

Kun Chang Lee and Namho Lee (2007)

CARDS: Case-Based Reasoning Decision Support Mechanism for Multi-Agent Negotiation in Mobile Commerce

Journal of Artificial Societies and Social Simulation vol. 10, no. 2, 4 <http://jasss.soc.surrey.ac.uk/10/2/4.html>

For information about citing this article, click here

Received: 01-Nov-2004 Accepted: 01-Jan-2007 Published: 31-Mar-2007



Abstract

Recent advent of mobile commerce or m-commerce suggests a need to incorporate intelligent techniques capable of providing decision support consistent with past instances as well as coordination support for conflicting goals and preferences among mobile users. Since m-commerce allows users to move around while doing business transactions, it seems imperative for the m-commerce users to be given high quality of decision support which should be timely and consistent with past instances. For this purpose, this paper presents two schemes ñ (1) both buyers and sellers engaged in m-commerce are represented by B-agents and S-agents so that the multi-agent framework can be applied, and (2) a case-based reasoning decision support (CARDS) mechanism is developed to provide a robust and consistent support for negotiation among the multi-agents. The primary mission of CARDS here is to match buyers and sellers all of whom want to maximize their own utilities. A real example of m-commerce was chosen to verify the validity of the proposed CARDS, in which perishable products should be sold to those buyers on time. Experiments were performed on the Netlogo, a multi-agent simulation platform running on Windows XP. Statistical tests were also conducted to see whether the experimental results are statistically valid.

Keywords:

Mobile Commerce, Case-Based Reasoning, Multi-Agents, Negotiation

Introduction

1.1

Modern mobile computing is characterized by both its ubiquitous connectivity and its ubiquitous resources (Edwards et al. 2004). Recent popular forms of mobile computing include short-range communications (e.g., infrastructure-based technologies such as WiFi and peer-to-peer technologies such as Bluetooth), and long-range communications such as cellular telephone networks. Based on a 2006 market research report, the overall global mobile managed services market is projected to more than double over the next five years — growing from \$22.2 billion in 2006 to \$52.2 billion in 2010 (Research and Markets 2006). Interest in the usage of mobile applications is increasing in enterprise application (<u>Varshney and Vetter 2002</u>; <u>Gebauer and Shaw 2004</u>), and m-commerce (<u>Stender and Ritz 2006</u>; <u>Pruthikrai et al. 2005</u>).

1.2

In this fast-growing environment, mobile commerce (m-commerce) has emerged as a new type of electronic commerce, and has penetrated into many online business applications. Briefly, m-commerce is any monetary transaction conducted via a mobile computing network (<u>Clarke 2001</u>; <u>Coursaris and Hassanein</u> 2002</u>). In some industries, m-commerce has provided a substantial competitive advantage (<u>Varshney 1999</u>; <u>Rodgera and Pendharkarb 2004</u>) and has helped to improve workflow and efficiency and to reduce costs and risk management (<u>Miah and Bashir 1997</u>; <u>Turisco 2000</u>; <u>Porn and Patrick 2002</u>).

1.3

Because of its relative novelty and the speed with which it has been adopted in many countries, much researches must still be done with regard to mcommerce. The first thing we have to consider is that m-commerce is primarily characterized by portability and mobility, in two ways: it provides real-time business capability regardless of geographical location, but it also imposes limitations on the mobile functions users can enjoy. This is because users engaged in a certain type of m-commerce are assumed to be on the move, and therefore forced to use the mobile devices in more limited way than they would if the devices were plugged into a desktop system. Therefore, m-commerce researches have tackled those m-commerce services such as mobile shopping, location-sensitive information delivery, telemetry, and mobile banking, in which a large number of participants are engaged. Since the customers engaged in m-commerce has very personal needs to maximize their utility in specific contexts, the m-commerce requires unique aspects of services like customization, personalization, location sensitivity, and context-awareness (Sadeh 2002). Though a number of researches exist tackling the characteristics of m-commerce above (Cabri et al. 2003; Gebauer and Shaw 2004; Liang and Wei 2004; Seager 2003), we still need to resolve the remaining issues-how to provide a consistent decision support for negotiation among the m-commerce entities over the limited resources.

1.4

Summarization of the research motivations so far is as follows:

1.5

First, in the generic context of m-commerce, a number of sellers and buyers try to strike a best deal among them, which naturally leads to conflicts over the limited resources. In addition, the entities (usually, buyers) engaged in m-commerce are on the move, and they cannot afford to refer to their mobile devices fully before making decisions. Therefore, if multi-agent systems or MAS are used to represent buyers and sellers, the agents are allowed freely to negotiate with each other to satisfy user's pre-requites and tastes, and the negotiation results are feed-backed to the users for confirmation, then user satisfaction will be greatly improved. For example, when a conflict occurs between buyers and sellers over limited resources, it is difficult for a single authority or committee to reconcile that conflict to the full satisfaction of all concerned. Therefore, use of MAS in the context of m-commerce would result in a more systematic and organized real world method, without unnecessary emotional and behavioral side effects.

1.6

Second, we adopt to incorporate CBR in order to help sellers provide an appropriate price to the potential buyers because it solves new problems by "remembering" previous situations that are similar and then using the consistent information and knowledge gained in that previous situation (<u>Aamodt and Plaza 1994</u>). For sellers, it is important to be consistent in determining the price because buyers are often sensitive to the changes in price. Therefore, using CBR for the problem-solving in the context of m-commerce indicates that we could expect that consistent way of offering the price is possible based on the extraction of consistent information and knowledge from the past similar cases and examples (<u>Kolodner 1993</u>).

1.7

In this respect, we propose a new type of an intelligent negotiation mechanism assuming that all m-commerce participants like sellers and buyers are represented by multi-agents, and that the multi-agents seek decision support which remains robust regardless of changes in m-commerce environment. To provide a robust decision support for negotiation among the multi-agents, we propose a pragmatic approach integrating a case-based reasoning or CBR, named CARDS (CAse-based Reasoning Decision Support). The novel aspect of this study is that case-based reasoning (CBR) is used to provide consistent and robust negotiation support to the agents. Through CARDS, both sellers and buyers can negotiate with potential partners for more desirable deal over a limited resource. For example, sellers can advertise their left-over products to potential buyers and adjust their price offer according to negotiation contexts. Also, buyers can make a counter-offer by modifying their utility function. In addition, all the negotiation procedures can be processed very effectively in a form of negotiation among the multi-agent simulation platform supported by Northwestern University (http://ccl.northwestern.edu/netlogo).

1.8

Section 2 discusses theoretical backgrounds in which comprise trends in m-commerce as well as multi-agent systems are addressed. Besides, brief elaboration on decision support mechanism is suggested. Section 3 goes into mode detail about CARDS, and experiments with CARDS are fully explained in section 4. Finally, section 5 provides contributions of this study and further research issues.

Theoretical Backgrounds

Trends in M-Commerce

2.1

Trends in m-commerce can be viewed from several perspectives such as competitiveness, mobile technology, e-commerce types, and research issues.

2.2

Firstly, let us think about the usefulness of m-commerce from the competitiveness perspective. In this perspective, we have to note how much organizations have successfully improved their competitiveness by using m-commerce. NTT DoCoMo, Vodafone, Verizon, Sprint PCS, and AT&T Wireless, to name a few, have provided "cybermediation" for greater efficiency in supply and marketing channels through m-commerce. M-commerce can help business transactions by providing more efficient payment systems, shortening time to markets for new products and services, realizing improved market reach, and customizing products and services (<u>Seader 2003</u>).

2.3

Secondly, the rapid proliferation of mobile technology including wireless devices, mobile phones, personal digital assistants (PDAs), and other handheld devices, has also made m-commerce a major driving force for the next wave of e-commerce (<u>Liang and Wei 2004</u>). Especially, as many organizations adopt m-commerce techniques increasingly for the sake of meeting customers' needs more promptly as well as saving costs and time in the work places, a wide variety of mobile technology is gaining importance and popularity in organizations (<u>Gaveski 2002</u>; <u>Andersen et al. 2003</u>; <u>Siau et al. 2003</u>; <u>Siau et al. 2004</u>), mobile payment and banking services (<u>Herzberg 2003</u>; <u>Mallat et al. 2004</u>), and electronic procurement application systems based on WAP using mobile phones and laptops (<u>Gebauer and Shaw 2004</u>).

2.4

Thirdly, of the three distinct identifiable classes of electronic commerce applications (business-to-customer (B2C), business-to-business (B2B), and intraorganization) (<u>Applegate et al. 1996</u>), m-commerce generally falls under the auspices of B2C. M-commerce supplies a Web presence with information about company products, and services and facilities for both online and offline purchases. M-commerce also facilitates such business-related activities as entertainment, real estate, financial investment, and coupon distribution. M-commerce sellers are usually required to make competitive offers in order to sell their products or services to target customers within a reasonable distance. This means that in location-based m-commerce applications, sellers must compete with each other to appeal to potential buyers because there might only be a few in a given area. For sellers, presenting timely and attractive offers to buyers on the move is challenging, because buyers are continually receiving information and offers from competing sellers. The real example adopted in this study belongs to this case. For details, refer to the problem description in section <u>4</u>.

2.5

Fourthly, let us take a look at the m-commerce from the research issues perspective. According to Ngai and Gunasekaran (2005), there are five categories of m-commerce research: m-commerce theory and research, wireless network infrastructure, mobile middleware, wireless user infrastructure, and m-commerce applications and cases. The multi-agent approach to m-commerce negotiation falls under the heading of mobile middleware, since agent technologies have been used to carry out negotiations (Paurobally et al. 2003) and search for products (Guan et al. 2002). Meanwhile, Liang and Wei (2004) has classified mcommerce applications into the six categories based on two major attributes such as mobility and reachability. (1) time-critical services which exploit the reachability property of mobile users for providing emergency and time-critical services (Hargreaves et al. 2003; Siau and Shen 2003; Yuan and Zhang 2003) (2) location-aware and location-sensitivity services which are possible if the necessary location information is available (Yuan and Zhang 2003; Varshney 2001; Varshnev and Vetter 2002), (3) identity-enacted services such as mobile financial applications (e.g., mobile banking and brokerage services, mobile money transfer, mobile micro-payments) that allow customers to conduct financial transactions (Varshney and Vetter 2001; Varshney and Vetter 2002), (4) ubiquitous communications and content delivery services such as mobile marketing and advertising, portable entertainment services, mobile distance education, and mobile news delivery services (e.g., the CNN Wireless news subscription service) (Kavassalis 2003; Senn 2000; Varshney and Vetter 2002), (5) business processing streamlining to enhance the efficiency of business processes that include location-sensitive or time-critical activities to reduce transaction costs or improve service quality (Varshnev and Vetter 2002), and finally (6) mobile office in which mobile devices may be used in offices to improve the productivity of office workers (Yuan and Zhang 2003). When considering the properties and advantages of the proposed CARDS where case-based reasoning technique is integrated with the multi-agent systems to improve the efficiency of mobile decision support for the m-commerce users, our study belongs to the time-critical service, and location-aware and sensitive service categories.

Multi-Agents

Fundamentals

2.6

Basically, an intelligent agent (or agent) is a computer system that is capable of flexible autonomous action in dynamic, unpredictable, typically multi-agent domains (<u>www.agentlink.org</u>, accessed on July 5, 2006), though it has various definitions because of the multiple roles it can perform (<u>Applegate 1996</u>; <u>Hoag</u> and <u>lennings 2001</u>; <u>Persson et al. 2001</u>; <u>Wooldridge 1997</u>; <u>Wooldridge and lennings 1995</u>). The term "intelligent agent" can be distilled down to two words: intelligence and agency. The degree of autonomy and authority vested in the agent is its agency, which can be measured, at least qualitatively, by the nature of the interaction between the agent and other entities in the system in which it operates. The degree of agency is enhanced if an agent represents a user in some way, so collaborative agents represent a higher level of agency, because they cooperate with other agents or programs or entities. The agent's intelligence can be stated as its degree of reasoning and learned behavior; its ability to understand the user's goals and to carry out the tasks it is given. In the proposed CARDS, agency is denoted as negotiation needs among the multi-agents representing both buyers and sellers engaged in m-commerce, while intelligence is secured by the case-based reasoning mechanism.

2.7

While m-commerce supports online purchasing through electronic channels (such as the Internet, via electronic catalogs or other innovative formats), customers procure products, services, and information through m-commerce (<u>Bailey and Lawrence 2001</u>). Potential customers can visit "virtual" malls and shops and browse their catalogues to examine products in detail. New areas of business opportunity for retailers, producers, and consumers can be developed from these virtual markets, and mobile information agents provide an effective method for supporting the electronic marketplace by reducing the effort involved in conducting transactions (<u>Wang et al. 2002</u>). Mobile agents can also help by searching other agents for contracting, service negotiation, auctioning, and bartering (<u>Mandry et al. 2001</u>). Agents roam through Internet sites to access information and resources locally (<u>Omicini and Zambonelli 1998</u>). The introduction of mobile agents into the electronic market scenario reduces the load and number of necessary connections to suppliers. In this way, the multi-agent approach is a feasible means of modeling and analyzing complex m-commerce applications.

Multi-Agent Systems (MAS)

2.8

The multi-agent system or MAS, in which multiple agents with diverse goals and capabilities work collaboratively to solve specific problems (<u>Cooper and</u> <u>Taleb-Bendiab 1998</u>; <u>Lottaz et al. 2000</u>; <u>Luo et al. 2001</u>; <u>McMullen 2001</u>; <u>Sillince and Saeedi 1999</u>; <u>Tung and Lee 1999</u>; <u>Ulieru et al. 2000</u>; <u>Wu 2001</u>), provides an effective platform for coordination and cooperation among disputing multiple entities in real world cases. For example, when a conflict occurs between buyers and sellers over limited resources, it is difficult for a single authority or committee to reconcile that conflict to the full satisfaction of all concerned. Therefore, use of MAS would result in a more systematic and organized real world method, without unnecessary emotional and behavioral side effects. MAS has been successfully exploited in a diverse range of sub-disciplines of information technology, including computer networks, software engineering, artificial intelligence, human-computer interaction, distributed and concurrent systems, mobile systems, telematics, computer-supported cooperative work, control systems, decision support, information retrieval and management, and electronic commerce (<u>www.agentlink.org</u>, accessed on July 5, 2006).

In this sense, the proposed CARDS which will be discussed in section 2 is based on the MAS approach in which m-commerce sellers and buyers are respectively represented by specific agents such as S-agents and B-agents, and each agent is supposed to get proper decision support from CARDS. When a target problem is composed of multiple factors and the factors are assumed to interact with each other influencing the formulation of final solutions, then MAS can be applied to solve the target problem by having an agent represent each factor. By simulating the MAS until a desirable solution is found, the target problem can be resolved very effectively. Similarly, the negotiation problem in m-commerce context can be represented by MAS in which an individual negotiation entity is represented by agent, and the MAS is applied to formulate the conflict resolution among the multiple agents to find a best deal for the entities. Most prominent advantage in using the MAS in a negotiation problem in m-commerce context is that it excludes any need of human intervention which would deter an efficient solving process and probably cause unexpected emotional/economic side-effects as well.

Decision Support Mechanism

2.10

It is well known that highly unstructured problems can be solved more easily and systematically when a case-based reasoning (CBR) is used as a consistent and effective decision support tool. M-commerce problem belongs to one of highly unstructured problems which are characterized such that they change very fast, and it is hard to find a consistent solving approach, and systematic explanation about the solution process is required. Decision support mechanism that seems suitable for the m-commerce problem should overcome the properties of highly-unstructured problems like this, providing consistent and explanation-rich solutions. For this purpose, we adopt to incorporate CBR because it solves new problems by "remembering" previous situations that are similar and then using the consistent information and knowledge gained in that previous situation (<u>Aamodt and Plaza 1994</u>). Therefore, using CBR for the problem-solving indicates that we could expect that consistent way of solving the problem is possible based on the extraction of consistent information and knowledge from the past similar cases and examples (<u>Kolodner 1993</u>). If such consistent information and knowledge is found, then explanation about why the proposed solution fits a new problem is also possible based on the analogy (<u>Soumitra et al. 1997</u>).

2.11

In comparison with the CBR like this, rule-based expert system has trouble adapting its solution process to dynamic change of the m-commerce problem situation because rules are basically static and relatively slow in processing input information. Similarly, the solution process provided by neural network is generically regarded as a (semi) black-box because the computation process using a number of connection weights cannot be explained and understood clearly to the human decision makers (<u>Chua and Li 2001</u>). CBR has been successfully applied in medical diagnosis (<u>Varma and Roddy 1999</u>), bankruptcy prediction (<u>Park and Han 2002</u>), scheduling and process planning (<u>Schmidt 1998</u>; <u>Chang et al. 2000</u>; <u>Sadek et al. 2001</u>), customer classification (<u>Chiu 2002</u>), fault diagnosis (<u>Liao et al. 2000</u>; <u>Yang et al. 2004</u>), prediction of information system outsourcing success (<u>Hsu et al. 2004</u>), concurrent product design (<u>Haque et al. 2000</u>), risk analysis (<u>Jung et al. 1999</u>), knowledge management (<u>Noh et al. 2000</u>), military control (<u>Liao 2000</u>), and negotiation (<u>Wilke et al. 1998</u>; <u>Esvin and Mustapha 2004</u>).

2.12

The key assumption of CBR is that if two problems are similar, then their solutions are probably similar, as well. CBR depends on this similarity measure to choose a set of candidate cases that approximate the current problem. Old problems and their solutions are stored in a case database ("case base") as collections of attribute-value pairs, representing the case hierarchical structure via inheritance, object decomposition, and other relationships between object parts. When there is a new problem to be solved, the CBR system searches for the old problem that is most similar to it. The solution to this old problem can then be adapted to more precisely meet the requirements of the new problem. Given a case base where a number of past instances are stored, CBR-based problem solving consists of several phases: indexing cases, retrieving the appropriate candidate cases from the case base, approximating potential solutions from them, testing whether the proposed solutions are successful, and learning to upgrade the decision quality by updating the case base and retrieval mechanism. CBR is therefore most applicable when (i) there is no decision model available; (ii) a specific decision model is too hard to acquire; or (iii) past cases are available or easy to generate.

🐬 CARDS

Basics

3.1

The proposed CARDS system assumes that a number of potential buyers are on the move around sellers' shop, and they may want to buy sellers' goods if offer is reasonable in terms of price and quality. Also another assumption is that there are a number of sellers competing with each other to find those buyers who may want to buy their goods if the sellers offer buyers reasonable bargaining conditions through the m-commerce devices. Therefore, the sellers are located on fixed shops and offering conditions through the CARDS to the potential buyers who are passing by. Some buyers are assumed to carry their own mobile devices that are connected to the CARDS through the telecommunication company. Therefore, for the sellers, it would be important to provide consistent bargaining conditions because they have to sustain a certain level of profit. In this sense, the CBR mechanism is necessary, basically relying on the extraction of useful and consistent bargaining information from a set of similar past instances.

3.2

Buyers and sellers are denoted as B-agents and S-agents to facilitate the negotiation process between them. CARDS is assumed to be stored into the server of telecommunication company, and provided as one of mobile services, accessible online as a commercial subscription. Therefore, CARDS is a virtual market service for both buyers and sellers. CARDS service is available on the buyers' mobile devices on a subscription basis. Besides, when sellers subscribe to CARDS through a telecommunications company, they can use CARDS through the back-office system devices like POS (Point Of Sales) whenever they want. The moment buyers and sellers connect to CARDS, the corresponding B-agents and S-agents are created in a virtual market and coordinated by CARDS. S-agents are equipped with a CBR function in order to maintain pricing consistency; meanwhile, CARDS gives B-agents ability to adjust their own utility function in accordance with buyers' preferences. In this sense, the CARDS provides location-aware services, time-critical and intelligent decision support to both sellers and buyers through the MAS composed of S-agents and B-agents. A schematic diagram of CARDS can be seen in Figure 1.

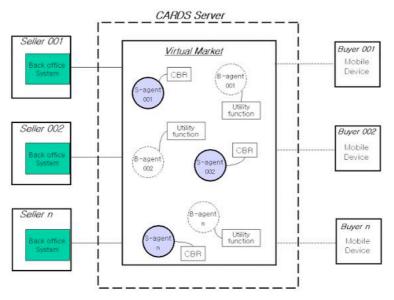


Figure 1. Schematic diagram of CARDS architecture

For buyers, CARDS allows buyers to specify their utility function based on a predetermined set of factors that depend on the type of m-commerce being used. In this way, B-agents may be personalized using a buyer's personal preferences about specific products/services, prices, quality, brands, and other properties. Meanwhile, though CARDS, sellers can launch S-agents capable of promoting their products to potential buyers when it is necessary.

3.4

Summarizing the comments above, the characteristics of m-commerce in this study is defined as follows: first, buyers have mobile devices, such as PDAs or mobile phones, to allow them to access the CARDS through their subscribed telecommunications company. Second, since the buyers themselves are mobile, location plays an important factor in determining their intention to buy products from sellers. In other words, if buyers are too far from one seller's shop, they will turn to other sellers who are closer. Third, sellers can send their product information to the mobile devices of potential buyers as a promotion, made possible through a contract with the local telecommunications company. Fourth, CARDS is stored in the local telecommunications company server, and is provided to customers as one of mobile services. Therefore, if buyers and sellers want to utilize CARDS, they would subscribe to the company first. If CARDS is needed during a specific m-commerce context, users would activate it via their mobile devices.

3.5

The CARDS-administered negotiation process is as follows: buyers and sellers are represented by B-agents and S-agents, respectively. S-agents calculate an initial bid price for a sales item using the CBR function of CARDS, then relay price offer to the B-agents through CARDS. Upon receiving the price offer, the B-agents compute their utility values. If CARDS detects a "best fit" between the B-agents' utility and the S-agents' price offer, the corresponding B-agents are notified and the negotiation process stops with a final deal between B-agents and S-agents. Otherwise, the negotiation process continues until a final deal is struck.

S-agent

3.6

The ultimate goal of the S-agent is to maximize profit. For this purpose, the S-agent seeks a potential buyer in the acceptable range of distance and within a specific time limit; then it calculates the bid price of the selling product/service based on the CBR function in the CARDS. Then the bid price is sent to the CARDS. The offer of the S-agents like this including price and product is delivered by CARDS to potential B-agents, which is also connected online to CARDS. A wide variety of past selling instances are stored in the case base, and the CBR uses the similarity index (or SI) below to select the candidate case that seems to fit the current selling situation most closely. Once a case has been chosen, a price offer can be made that approximates the price information of the selected case.

$$SI_{i} = \sqrt{\sum_{j=1}^{n} (N_{j} - S_{jj})^{2}}$$
(1)

where N_j indicates jth attribute value of a new case (j = 1, 2, ..., n), and S_{ij} denotes *j*th attribute value of *i*th case in the case base of CBR (i = 1, 2, ..., m). Netlogo source code for implementing the CBR function of CARDS using SI is listed in Table 1. $N_1, ..., N_4$ are attributes of cases (N_1 : Current inventory level, N_2 : remaining period of validity, N_3 : freshness level, N_4 : number of potential buyers within reasonable range of distance from store). Table 1 describes how the case based reasoning performs.

```
to change-CBR-price
locals [temp_t temp_i temp_si temp_optimal_si temp_item]
set temp t(1)
repeat seller number [
ask seller with [reg_number = temp_t and mobile_service = 1 and CARDS_service = 1 ] set temp i (0)
repeat length CBR_price [
set temp_si sqrt([N1_Current_Value - item (temp_i) CBR_N1_List) ^ 2
+ ((N2_Current_Value - item (temp_i) CBR_N2_List) ^ 2
+ (N3_Current_Value - item (temp_i) CBR_N3_List) ^ 2
+ (N3_Current_Value - item (temp_i) CBR_N3_List) ^ 2
+ (N4_Current_Value - item (temp_i) CBR_N3_List) ^ 2
+ (N4_Current_Value - item (temp_i) CBR_N4_List) ^ 2)
if (temp_i = 0)[set temp_optimal_si (temp_si) set temp_item (temp_i)]
if (temp_i >= 1) [ if(temp_si < temp_optimal_si) [set temp_optimal_si (temp_si)
set temp_item (temp_i )]
1
set temp_i (temp_i + 1)
set offer_product_price (item temp_item CBR_price)
1
set temp_t(temp_t + 1)
end
```

Table 1. CBR function of CARDS

3.7

Since CARDS is connected online and basically administered by the telecommunication company, it should be noted that cases are updated when either a new bid price is offered or new cases of adjusted price offers from the buyers under the past cases are received.

B-agent

3.8

B-agents seek to maximize their own utility in the process of negotiating with S-agents. Buyers can activate CARDS online, and refer to it when necessary during m-commerce. B-agents incorporate the following utility functions where i = 1, 2, ..., m (number of sellers), and j = 1, 2, ..., n (number of utility factors):

$$=\sum_{j=1}^{n} W_{ij} \Box F_{ij}, \alpha_{ij} \le F_{ij} \le \beta_{ij}$$
(2)

 U_i denotes *i*th buyer's utility, W_{ij} buyer's preference for *j*th utility factor, and F_{ij} *i*th buyer's *j*th utility factor. It is certain that $\sum_{i=1}^{n} W_{ij} = 1$. Examples of utility

factors include not only price, product, and quality, but also contextual information such as the buyer's current location and environmental constraints. As shown in Table 5, we consider five factors such as F_1 :Distance, F_2 :Freshness, F_3 :Category, F_4 :Price, F_5 :Timeliness. Therefore, five weights $W_1 \sim W_5$ are assigned to each factor. Table 2 shows Netlogo source code for calculating the B-agent's utility function.

^ 2

```
;; to Calculate-Util
set temp (1)
set temp_id (1)
repeat customer_number [
ask customer with [reserve != 1 and id_number = temp_id] [
set temp_distance (p_distance )
set temp_time (p_time )
set temp_customer_x (current_x) set temp_customer_y (current_y)
set utility (0)
set temp_selected_seller (0)
repeat seller_number [
ask seller in-radius-nowrap (remaining_time / time_per_patch)
with [available_product_number > 0 and reg_number = temp1][
```

set actual_distance (abs (sqrt((temp_customer_x - location_x))

 U_i

```
+ (temp_customer_y - location_y) ^ 2 ) ))
;; Convert factor point
set temp_util ( temp_W1 * temp_point_F1
                         temp_w1 * temp_point_F1
temp_W2 * temp_point_F2
temp_W3 * temp_point_F3
+ temp_W1 * temp_point_F4
+ temp_W5 * temp_point_F5)
if (temp_util > utility) [ set utility (temp_util)
                                set temp_selected_seller (reg_number) ]
                                                  1
                         set temp1 (temp1 + 1)] set temp1 (1)
                         set utility_without_mobile (utility)
set normal_selected_seller (temp_selected_seller) ]
set temp_id (temp_id + 1)
                            1
end
```

Table 2. B-agent's utility calculation

3.9

If a B-agent gets a price offer from an S-agent through CARDS and the offer does not meet the buyer's goal utility, the B-agent will suggest a new price using the mechanism shown in Table 3. If the seller accepts the new price offered by the buyer, the deal is completed. However, if no sellers accept the price, the Bagent will increase the price, decreasing its goal utility. In this case, a new round of negotiation ensues.

```
ask buyer with [deal !=1 ] [
set goal_utility (Current_utility + (utility_adjustment / 100) * Current_utility )
set temp (selected_buyer)
        ask seller with [reg_number = temp ][
           if (available_product_number > 0) [
if (p_temp > 0 ) [
 set temp_price_down_request int((goal_utility - Current_utility) / p_temp) ]]]
                            Table 3. B-agent's price update process
```

Coordination mechanism of CARDS

3.10

Coordination mechanism of CARDS is basically related to the negotiation process. In Figure 2 where the negotiation procedures of CARDS are displayed in a logical chart form, message flows occurring in the process of negotiation between sellers and buyers are observed. For example, they include price offer by sellers, list of potential buyers, and adjusted price by buyers. Additionally, Table 4 summarizes the message flows in machine-readable codes.

3.11

CARDS finds sellers who can maximize a buyer's utility on behalf of buyer, and searches for buyers who can maximize profit for a seller. In this sense, CARDS can act as a coordinator allowing both buyers and sellers to negotiate with each other over limited resources and options such as products and prices. Assuming that CARDS is connected online to a telecommunications company's server, potential B-agents and S-agents are able to negotiate with each other until a final deal is made. The coordination mechanism used by CARDS is based on the procedural algorithm in Table 4.

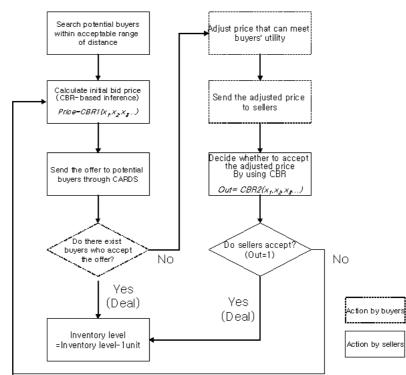


Figure 2. Logical diagram showing how CARDS works to coordinate between sellers and buyers

```
to give-offer-to-CARDS-buyer
locals [temp]
ask customer [set negotiating_shop_list []]
ask shop with [unsold_product_number > 0 and mobile_service = 1 ]
  ſ
  set temp (reg_number)
  without-interruption [
  foreach negotiating customer list [
              ask customer with [id_number = ? and reserve != 1 and mobile_service = 1]
                                [set negotiating_shop_list lput temp negotiating_shop_list ]
]]
```

end

to nego-offer-to-shop [remaining_time] locals [temp temp_id temp_seller_no temp_no actual_distance] set temp_no (1)
ask shop [set mss_nego_custom_list []] repeat customer_number [

set temp_no (temp_no + 1)
]

end

Table 4. CARDS negotiation processing process

🐬 Experiments

Problem Description

4.1

It is assumed that buyers want to buy perishable products at a discounted price if possible, while sellers want to sell those perishable products before their freshness fades. CARDS is assumed to be administered by a telecommunications company as one of mobile services provided to buyers and sellers on a commercial subscription basis. If a buyer registers to use CARDS, he/she is able to access it when necessary in m-commerce contexts. This also applies to sellers. Therefore, those buyers and sellers using CARDS can negotiate terms with each other in any m-commerce situations.

4.2

In Seoul (capital of South Korea) where the experiments were performed, it is highly competitive for a number of small grocery shops to attract potential buyers. It is because Big 3 discount shops like E-mart (<u>http://www.emart.co.kr</u>), Lotte mart (<u>http://www.lottemart.com</u>), Home Plus (<u>http://www.homeplus.co.kr</u>), have already dominated retail market throughout country, and there remains very limited market in which small grocery shops can sell their own products to potential buyers. Since buyers already recognize that electronic goods or other factory-made products available in the Big 3 shops are very price-competitive, the only viable option for the small grocery shops is to provide an attractive price offer to the potential buyers.

4.3

Especially, one of the most popular items that buyers can purchase from the small grocery shops is perishable products because buyers want to purchase the products in a rather small unit, and the small grocery shops are easily accessible from buyers' residence area, in comparison with the Big 3 shops which are located in a remote place only accessible by car. Therefore, the small grocery shops are usually inclined to perform a pop-bargain sales activity during night-time operation by which the product information about those perishable products they want to sell quickly due to the deteriorating freshness is advertised to the potential buyers. Especially, information about the freshness of the perishable products is always shared with the potential buyers with strict precision and reliability. Any betrayal of buyers' trust about the freshness of the products will result in serious blow to the seller's position in the market, and even expulsion from it. Therefore, the perishable products can be traded even when buyers cannot check the freshness level directly before making purchase decision.

4.4

For the sake of experiment, both buyers and sellers are divided into three groups depending on whether or not they use mobile decision support from CARDS. The first group, called the "Non-Mobile Group", does not use mobile devices, and must meet face-to-face in order to negotiate for products. The members of the second group, the "Passive-Mobile Group", use mobile devices, but not CARDS. Buyers and sellers belonging to this group cannot negotiate directly via CARDS; instead, each buyer receives information about products from sellers on an advertisement basis, via a telecommunications company contract with sellers. Members of the third group, the "Active -Mobile Group", carry mobile devices connected to CARDS, and are able to negotiate with each other directly using it. Our simulation experiment shows the validity of CARDS for each group.

4.5

To deduce real assumptions about sellers, we interviewed 40 grocery stores in the Seoul metropolitan area that sell perishable goods such as vegetables, fish, fruit, and dairy products. The store managers (or owners) were asked questions regarding list prices, their experience negotiating the price of perishable goods with buyers, and the appropriate range of product freshness levels, among other things. Thirty buyers (Seoul housewives) were also selected, and were asked to describe the utility factors they considered when negotiating with sellers. Based on these interview results, we established assumptions about sellers and buyers which we incorporated into our CARDS experiment <u>below</u>.

4.6

With regard to sellers, it is assumed that each grocery store sells four categories of perishable goods whose freshness level can be categorized into 10 levels (level 1 is "Most fresh"). List price is fixed for each product, but price discounts can be negotiated depending on inventory and freshness levels and the buyer's taste. Price discrimination is decided on the basis of negotiation with buyers. Sellers belonging to the Non-Mobile Group and the Passive Mobile Group were not able to negotiate directly with buyers using mobile devices; however, sellers in the Passive Mobile Group could send information about their products to potential buyers randomly, via a telecommunications company server. CARDS provides CBR support to each seller to help determine price discounts for each potential buyer, using five attributes: current inventory level, remaining period of validity, freshness level, number of potential buyers within reasonable range of distance from store, and possible price. Active Mobile Group buyers attempt to negotiate price with sellers using the support of CARDS, and sellers are assumed to refer to another kind of the CBR support in which a case is composed of four input attributes (price gap, expected profit, remaining period of validity, and inventory level) and one output attribute (1 for "Accept the price offer", 0 for "Reject the price offer").

4.7

Meanwhile, buyers have different utility function. The buyer's first concern is his or her current location. If it is too far from the seller who is offering the deal or product information, business talk will not ensue. For this reason, distance factor *D* must be considered when setting up the buyer's utility function. Product's freshness level (*F*) and category (*C*) should also be incorporated into the function. Price (*P*) is another crucial factor affecting the potential buyer's intention to purchase a product. In the case of the Active Mobile Group, we assume that price can be negotiated using CARDS. Finally, timeliness (*T*) indicates how much the potential buyer needs the product at the very moment when a deal starts. By incorporating these five factors, a utility function can be formulated for each buyer: where *i* denotes *i*th buyer, and weight for each factor depends on its relative importance level:

(3)

$$U_i = w_{D_i} \cdot D_i + w_{F_i} \cdot F_i + w_{C_i} \cdot C_i + w_{F_i} \cdot P_i + w_{T_i} \cdot T_i$$

Depending on the situation that the potential buyer is facing at the time, the utility is determined as follows (Table 5).

Table 5: Buyer's utility

Utility factor	Condition	Converted utility		
Distance (D)	Within 20 minutes	50		
	Within 30 minutes	40		
	Within 40 minutes	30		
	Within 50 minutes	20		
	More than 60 minutes	10		
Freshness (F)	1,2	50		
	3,4	40		
	5,6	30		
	7,8	20		
	9,10	10		
Category (C)	Preferred category	50		
	Otherwise	0		
Price (P)	Price negotiation	50 – (new price/list price) * 50		
Timeliness (T)	If the buyer wants the product on offer	50		
. /	Otherwise	0		

Basics

4.8

Real assumptions compiled from our interviews with potential sellers and buyers were incorporated into NetLogo. The <u>CARDS prototype</u> was developed on the NetLogo platform, a programmable multi-agent modeling environment that simulates a wide variety of decision making problems, and is particularly well-suited for modeling complex systems that develop over time. NetLogo (available at http://ccl.northwestern.edu/netlogo/download.shtml) is very easy to install and to operate: Users can explore models without any technical knowledge; an extensive "models library" exists so that users can refer to the types of models that have been made using the toolkit. These are generally well documented, the documentation being easily accessible through the "information" tab within the program. Parameters of the model are easily changed using graphical "sliders." For those who want to change the details in a model, clicking on the "procedures" tab brings up the entire model code, which can easily be changed in order to extend the sample models. NetLogo provides a very accessible introduction to agent-based modeling. This is a very useful first step after which users can decide whether the technique is one that warrants further investigation. Using the NetLogo platform, B-agents are introduced to denote buyers, and S-agents, sellers. CARDS has six types of user interface components, shown in Figure 3.

- 1. Control button prepares and prompts simulation.
- 2. Slider controls the initial conditions of simulation such as number of customers, number of sellers, etc.
- 3. *Monitor* shows the number such as rounds of simulation, and simulation time.
- 4. Behavior space shows the customer (or buyer)'s movement and the location of stores. The human shape indicates a buyer and the house shape represents a store. The color gray means group 1, green group 2, and pink group 3. All customers are designed to move one unit of position over to the random direction at a time. The customers leave the simulation after they have purchased products.
- 5. Graph monitors the change of values such as number of customers, product inventory, the number of customers who have not bought products, the customer's average utility, and the store's average profits.
- 6. Command center shows temporary data generated from the agent activities.

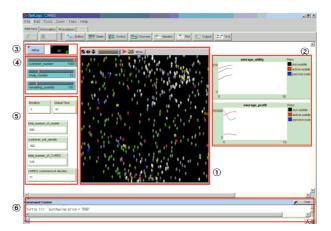


Figure 3. CARDS prototype implemented on Netlogo

Simulation Process

4.9

Logical procedures related to simulation are already depicted in Figure 2. For the sake of simulation on Netlogo, S-agents and B-agents are randomly located on a two-dimensional virtual space provided by Netlogo, where X axis as well as Y-axis is ranging from -20 to 20. Each B-agent is given weights for the five

utility factors mentioned in 4.1 on a random basis ($\sum_{i=1}^{2} w_i = 1.0$). Similarly, B-agents are given product category (1 ~ 3), potential purchase period (1 ~ 50

time), and minimum utility level. For example, the B-agent with potential purchase period 30 time indicates that the buyer thinks 30 time after start as the most appropriate purchase moment. When the buyer purchases the target product at the desired time, we assume that the utility will increase. Otherwise, the buyer's utility is assumed to possibly decrease. Besides, buyers are believed to purchase the product when the utility calculated by the seller's offer is greater than the minimum utility level.

4.10

Simulation restarts another round if met is one of the stopping conditions such as (1) negotiation is not available any more, (2) seller's inventory is out of stock, (3) all the potential buyers purchased the products, and (4) 5 time passes without a successful negotiation. At the start of a new round of simulation, all the B-agents and S-agents are given a new information as mentioned previously. S-agents are looking for the B-agents who are mobile within 20 distance by using 'In-Radius' command. Also S-agents determine an initial bid price on the basis of the CBR, and deliver the price to the potential B-agents. In response to the S-agents' offer like this, the B-agents calculated their own utility based on the information in Table 5. If the calculated utility is greater than the minimum level, then B-agents accepts the offer and reserves the target products, moving to the S-agent's shop to purchase the products. Otherwise, the B-agents assigned to Active Mobile Group adjust price based on the price adjustment formula such as

$$P_{buyer_{i}} = \frac{U_{\min.} - (w_{D_{i}} \cdot D_{i} + w_{F_{i}} \cdot F_{i} + w_{C_{i}} \cdot C_{i} + w_{T_{i}} \cdot T_{i})}{w_{D_{i}}}$$

which is derived from the utility function

$$U_i = w_{D_i} \cdot D_i + w_{F_i} \cdot F_i + w_{C_i} \cdot C_i + w_{P_i} \cdot P_i + w_{T_i} \cdot T_i$$

and send the adjusted price to the S-agents as a counter-offer. By consulting with CBR, S-agents determine whether to accept the counter-offer or not. If output attribute is 1, then the S-agents accept the counter-offer. Otherwise, the counter-offer is rejected.

Results and Implications

4.11

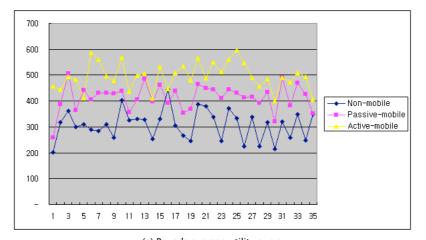
35 simulation rounds were performed using the assumptions stated in 4.1. The number of S-agents was set as 12, with 3 stores in each Group (Non-Mobile Group, Passive Mobile Group, Active Mobile Group). B-agents were generated randomly using normal distribution functions, with mean 1000 and standard deviation 200. Table 6 shows the buyer's average utility and the seller's average profit, where the Active-Mobile Group outperforms both the Passive-Mobile Group and the Non-Mobile Group, and the Passive Mobile Group surpasses the Non-Mobile Group.

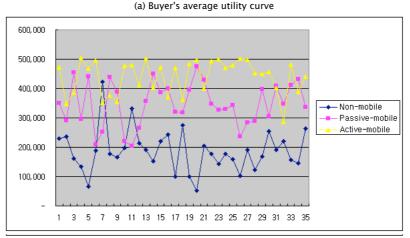
4.12

the previous simulation process, all the initial conditions are reset at the start of each round of simulation. Based on the results in Table 6, statistical tests were performed. F-test results shown in Table 7 reveals that the Active Mobile Group's average utility for buyers is significantly greater than both the Passive-Mobile Group and the Non-Mobile Group, less than 99% confidence level. It is the same with average profit for sellers. Specifically, a T-test was performed for average utility: t=8.175 between the Passive-Mobile Group and the Non-Mobile Group, t=6.750 between the Active-Mobile Group and the Passive-Mobile Group, and t=14.453 between the Active-Mobile Group and the Non-Mobile Group. For average profit, t=9.087 between the Passive-Mobile Group and the Non-Mobile Group, and t=16.048 between the Active-Mobile Group and the Non-Mobile Group, and t=16.048 between the Active-Mobile Group and the Non-Mobile Group. T-test results also revealed that a less than 99% confidence level for the Active-Mobile Group is greater than that of the two mobile groups, and the Passive-Mobile Group.

4.13

Implications are as follows. First, multi-agents are both convenient and effective for m-commerce entities when CARDS are used to handle the decision making process. This is because agents are capable of autonomous operation once the entity's preference is predefined and stored into their memory. In the CARDS environment, therefore, users do not have to interact directly with negotiation partners. Second, both preferences and conditions that users want their agents to consider in the process of negotiation coordination can be easily incorporated into the agents. Since CARDS is based on the central server of a telecommunications company an accessible online, it is very easy to use. Third, since m-commerce users are limited by the narrow screen and specified functions of their mobile devices, and since agents are capable of replacing users in the real negotiation process in an almost automatic manner, the use of a negotiation coordination mechanism such as CARDS would greatly contribute to enhancing users' utilities and profits.





(b) Seller's average profit Figure 4. Average utility and profit curves

Table 6: Simulation results for three mobile groups

Simulation Round	Buyer's Average Utility			Seller's Average Profit		
	Non-Mobile Group	Passive-Mobile Group	Active-Mobile Group	Non-Mobile Group	Passive-Mobile Group	Active-Mobile Group
1	202	259	458	228,750	349,475	472,046
2	319	388	445	237,500	290,900	346,985
3	361	506	492	160,500	454,500	387,420
4	299	365	482	134,250	295,250	505,576
5	311	441	410	66,000	441,925	467,940
6	289	406	587	188,500	208,225	496,251
7	285	431	559	423,000	253,225	353,273
8	309	432	497	178,000	438,750	377,081
9	259	428	477	165,750	389,725	354,953
10	402	439	568	197,250	219,950	477,409
11	326	355	436	332,000	204,250	479,741
12	332	405	498	214,750	265,500	410,366
13	327	485	506	190,250	356,425	501,517
14	252	398	412	151,750	451,000	402,775
15	331	463	533	220,000	385,975	473,341
16	445	393	448	242,750	400,125	370,576
17	305	438	508	101,000	321,400	469,929
18	265	354	534	274,250	317,650	361,821
19	245	370	480	99,250	394,975	484,309
20	387	464	565	52,000	475,425	497,923

Average	215	290	347	130,760	242,752	307,916
35	349	350	406	263,750	337,250	440,755
34	247	426	492	146,500	431,200	388,419
33	350	469	509	157,000	410,750	482,582
32	257	381	474	220,000	347,750	287,404
31	321	491	492	190,250	408,975	401,334
30	213	322	401	255,000	304,525	457,196
29	319	434	487	169,250	396,650	448,992
28	225	392	457	123,750	288,000	451,497
27	338	416	492	192,000	283,175	498,108
26	225	413	547	102,750	235,650	502,448
25	334	431	597	158,750	344,250	480,545
24	371	444	562	178,000	330,050	470,821
23	245	411	512	143,000	328,175	501,041
22	339	444	551	176,250	347,400	492,709
21	381	449	488	204,250	429,150	400,736

Table 7a: F-test for buyer's utility

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	624,207	2	312103.4	111.2982	0.00
Within Groups	286,029	102	2804.209		
Total	910,236	104			

Table 7b: F-test for seller's profit								
	Sum of Squares	df	Mean Square	F	Sig.			
Between Groups	1,146,975,891,893	2	573,487,945,946	121.8049	0.00			
Within Groups	480,241,710,489	102	4,708,252,064					
Total	1,627,217,602,382	104						

Concluding Remarks

5.1

M-commerce requires high level of decision support because of its prominent features like portability and mobility. Therefore, m-commerce users need such decision support as context-aware and time-critical. Besides, m-commerce users are forced to use mobile devices that are relatively functionally limited because users engaged in a certain type of m-commerce are usually assumed to be on the move. The primary contributions of the proposed CARDS are as follows:

5.2

First, CBR has never been seriously incorporated into the MAS-driven m-commerce problems. As well, sellers linked to CARDS were able to maximize their own profit in a statistically significant way (See Table 7).

5.3

Second, buyers' utility can be upgraded when they consult with CARDS, which is also statistically significant (See Table 7).

5.4

Third, MAS adopted in CARDS proved also to be very effective way of solving complicated m-commerce problems. Agents can behave autonomously once a basic guideline is provided by their human decision makers. Therefore, CARDS have a great deal of potential for being applied to a wide variety of m-commerce problems.

5.5

Fourth, CARDS can be ported onto a server from which a large number of m-commerce users can access whenever they need negotiation decision support.

5.6

Fifth, multi-agents were very useful in the process of m-commerce negotiations. This approach has proven both useful and effective in a wide variety of problems in literature, but its potentials had not been proven within an m-commerce context, until this study.

5.7

This study does have limitations, in that: (i) the information used in our experiment is partially based on interview data with sellers and buyers; (ii) we do not suggest rigorous mechanisms for extracting the buyer's preference; (iii) only quantitative performance measures such as average utility and profits are considered. To overcome these limitations, a new study is under way in which B-agents adjust their utility mechanism automatically by using causal map techniques, and neural network technique is adopted to provide learning capability to the agents so that the performance of CARDS can improve drastically. One of the future study issues is to extend the proposed m-commerce support mechanism into encompassing the mobile services so that buyers and sellers can benefit more when using it in the practical contexts.

Acknowledgements

This work was supported by grant No. B1210-0502-0037 from the University Fundamental Research Program of the Ministry of Information & Communication in Republic of Korea, 2005.

References

AAMODT A and Plaza E (1994). Case-based reasoning: foundational issues, methodological variants, and system approaches. AI Communications, 7(1), pp. 39-59

ANDERSEN K V, Forgegren-pedersen A, Varshney U (2003), Mobile organizing using information technology (MOBIT). *Information Communication and Society*, 6 (2), pp.211-228.

APPLEGATE L M, Holsapple C W, Kalakota R, Radermacher F J and Whinston A B (1996). Electronic commerce: Building blocks of new business opportunity, *Journal of Organizational Computing & Electronic Commerce*, 6(1), pp.1–10.

BAILEY M N and Lawrence R L (2001). Do we have a new economy? American Economic Review, 91(2), pp. 308-312.

CABRI G, Leonardi L, Mamei M, and Zambonelli F (2003). Location-dependent services for mobile users, IEEE Transactions on Systems, 33(6), pp. 667-681.

CHANG H C, Dong L, Liu F X and Lu W F (2000). Indexing and retrieval in machining process planning using case-based reasoning. Artificial Intelligence in Engineering, 14(1), pp.1-13.

CHIU C (2002). A case-based customer classification approach for direct marketing. Expert Systems with Applications, 22(2), pp. 163-168.

CHUA D K H, Li D Z (2001). Case-Based Reasoning Approach in Bid Decision Making. Journal of Construction Engineering & Management, 127(1), pp.35-44

CLARKE I (2001). Emerging value propositions for m-commerce. Journal of Business Strategies, 18(2), pp.133-148.

COOPER S and Taleb-Bendiab A (1998). CONCENSUS: Multi-party negotiation support for conflict resolution in concurrent engineering design. Journal of Intelligent Manufacturing, 9(2), pp. 155-159.

COURSARIS C and Hassanein K (2002) Understanding m-commerce. Quarterly Journal of Electronic Commerce, 3(3), pp. 247-271.

EDWARDS W K, Newman M W, Sedivy J Z and Smith T F (2004). Supporting serendipitous integration in mobile computing environments. International Journal of Human-Computer Studies, 60, pp. 666–700.

ESYIN C and Mustapha S M F D S (2004). Negotiation in a multi-dimensional CBR system, Cybernetics and Intelligent Systems, 2004 IEEE Conference, 2, pp.1192 - 1195

GAYESKI D M (2002), Learning Unplugged. American Management Association, New York, New York.

GEBAUER J and Shaw M J (2004). Success factors and impacts of mobile business applications: results from a mobile e-procurement study. International Journal of Electronic Commerce. 8 (3), pp.19-41.

GUAN S, Ngoo C S, Zhu F (2002). Handy broker: an intelligent product-brokering agent for m-commerce applications with user preference tracking, *Electronic Commerce Research and Applications*, 1(3), pp. 314–330.

HARGREAVES D, Knight T, Brownsword P and Macdonald D (2003), real-time emergency management via satellite: Status update and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 57(4), pp. 273-280.

HAQUE B U, Elecheanu R A, Barson R J and Pawar K S (2000). Toward the application of case based reasoning to decision-making in concurrent product development (concurrent engineering), *Knowledge-Based Systems*, 13(2-3), pp. 101–112.

HERZBERG A, (2003). Payments and banking with mobile personal devices. Communications of the ACM, 46 (5), pp.53-58.

HOGG L M I and Jennings N R (2001). Socially intelligent reasoning for autonomous agents. IEEE Transactions on Systems, Man, & Cybernetics Part A: Systems & Humans, 31(5), pp. 381–393.

HSU C I, Chiu C and Hsu P L (2004). Predicting information systems outsourcing success using a hierarchical design of case-based reasoning, *Expert Systems* with Applications, 26(3), pp. 435-441.

JUNG C, Han I and Suh, B (1999). Risk analysis for electronic commerce using case-based reasoning. International Journal of Intelligent Systems in Accounting, Finance and Management, 8(1), pp. 61-73.

KAVASSALIS P, Spyropoulou N, Drossos D., Mitrokostas E, Gikas G and Hatzistamatiou A (2003). Mobile permission marketing: Faming the market inquiry. International Journal of Electronic Commerce, 8(1) pp. 55–79.

KOLODNER J (1993). Case-Based Reasoning. San Ma-teo, CA: Morgan Kaufmann

LIANG T P and Wei C P (2004), Introduction to the Special Issue: Mobile Commerce Applications, International Journal of Electronic Commerce, 8(3), pp.7-17

LIAO S H (2000). Case-Based decision support system: architecture for simulating military command and control, *European Journal of Operational Research*, 123(3), pp. 558-567.

LIAO T W, Zhang Z M and Mount C R (2000). A case-based reasoning system for identifying failure mechanisms, *Engineering Applications of Artificial Intelligence*, 13(2), pp.199-213.

LOONEY C A, Jessup L M, Valacich J S (2004). Emerging business models for mobile brokerage services. Communications of the ACM, 47 (6), pp.71-77.

LOTTAZ C, Smith I F C, Robert-Nicoud Y, and Faltings B V (2000) Constraint-based support for negotiation in collaborative design, Artificial Intelligence in Engineering, 14(3), pp. 261–280.

LUO X, Zhang C, and Leung H F (2001) Information sharing between heterogeneous uncertain reasoning models in a multi-agent environment: A case study. *International Journal of Approximate Reasoning*, 27(1), pp. 27-59.

MALLAT N, Rossi M, Tuunainen V K (2004). Mobile banking services. Communicates of the ACM 47, (5), pp.42-46.

MANDRY T, Pernul G, and Rohm A W (2001) Mobile agents in electronic markets: opportunities, risks, agent protection, International Journal of Electronic Commerce, 5(2), pp. 47-60.

MCMULLEN P R (2001) An ant colony optimization approach to addressing a JIT sequencing problem with multiple objectives, Artificial Intelligence in Engineering, 15(3), pp. 309-317.

MIAH T and Bashir O (1997) Mobile workers: Access to information on the move. Computing and Control Engineering, 8, pp.215-223.

NAH F, Siau K, Sheng H (2005). The value of mobile applications: a study on a public utility company. Communications of the ACM, 48 (2), 85-90.

NGAI E W T and Gunasekaran A (2005). A review for mobile commerce research and applications, Decision Support Systems, available online at

www.sciencedirect.com.

NOH J B, Lee K C, Kim J K, Lee J K and Kim S H (2000). A case based reasoning approach to cognitive map-driven tacit knowledge management. *Expert Systems with Applications*, 19(4), pp. 249-259.

OMICINI A and Zambonelli F (1988) Co-ordination of mobile information agents in Tucson, Internet Research: Electronic Networking Applications and Policy, 8(5), pp. 400-413.

PARK C S, Han I (2002). A case-based reasoning with the feature weights derived by analytic hierarchy process for bankruptcy prediction, *Expert Systems with Applications*, 23(3), pp.255-264.

PAUROBALLY S, Turner P J, Jennings N R (2003), Automating negotiation for m-services, IEEE Transactions on Systems, Man and Cybernetics, Part A 33 (6), pp.709-724.

PERSSON P, Laaksolahti J, and Lonngvist P (2001). Understanding Socially intelligent Agents – A Multilayered Phenomenon. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 31(5), pp. 349–360.

PORN L M and Patrick K (2002). Mobile computing acceptance grows as applications evolve. Healthcare Financial Management, 56(1), pp.66-70.

PRUTHIKRAI M H, Wen J and Lim B (2005), Consumer-based m-commerce: exploring consumer perception of mobile applications, *Computer Standards & Interfaces*, 27(4), pp.347-357

RODGERA J A and Pendharkarp P C (2004). A field study of the impact of gender and user's technical experience on the performance of voice-activated medical tracking application. International Journal of Human-Computer Studies, 60, pp.529-544.

SADEH N (2002). M-Commerce: Technologies, Services, and Business Models. Wiley, USA .

SADEK A W, Smith B L and Demetsky M J (2001). A prototype case-based reasoning system for real-time freeway traffic routing, *Transportation Research Part C: Emerging Technologies*, 9(5), pp. 353-380.

SCHMIDT G (1998). Case-based reasoning for production scheduling, International Journal of Production Economics, 56-57, pp.537-546.

SEAGER A (2003). M-commerce: An integrated approach. Telecommunications International, 37(2), pp.36.

STENDER M and Ritz T (2006). Modeling of B2B mobile commerce processes. International Journal of Production Economics, 101(1), pp.128-139

SENN J A (2000). The emergence of M-Commerce. Computer, 33(12), pp. 148-150.

SIAU K, Sheng H, Nah F (2003). Developing a Framework for Trust in Mobile Commerce Proceedings of the Second Annual Workshop on HCI Research in MIS, Seattle, WA 2003, pp.85-89.

SIAU K, Sheng H, Nah F (2004a). The Value of Mobile Commerce to Customers Proceedings of the Third Annual Workshop on HCI Research in MIS, Washington, DC

SIAU K, Sheng H, Nah F, Davis S (2004b). A qualitative investigation on consumer trust in mobile commerce. International Journal of Electronic Business, 2 (3), pp.283-300.

SILLINCE J A A and Saeedi M H (1999). Computer-mediated communication: Problems and potentials of argumentation support systems. *Decision Support Systems*, 26(4), pp. 287-306.

SOUMITRA D, Berend W, and Arco D (1997), Case-Based Reasoning Systems: From Automation to Decision-Aiding and Stimulation, *IEEE Transactions On Knowledge And Data Engineering*, 9(6) pp.911-922

TSANG, M M., Ho S C and Liang T P (2004). Consumer attitudes toward mobile advertising: An empirical study. International Journal of Electronic Commerce, 8(3), pp.65–78

TUNG B and Lee J (1999). An agent-based framework for building decision support systems, Decision Support Systems, 25(3), pp.225-237.

TURISCO F (2000). Mobile computing is next technology frontier for healthcare providers. *Healthcare Financial Management*, 54(11), pp.78–80.

YUAN Y and Zhang J J (2003). Towards an appropriate business model for m-commerce. International Journal of Mobile Communications, 1(2), pp.35-56.

ULIERU M, Norrie D, Kremer R, and Shen W (2000). A multi-resolution collaborative architecture for web-centric global manufacturing. *Information Sciences*, 127(1-2), pp. 3-21.

VARMA A, Roddy N (1999). ICARUS: Design and deployment of a case-based reasoning system for locomotive diagnostics. Engineering Applications of Artificial Intelligence, 12(6), pp. 681-690.

VARSHNEY U (1999). Networking support for mobile computing, Communications of AIS, 1(1), pp.1-30.

VARSHNEY U (2001). Location management support for mobile commerce applications. In Proceedings of the 1st International Workshop on Mobile Commerce. New York: ACM Press, 2001, pp.1-6.

VARSHNEY U and Vetter R (2001). A framework for the emerging mobile commerce applications, In Proceedings of the 34th Annual Hawaii International Conference on System Sciences.

VARSHNEY U and Vetter R (2002). Mobile commerce: Framework, applications and net-working support. Mobile Networks and Applications, 7. pp.185-198.

WANG Y, Tan K L, and Ren J (2002). A study of building Internet marketplaces on the basis of mobile agents for parallel processing. *World Wide Web*, 5(1), pp. 41-66.

WILKE W, Bergman R and Wess S (1998). Negotiation During Intelligent Sales Support with CBR, Proceedings of the 6th German workshop on Case Based Reasoning, GWCBR'98

WOOLDRIDGE M (1997). Agent based software engineering, IEEE Proceedings of Software Engineering, 144(1), pp. 26-37.

WOOLDRIDGE M and Jennings N (1995). Intelligent agents: Theory and practice. The Knowledge Engineering Review, 10(2), pp. 115-152.

WU D J (2001). Software agents for knowledge management: Coordination in multi-agent supply chains and auctions. *Expert Systems with Applications*, 20(1), pp. 51-64.

YANG, B S, Han T H and Kim Y S (2004). Integration of art-Kohonen neural network and case-based reasoning for intelligent fault diagnosis, *Expert Systems with Applications*, 26(3), pp. 387-395.

Return to Contents of this issue

Copyright Journal of Artificial Societies and Social Simulation, [2007]

