figures 4a-c represents the overall QoD. It indicates the quality of data that is available for the decision support procedure in producing a recommendation to pay the product/service today, using transaction history that is locally available in the system. The measure of QoD is visually represented here as a bar graph. One bar indicates very low QoD while 4 bars indicate very high QoD.

When QoD is critically low, the QoD bar is replaced by a QoD bell with sound alert as shown in Figure 5a.



Transaction Date	Type of Transaction	Amount of Transaction	Scenario 1		
			Cash	Sav1	Sa
Today's Purchase	Car Service	-450 cash or -500 credit, EFTPOS	800	500	75
Day 24	Gas	-132		1435	
Day 25	Pay Credit Card	-3000		795	54
Day 26	Grocery,	-190, -38	274		

5c

5a 5b

Figure 5: QoD indicators and calendar in iAccountsMgr.

Predicted QoD for selected days (e.g. Day 24 or Day 31 in Figure 5c) can also be visually represented as shown in Figure 5b. This QoD graph gives an overall view of possible changes in QoD over time. Selecting one of QoD bars will display a calendar indicating expected transactions, expenses and fees from the selected day until the end of the month. The user may then bypass some predefined settings or rules as desired and new predictions can be calculated.

6 Conclusions

Decision support tools for real-time decision-making are in high demand when users need to make informed decisions especially during critical situations. Due to the complexities and uncertainties in mobile computing, most context-aware computing applications are limited to mobile information access. Real-time access to information, however, does not always support decision-making activities. In this perspective, we exploit the possibility of extending context-aware computing to context-aware mobile decision support.

In this chapter we review the current technologies available for providing mobile decision support. The challenges faced by such systems are highlighted, and what we perceive to be current limitations are discussed. In attempting to address today's requirements of mobile systems, we propose a framework by which information provided by a mobile DSS can be evaluated and assessed in terms of its usefulness and relevance for the decision being made. By combining strategic information relating to the decision at hand with a measure of the quality of the information (the QoD score), we feel provides the decision maker with the ability to make an informed choice based on the most up-to-date, relevant information available.

The application area of mobile accounts management is described as a means for exemplifying how such a framework could be utilised. We present a prototype system, iAccountsMgr which is tailored to provide mobile decision support for this area. We have proposed a procedure that aims at providing a mobile user with on-the-spot assistance for decision making concerning the payment method for products and services aiming at efficient management of the periodic (monthly) budget. Equipped with the proposed system the user will be able to assess the future consequences of a choice, and alerted about the implications when buying an item on the move, or before charging emergency purchases against her bank accounts. The main innovation of the mobile DSS is that together with calculating possible scenarios the system provides a measure of reliability – QoD - of each scenario according to the data used in calculating these scenarios.

The realities of the changing way in which we make decisions and the advances in mobile technology create multiple challengers for decision makers and computer system developers alike. Making decisions on the move under uncertainty requires decision support systems that can adequately provide up-to-date, context specific, complete information in a way that is understandable and useful to the decision maker. We feel that by embracing the technologies that facilitate mobile decision support, building on well-founded methodologies to model scenarios whilst accommodating a measure of the quality of the information provided, decisions on the move can be supported just as effectively as those made behind the desk.

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APPENDIX

Table 1. Scenarios associated with payment options

Transaction Date	Type of Transaction	Amount of Transaction	Scenario 1: Pay by Cash					Scenario 2: Pay by Credit Card					Scenario 3: Pay by EFTPOS				
			Cash	**Sav1**	**Sav2**	**CCard**	**TFees**	**Cash**	**Sav1**	**Sav2**	**CCard**	**TFees**	**Cash**	**Sav1**	**Sav2**	**CCard**	**TFees**
Today's Purchase	Car Service	-450 cash or -500 credit, EFTPOS	800	500	7500	-2500	0	800	500	7500	-2500	0	800	500	7500	-2500	0
Day 17	Car Loan	-245	350	255					255		-3000			188	7067		-2.5
Day 18	Health Insurance	-60		195					195	4500	0	-2.5		128			
Day 19	Grocery	**-190**				-2690					-190					-2690	
Day 20	Phone	**-128**		67					67					0			
Day 21	Petrol	**-30**				-2720					-220					-2720	
Day 22	Market	**-38**	312					762					762				
Day 23	Pay salary	1500		1567					1567					1500			
Day 24	Gas	-132		1435					1435					1368			
Day 25	Pay Credit Card	**-3000**		795	5420	0	-2.5		1215		0			795	4920	0	-2.5
Day 26	Grocery, Market	**-190, -38**	274			-190		724			-190		724			-190	
Day 27	Other Income	250			5670					4750					5170		
Day 28	Petrol	**-30**				-220					-220					-190	
Day 29	Mobile, Market	**-50, -38**	236	745				686	1165				686	745			
Day 30	School	**-500**	0	481				186					186				
Day 31	Car Loan	-245		236	5406		-2.5		920					500			
End-of-Month Balance			0	500	5406	-220	-11.6	186	920	4750	-220	-9.1	186	500	5170	-220	-11.6
Weighted Sum (.2, .2, .2, .2, .2)							1135					1123					1123
Weighted Sum (0, .6, .2, 0, .2)							1379					1500					1332