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Zigbee Based E-Menu Ordering System

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Abstract: Traditional restaurant service is typically passive: Waiters must interact with customers directly before processing their orders. However, a high-quality service system should be customer centered; it should immediately recognize customer identities, favorite menus, and expenditure records to provide customer-centric services. To achieve this goal, this study integrates wireless local area network, database technologies, and a menu recommender to develop an intelligent e-restaurant for customer-centric service. This system enables waiters to immediately identify customers via recommend the most appropriate menus through menu recommender for customers. Experimental results that are obtained from a case study conducted in two Taipei restaurants indicate that the proposed system has practical potential in providing customer-centric service.

Keywords: Intelligent E-Restaurant, Menu Recommender, Wireless Local Area Network (WLAN).

I. INTRODUCTION

Restaurant service such as making reservations, processing orders, and delivering meals generally requires waiters to input customer information and then transmit orders to the kitchen for menu preparation. When the customer pays the bill, the amount due is calculated by the cashier. Al-though this procedure is simple, it may significantly increase the waiter's workload and even cause errors in menu ordering or in prioritizing customers, especially when the number of customers suddenly increases during busy hours, which can seriously degrade overall service quality. Therefore, using advanced technologies to improve service quality has attracted much attention in recent years. For instance, the counter system of many fast food restaurants in Taiwan is equipped with a touch screen, keypad, or mouse control interface to enable cashiers to address customer needs. Such systems typically have common point-of-sale (POS) functions that allow waiters to use an optical scanner to directly read 2-D barcodes for order details and billing. How-ever, the POS system requires the waiter to determine customer needs and then enter the information, thereby providing passive service. However, a high-quality service system should be customer centered, i.e., it should immediately recognize customer identities, favorite menus, and expenditure records to provide customer-centric services.

Touch screen has been identified as one of the ten greatest contributory technologies of the 21st century [1], which features more distant reading ability, larger memory capacity, and faster processing capability than the bar code system. Touch screen can also be used to identify objects or human beings. Because of its many advantages, RFID has been applied in many areas [1], such as supply chain management [2], telemedicine [3], manufacturing [4], warehouse management [5], construction industry [6], and digital learning [7]. While many fields have successfully employed Touch screen, studies need to further explore its innovative applications to enhance enterprise competitive advantage and quality of life. For example, innovative applications of Touch screen are still rare in the restaurant industry. Recently, Ngai et al. [8] have developed an Touch screen -based sushi management system in a conveyor-belt sushi restaurant to enhance competitive advantage. Their case study showed that Touch screen technology helps improve food safety, inventory control, service quality, operational efficiency, and data visibility in sushi restaurants. Unfortunately, this system does not support customer-centered service because it cannot actively identify customers. The recommendation system, which is defined as a system which recommends an appropriate product or service after learning customers' preferences and desires, is a powerful tool that allows companies to present personalized offers to their customers. To help researchers to construct their own recommender system, a taxonomy of intelligent recommenders has been explored [9].

This work has analyzed 37 different systems together with their references and has sorted them into a list of eight classification dimensions: five in terms of profile generation and maintenance and three in terms of profile exploitation. These eight dimensions are then used to establish a taxonomy under which the systems being analyzed are classified. In terms of profile exploitation, this research also indicates that three main dimensions characterize intelligent recommending systems: the information filtering method (demographic, content-based (CB), and collaborative), the item-profile matching (when CB), and the user-profile matching (when collaborative) techniques [9]. Recently, Choi et al. [10] have categorized the recommending systems as CB filtering and collaborative filtering (CF), or hybrid ones according to the type of information used to form their responses to customers. Moreover, they have combined CB filtering and CF algorithm with reduced data as a way to deal with large-scale recommendation problems and have demonstrated that the use of reduced datasets saves computational time, and neighbor information improves performance. Several studies [11]–[14] have recently developed various product recommendation systems to enhance customer satisfaction and perceived value. Extracting users' preferences through their buying behaviors and histories of purchased products is the most important element of such a system [11].

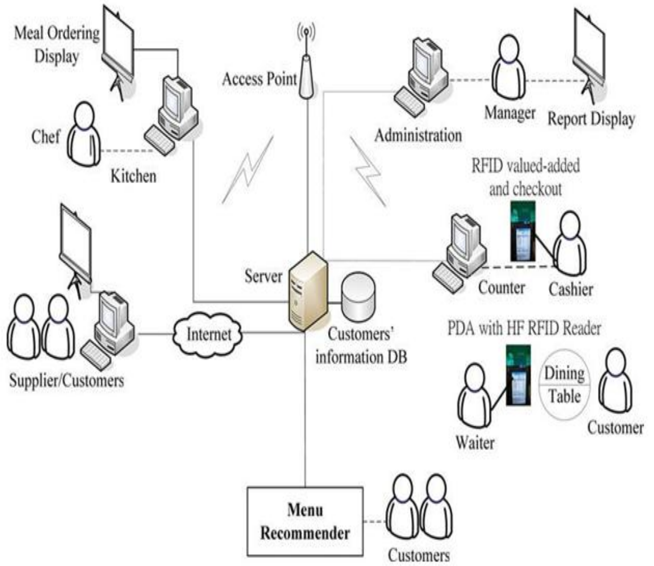

Fig.1.Framework of intelligent e-restaurant for customer-centric service.

In [12], a personal recommender system is designed to recommend vendors' web pages to interested customers. It employed a location-aware mechanism that enables customers to receive the information of their preferred vendors that are in their neighborhood. The experimental results revealed that vendor information can be ranked according to the match with the preferences of a customer. Wang et al. [13] proposed a recommendation system to ensure customer satisfaction and avoid churns. Their study made different strategies that are readily available to help maintain amiable customer relationships and suit new marketing conditions and circumstances. The research in [14] investigated the use of a mobile recommendation agent (MRA) for product information acquisition in in-store purchase situations. The MRA implemented on an RFID-enabled mobile device is able to identify products, which extends traditional product information capabilities on printed product labels by providing relevant product information on demand. To better understand the impact of MRAs on usage intentions, product purchases, and store preferences of consumers, a model is also developed based on theory of planned behavior, innovation diffusion theory, and a technology acceptance model. Recently, Choi and Ahn [15] have presented a method to identify customer preferences and recommend the most appropriate product based on the data captured from customer's real-time web usage behavior, such as viewing, basket placement, and purchasing of products. This method can identify customer preferences for products with insufficient information or even with lack of purchase history.

In order to enhance customer service quality and improve restaurant industry competitiveness, an intelligent e-restaurant that integrates RFID, wireless local area network (WLAN), database technologies, and a menu recommender was implemented. It enables waiters to immediately identify customers via their own RFID-based membership cards and then actively recommends the most appropriate menus for customers. The proposed system provides waiters the functions to access customer information and make orders using the personal digital assistant (PDA), which in turn transmits customer orders instantly via WLAN to the kitchen for menu preparation and to the cashier for bill preprocessing. With this intelligent system, a restaurant can provide high-quality service to customers. The rest of this paper is organized as follows. Section II illustrates the proposed system framework. The menu recommender is presented in Section III. Section IV demonstrates the system implementation, experimental setup, system evaluation, limitations, and lessons learned. Finally, brief discussions are made and concluding remarks are drawn in Section V.

II. PROPOSED INTELLIGENT E-RESTAURANT

Fig. 1 shows a framework overview of the proposed intelligent e-restaurant for customer-centric service. This system pro-vides online menu-ordering and reservation-making functions, as well as a personal menu recommendation service. The menu recommender enables waiters to immediately identify customers via RFID-based membership cards and then actively recommend the most appropriate menus for customers according to their consumption records. For new customers, the service staff provides recommendations based on meal popularity and then creates customers' preferences to store in the back-end database; for long-time customers, service staff uses a multiple-criteria decision-making (MCDM) approach, as detailed in Section III, to infer items preferred by customers or items close to those preferred items based on customers' preference data stored in the system. This system, therefore, helps service providers increase their customer interactions and provides fast and thoughtful services. In this system, the waiter uses a PDA to take customer orders and then wirelessly sends the order to the kitchen server. The chefs prepare the menu from the message shown on the order display system built in the kitchen. The restaurant manager can also use the system to view statistics of the current inventory, sales records, staff information, and other information. Once the customer has finished the meal, the cashier uses the Touch screen -based PDA to identify the membership ID to check out the bill.

III. MENU RECOMMENDER

A. Multicriteria Decision Making Approach

Many researchers have suggested the MCDM approach [15]–[19] as a way for personalized recommendation schemes in electronic commerce by considering multiple aspects of the products. Specifically, the investigation in [15] developed a scheme based on MCDA approach by considering the ordinal relationships among the products and the multiple aspects of products. The MCDM approach that is proposed in [15] is extended to fit the requirement of this study to develop a menu recommender for customer-centric service in an intelligent e-restaurant. The MCDM approach can be effectively utilized to evaluate alternatives (i.e., menus) because it evaluates items that are available for selection by using multiple criteria (e.g., specifications). Thus, for users stating their preference for one meal over another, value of the preferred alternative is assumed to be greater than that of the less preferred alternative. To deal with this situation, this study integrates the MCDM approach, several intelligent algorithms, and customers' information database (DB) to develop a menu recommender. The pro-posed e-restaurant enables service staff to immediately identify a customer's status, preference, and consumption record by reading his RFID membership card and utilize the built-in menu recommender to offer optimal menu choices to the customer.

The proposed menu recommendation procedure consists of creating the price-flavor-material (PFM) model, estimating the pairwise dominance (PWD) relationships using the hybrid mutated particle swarm optimization (HMPSO) algorithm, transforming the dominance values into the strength of preference, and calculating the domination degree (DD) of each customer. Fig2 shows the proposed menu recommendation procedure that consists of the four aforementioned phases, and each phase is described as follows. Phase 1 (Creating the Price-Flavor-Material Model): This paper presents a PFM model for simplicity to determine the alternative criterion value by using the following control criteria: price (P) (menu price), flavor (F) (e.g., spicy, curry flavored, bean paste-flavored, homemade flavor, and sweet, and sour), and material (M) (e.g., seafood, vegetables, meat, and soybean products). Linear attributes, such as price, must be normalized to 0–1 before estimating the PWD relationships. For nonlinear attributes, for example, flavor and material, conversions to linear functions have to be done before normalization. The PFM model can also resolve the issue of product/service attribute in a recommendation system that the conventional MCDM techniques, such as in [15] and [20], do not deal with. For example, it can be employed to the application to recommend laptop computer products, which contain nonlinear at-tributes like color, to customers.

The service staff can provide recommendations that are based on menu materials or meal popularity for new customers and, then, store their preferences in the system. Next, the PFM model is constructed for customers who have visited the e-restaurant five times, in which training data include price, flavor, and materials. Restated, each customer must have visited at least five times to receive customer-centric service that is provided by the menu recommender. Table II displays an example of the customer expenditure record. The criteria values can be obtained as follows. [25]. Among them, PSO [25] has attracted much attention in recent years because of its many advantages, such as simple in implementation and capable of quickly converging to a reasonably good solution [25]. Kennedy and Eberhart [8] originally proposed the PSO algorithm, which is an evolutionary computation technique using the concept of swarm intelligence. Recently, Lin et al. [9] have proposed a cultural cooperative particle swarm optimization learning method, which combines the cooperative particle swarm optimization and the cultural algorithm, to increase global search capacity. It is efficient to avoid being trapped in a suboptimal solution and to ensure that a nearby global optimal solution can be found. Genetic algorithm (GA) is also a commonly used evolutionary searching scheme. The similarity between PSO and GA is that both randomly generate initial populations, and both search for the optimum value by evolution. However, different to GA, instead of using crossover and mutation to evolve, the PSO algorithm evolves by following the best particle of the swarm in the searching space. The original PSO algorithm [8] updates the position and velocity of particles (solutions) for the next generation with the following rule:

TABLE I: Calculated Strength of Preferences Between Alternatives

Alt.	*Alternatives* 1	2	3	4	5	6	7	8	9	10
a_1	–	0	0.53	0.5	0.7	0.88	0.98	0.25	0.88	0.84
a_2	1	–	0.21	1	0	0.367	1	1	0.125	0.015
a_3	0.47	0.79	–	0.098	0	0.96	0.928	0.018	0.605	0.99
a_4	0.50	0	0.902	–	0.439	1	1	0.008	0.093	0.987
a_5	0.30	1	1	0.561	–	1	1	1	0.002	1
a_6	0.12	0.633	0.040	0	0	–	0.946	1	0	0.996
a_7	0.02	0	0.072	0	0	0.054	–	1	1	0.383
a_8	0.75	0	0.982	0.992	0	0	0	–	0	0.723
a_9	0.12	0.875	0.395	0.907	0.998	1	0	1	–	0.956
a_{10}	0.16	0.985	0.010	0.013	0	0.004	0.617	0.277	0.04	–

TABLE II: Calculated DD of Each Menu

	Alternatives 1	2	3	4	5	6	7	8	9	10
DD	0.162	0.125	0.1264	0.1263	0.208	0.082	0.052	0.076	0.179	0.045
Idealized DD	0.778	0.601	0.6077	0.6072	1	0.394	0.25	0.365	0.861	0.216
Ranking	3	6	4	5	1	7	9	8	2	10

$+ d(a_1, a_3) \times WA_6 + d(a_8, a_3) \times WA_7 + d(a_4, a_3)$

$\times \quad WA_8 + d(a_5, a_3) \times WA_9$

$= \quad 0.99 \times 0.0217 + 0.96$

$\times \quad 0.0173 + 0.928 \times 0.021 + 0.79 \times 0.03 + 0.605$

$\times \quad 0.035 + 0.47 \times 0.039 + 0.098 \times 0.048 + 0.018$

$\times \quad 0.052 + 0.0 \times 0.735$

$= \quad 0.1264.$

A final decision can be made by the customer's DD, where the larger the DD of a menu, the better it is. The idealized DD values are obtained from the DD values by dividing each value by the largest value in that column. The magnitudes of idealized DDs indicate that menu as is the best one from the customer's perspective (see Table VI). Then, the system actively recommends the most appropriate menus for customers according to the DD value.

IV. SYSTEM IMPLEMENTATION AND EVALUATION

A. System Implementation

The user interface of the proposed system is built with Visual C# 2005 and embedded Visual C++. The database is built on a Microsoft SQL Server 2005 for server management and statistic reporting. Fig. 6(a)–(c) shows the system login interface, menu information, and food inventory level, respectively. The ordering result, recommended result, and ordering information that are displayed in kitchen side are presented in Fig. 7(a)–(c), respectively.

B. Experimental Setup

The experiments are set up as follows. This study included a case study that involves two small- and medium-scaled cooperated branch restaurants located in downtown Taipei City near our university. The e-restaurant provides ten menus during the test phase. Experiments are performed during operating hours from August 2009 to August 2010, with 30 waiters who served continuously during this period and 90 customers who agreed to participate in the experiment. Participating customers were not limited in terms of gender and age.

C. System Evaluation

This study employed the technology acceptance model (TAM) [10] to measure usefulness, ease of use, and behavioral intention (BI) of the proposed system. TAM is an information system model used to evaluate why individuals accept and use a new technology. It posits that two particular beliefs, i.e., perceived ease of use and perceived usefulness, are of primary relevance. Perceived ease of use is the degree to which the prospective waiter perceives the information system easy to use. Perceived usefulness is defined as the subjective belief that the use of a given information system improves waiter working efficiency. BI is a function of perceived usefulness and perceived ease of use that directly influences actual usage behavior of waiters. In addition, outcome quality including waiting time, tangibles, and valence was applied to evaluate perceived quality of service of the proposed system [11]. At least five visits are required for each customer to benefit from the customer-centric service provided by the menu recommender. Customers whose visits are less than six times are recommended with most frequent ordered menus similar to new customers. Following completion of the case study, a questionnaire (see Table VII) was administered to 30 waiters to assess the perceived ease of use (PEU, Part A), perceived usefulness (PU, Part B), and BI toward using the proposed e-restaurant system (BI, Part C). In addition, 90 customers who had visited the restaurant for more than five times were asked to fill a questionnaire to evaluate the degree of service quality (Part D).

Although Davis adopted six items to test perceived usefulness and six items for PEU, in most of the following studies, only subset of the questionnaire was adopted. For example, in addition to overall usefulness, only effectiveness, performance, and productivity were adopted for PU. Wu et al.[13] only adopted two questions (i.e., performance and effectiveness) to test PU and three questions (i.e., learning is easy, easy to get system to do the desired task, and easy to become skillful) to test PEU, respectively. Regarding PU, we intended to ignore productivity since we emphasized on improving the quality of service rather than elevating the number of customers for the restaurant. Additionally, we focused on the design of friendly GUI to make the system easy to operate. Hence, the questions of PEU were modified as follows: 1) the interface is user friendly; and 2) the system provides sufficient functions and is easy to operate. The first question implies "learning is easy?" while the second question mimics "easy to get system to do the desired task" and "easy to become skillful." Relationship quality is increasingly emerging as a strategy for organizations that strive to retain loyal and satisfied customers in today's highly competitive environment [24]. Particularly, in labor-intensive services such as restaurants, quality is created during the process of service delivery when servicing staff and customers encounter. Therefore, an instrument to measure service quality must have adequate means of assessing customers' perceptions of service quality during these service encounters [5], [6].

Rust and Oliver [41] suggested that the overall perception of quality of service should include three dimensions: customer–employee interaction, service environment, and outcome quality. In this study, we evaluate perceived quality affected by adopting the proposed system based only on the outcome quality measured by three sub-dimensions, i.e., waiting time, tangibles, and valence [4]. As shown in Table VII, waiting time sub-dimension is delineated by question D1, whereas tangible and valence sub-dimensions by question D2. Responses were measured using a five-point Likert-scale ranging from 1 (strong disagreement) to 5 (strong agreement). Table VII reveals that the mean values of all questions are significantly higher than neutral value (3) at the level of 0.001 tested with one-sample t-test. This table also lists the standard deviation of each question. Additionally, accuracy of the recommended menus is predicted using the hit rate (HR) to evaluate the effectiveness of the proposed recommending system. The hit count is calculated from the customer orders after the sixth visit, which matches exactly the menus that are provided by the proposed recommending system. Data are analyzed from 90 customers who had visited the restaurants more than five times and filled in the questionnaires, resulting in 261 hits among 399 predictive menu recommends. According to those results, the average HR achieves 65.41% indicating that the proposed system can recommend favorite menus for customers with a reasonable accuracy in most of their restaurant visits.

D. Limitations and Lessons Learned

Some limitations of the proposed system and lessons learned from this study are described as follows to serve as the guideline for system refinement in the future.

Limitations: Each customer must visit at least five times to benefit from the customer-centric service that the proposed menu.

V. RESULTS

Results of this paper is shown in bellow Figs.2 and 3.

Fig.2.EMenu system ordering.

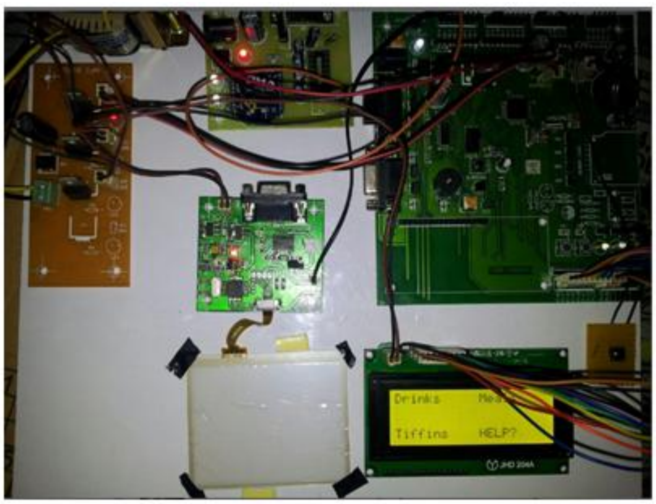

Fig.3.Hardware circuit.

VI. DISCUSSIONS AND CONCLUSION

This study constructed an intelligent e-restaurant system using RFID, WLAN, database technologies, and a menu recommender to offer customer-centric service to enhance customer service quality and improve restaurant industry competitiveness. It enables waiters to immediately identify customers via their own RFID-based membership cards and then actively recommend the most appropriate menus for customers. On the other hand, customers can also use the RFID-based member-ship card to pay bills instead of using cash. The proposed sys-tem enhances dining table service by enabling waiters to access customer information and make orders using the PDA. The PDA-based service unit enables customer orders to be instantly transmitted via WLAN to the kitchen for menu preparation. Expenditure information can also be sent to the cashier for bill preprocessing. Restaurant managers can access the database to evaluate business status anytime and make appropriate redeployments for food materials. All ordering and expenditure information is digitized for database storage, which allows restaurant owners to consider discounts or customer promotions based on expenditure statistics. Customers can thus appreciate high-quality service, which in turn highly promotes enterprise image and increases business revenue for the restaurant.

The proposed menu recommendation procedure consists of creating the PFM model, estimating the PWD relationships using the proposed HMPSO algorithm, transforming the dominance values into the strength of preference, and calculating the DD of menus for each customer. The greater the DD of a menu, the more it is preferred. An additional concern is that although the system provides recommendations only to members, the waiter also records the menus for other nonmember customers if the orders are made jointly. At the same time, the waiter convinces nonmember customers to join customer-centric service. The recommendation system is effective to foster customer relations and increase the working efficiency of waiters, while not affecting the waiter's benefits. A case study is conducted in two Taipei restaurants with a questionnaire survey to 30 waiters in terms of perceived ease of use, perceived usefulness, and BI toward using the proposed system based on the TAM and another survey to 90 customers in terms of outcome quality being administered. The survey results verified the effectiveness of the proposed system in providing customer-centric service, thus facilitating the developments of RFID-related industry, ultimately raising overall global competitiveness. We will conduct a full-scale experiment in the near future with more restaurants and improve system functions based on the experimental results and participants' feedback to meet practical application requirements. In addition, user and customer behavior and social impact after the adoption of information systems and technologies need to be further studied in the future. Furthermore, a comparison between recommendations made by the waiters and by the recommender system will also be conducted.

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