Developing an Intelligent e-Restaurant With a Menu Recommender for Customer-Centric Service
Tan-Hsu Tan, Ching-Su Chang, and Yung-Fu Chen

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 radio frequency identification (RFID), 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 RFID-based membership cards and then actively 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.

Index Terms—Intelligent e-restaurant, menu recommender, radio frequency identification (RFID), 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. Although 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 touchscreen, 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. However, 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.

Radio frequency identification (RFID) 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. RFID 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 RFID, studies need to further explore its innovative applications to enhance enterprise competitive advantage and quality of life. For example, innovative applications of RFID are still rare in the restaurant industry. Recently, Ngai et al. [8] have developed an RFID-based sushi management system in a conveyor-belt sushi restaurant to enhance competitive advantage. Their case study showed that RFID 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]. 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 provides online menu-ordering and reservation-making functions, as well as a personal menu recommendation service. The menu
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. A well-known method to evaluate alternatives over multiple criteria is to use an additive form which adds various values (scores or performances) of an alternative, measured with respect to each of the criteria, together to obtain an overall score of the alternative across multiple criteria, as defined in the following equation:

\[ S(a_j) = \sum_{i=1}^{N} w_i v_i(a_j) \]  

(1)

where \( S \), \( 0 \leq S \leq 1 \), is the overall multiple criteria value with respect to alternative \( a_j \); \( w_i \) is a scaling factor representing the relative importance of the criterion; \( v_i(a_j) \), \( 0 \leq v_i(a_j) \leq 1 \), is a single criterion value of alternative \( a_j \) with respect to criterion \( v_i \); and \( N \) indicates the number of alternative items. By considering two alternatives \( a_k \) and \( a_m \), the fact that \( a_k \) is preferred to \( a_m \) is denoted by

\[ S(a_k) \geq S(a_m) \]  

(2)

or

\[ \sum_{i=1}^{N} w_i v_i(a_k) \geq \sum_{i=1}^{N} w_i v_i(a_m). \]  

(3)

Example: Assuming that menu \( a_1 \) is preferred to \( a_2 \), \( a_2 \) is preferred to \( a_3 \), and \( a_3 \) is preferred to \( a_4 \), these ordinal relationships between menus can be denoted as \( S(a_1) \geq S(a_2) \), \( S(a_2) \geq S(a_3) \), and \( S(a_3) \geq S(a_4) \). Furthermore, we assume that each of the menus is evaluated by the three criteria (i.e., \( CR-1 \), \( CR-2 \), and \( CR-3 \)) shown in Table I, and then, the weights \( w_i \), \( i = 1, 2, 3 \), where \( w_i \in [0, 1] \) and \( \sum_{i=1}^{3} w_i = 1 \) can be obtained by solving

\[
\begin{align*}
S(a_1) - S(a_2) &\geq 0 \quad \Rightarrow -0.2w_1 - 0.5w_2 + 0.6w_3 \geq 0 \\
S(a_2) - S(a_3) &\geq 0 \quad \Rightarrow -0.1w_1 + 0.2w_2 - 0.1w_3 \geq 0 \\
S(a_3) - S(a_4) &\geq 0 \quad \Rightarrow 0.2w_1 + 0.1w_2 + 0.2w_3 \geq 0.
\end{align*}
\]

(4)

Suppose two menus \( a_s \) and \( a_t \) are not included in the alternatives and need investigating to identify which menu the customer ranks more highly. To compare two alternatives under the feasible region of criteria weights, this study designs an optimization algorithm to calculate the degree of \( a_s \) over \( a_t \) (or, inversely, the degree of \( a_t \) over \( a_s \)) on two extreme points, i.e., pessimistic and optimistic. The degree of \( a_s \) over \( a_t \) in the interval \([\zeta_{\min}(a_s, a_t), \zeta_{\max}(a_s, a_t)]\) represents the range of possible differences of evaluation values between \( a_s \) and \( a_t \). The intervals can be obtained from the following equations:

\[
\begin{align*}
\zeta_{\min}(a_s, a_t) &= \min_i \sum_{i=1}^{N} w_i [v_i(a_s) - v_i(a_t)] \\
&\text{subject to constraint set } C \quad (5)
\end{align*}
\]

\[
\begin{align*}
\zeta_{\max}(a_s, a_t) &= \max_i \sum_{i=1}^{N} w_i [v_i(a_s) - v_i(a_t)] \\
&\text{subject to constraint set } C. \quad (6)
\end{align*}
\]

To obtain a ranking among the alternatives as the number of alternatives increases becomes difficult. In other words, the number of nondominated menus [16] (an alternative \( X \) is utility dominated if and only if there exists \( X' \in A \) such that \( X' \) is preferred to \( X \) subject to a constraint set \( C \)). Otherwise, \( X \) is
utility nondominated) resulting from solving (5) and (6) is generally larger than we would like.

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 proposed 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. Fig. 2 shows the proposed menu recommendation procedure that consists of the four aforementioned phases, and each phase is described as follows.

**Phase 1 (Creating the PFM 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.

**Phase 2 (Estimating the Pairwise Dominance (PWD) Relationships using the HMPSO algorithm):**

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 attributes 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 by using the following control criteria.

<table>
<thead>
<tr>
<th>Menu</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price (CR-1)</td>
</tr>
<tr>
<td>$a_1$</td>
<td>970</td>
</tr>
<tr>
<td>$a_2$</td>
<td>320</td>
</tr>
<tr>
<td>$a_3$</td>
<td>450</td>
</tr>
<tr>
<td>$a_1$</td>
<td>970</td>
</tr>
<tr>
<td>$a_1$</td>
<td>970</td>
</tr>
</tbody>
</table>

Phase 2 (Estimating the Pairwise Dominance Relationships Using the Hybrid Mutated Particle Swarm Optimization Algorithm): A PWD judgment expresses an opinion about the dominance (importance, preference, or likelihood) of one element over the other. The values of PWD relationships between menus exist over intervals of $[\min(a_j, a_i), \max(a_j, a_i)]$. To obtain accurate PWD relationships between menus, this study presents a HMPSO algorithm by incorporating the enhanced Nelder–Mead simplex-PSO-Center particle (NM-PSO-C) search scheme [22], [23] and mutation operation [24]. The detail of HMPSO is described as follows.

Previous studies have developed evolutionary algorithms for many years to solve complex constrained optimization problems...

![Diagram of Proposed Menu Recommender](image-url)
[25]. Among them, PSO [25]–[30] 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 [28] originally proposed the PSO algorithm, which is an evolutionary computation technique using the concept of swarm intelligence. Recently, Lin et al. [29] 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 [28] updates the position and velocity of particles (solutions) for the next generation with the following rule:

\[
\begin{align*}
    v_i^{g+1} &= v_i^g + c_1 \times \text{rand()} \times (b_i^{\text{gbest}} - b_i^g) \\
    b_i^{g+1} &= b_i^g + v_i^{g+1}
\end{align*}
\]

where \( b_i^g = [b_{i,1}^g, b_{i,2}^g, ..., b_{i,K}^g] \) is the \( i \)-th particle in the \( g \)-th generation whose dimension is \( K \), \( v_i^g \) is the \( i \)-th particle’s \( K \)-dimensional velocity in the \( g \)-th generation, \( v_i^{g+1} \) is the \( i \)-th particle’s velocity in the \( (g+1) \)-th generation, and \( c_1 \) and \( c_2 \) are learning factors that are called individual factor and social factor, respectively. This means that each particle cooperates and shares information with the others, and \( c_1 = c_2 = 2 \). Typically, \( b_i^{\text{gbest}} \) is the best position of the \( i \)-th particle recorded in its individual memory and \( b_i^{\text{gbest}} \) is the best particle in the swarm. The function \( \text{rand()} \) is a random variable generator that is used to generate \( K \)-dimensional random variables uniformly distributed over \([0, 1]\). The value of \( |v| \) is limited to the upper bound of \( v_{max} \); the larger \( v_{max} \) helps with the global search and the smaller \( v_{max} \) helps with the local search. Notably, \( v_{max} \) determines the convergence speed of PSO.

As a global optimizer, previous studies have widely adopted PSO to optimize a wide range of continuous functions. Practical engineering problems are, however, very complex with high search space dimensions, which makes existing PSOs perform less satisfactorily in terms of accuracy and convergence. Actually, most existing PSOs have not achieved the balance between exploration and exploitation.

To overcome the aforementioned difficulty, a new PSO-based approach is presented by introducing the mutation operation [24] into the NM-PSO-C search scheme [22], [23]. A rationale of this approach is that mutation and enhanced NM simplex search can be used to improve exploration search and the exploitation search of PSO, respectively.

First, the enhanced NM simplex search produces extra \( N \) points around \( gbest \) to generate a simplex of \((N + 1)\) vertex points to offer a thorough exploitation in the promising direction along the best solution \( gbest \) so far obtained by PSO. Then, a center particle is calculated according to (9) and (10) with \( P = (N + 1) \) to replace the particle with a poorer fitness in the swarm because center particle benefits PSO to find best solution [30]

\[
\begin{align*}
    b_{c,p} = \frac{1}{P} \sum_{i=1}^{P} b_i \\
    v_{c,p} = \frac{1}{P} \sum_{i=1}^{P} v_i
\end{align*}
\]

In addition, it has been reported [31] that the solution may easily be trapped at local optimum if the PSO particles lack diversity in exploration search. Thus, a mutation is suggested to be introduced into PSO [31], as illustrated in Fig. 3. For a population of \( P \) particles, in the first stage, \( \alpha_1 \times P \) particles are selected. In the second stage, one mutation point for each selected particle is randomly chosen and, then, is mutated with a rate of \( \alpha_2 \). That is, the sign of each selected point is changed from positive (negative) to negative (positive) if a uniformly generated random number \( \gamma \) is smaller than or equal to \( \alpha_2 \). The second stage aims to increase particle diversity meanwhile prevent the population from being randomized. In other words, \( \alpha_2 \) compromises the diversity and convergence of the PSO algorithm.

Fig. 4 depicts the proposed HMPSO. Its input and output parameters are \( w_i \) and the interval value \([\gamma_{\text{min}}(\cdot), \gamma_{\text{max}}(\cdot)]\), respectively, as given in (1), (5), and (6). The following describes important operation steps of the HMPSO:

1) Generating initial population: randomly generate \( P \) particles.

2) Ranking population: calculate fitness \( S(\alpha_j) = \sum_{i=1}^{N} w_i \cdot v_i(\alpha_j), j = 1, 2, ..., N \), for each particle \( w_i^g = [w_{i,1}^g, w_{i,2}^g, w_{i,3}^g] \) in the \( g \)-th generation and then sort the particles according to their fitness in descending order.

3) Calculating center particle: calculate the position and velocity of the center particle and replace the \( m \)-th particle \((m \neq 1)\) in the current swarm by the center particle.

4) Exploitation search: choose the best particle \( gbest \) every \( K \) iterations. Generate \( N \) vertex points around \( gbest \) to allow the enhanced NM simplex search to produce a new individual \( gbest_{\text{new}} \). Replace \( gbest \) by \( gbest_{\text{new}} \), if \( gbest_{\text{new}} \) is better than \( gbest \), for further evolution.
Exploration search: based on gbest, new particles can be generated by performing PSO with mutation operation to form a new population.

Termination: if terminating condition is satisfied, stop evolution and return the best solution. Otherwise, repeat steps 2–5.

After the best particle of $w_i$ was found, it can be substituted into (5) and (6) to obtain the minimum and maximum values of PWD relationships. An experiment was conducted to compare the performances of GA and PSOs on estimation of minimum and maximum values of PWD relationships. The population size (chromosomes/particles) of the three schemes is set to 100. Crossover rate and mutation rate that are employed in GA are 1.0 and 0.3, respectively. Experimental results that are presented in Fig. 5(a) and (b) indicate that the proposed HMPSO achieves the best performance since the HMPSO tends to converge toward the global minimum and maximum solutions, while the others do not.

As illustrated in Fig. 5, the interval that is obtained by the HMPSO scheme is greater than the other two schemes. The DD values that are obtained by HMPSO, NM-PSO-C, and GA are 0.130, 0.128, and 0.124, respectively. Notably, a wider interval leads to a higher strength of preference as indicated in (11), which in turn gains a higher domination as implied in (14) and, consequently, achieves the best ranking of alternatives.

Phase 3 (Transforming the Dominance Values Into the Strength of Preference): In this phase, the interval values $[\zeta_{\text{min}}(a_s, a_t), \zeta_{\text{max}}(a_s, a_t)]$ that are derived in Phase 2 are transformed into strength of preferences $d : A \times A \rightarrow [-1, 1]$, where $A = \{a_1, \ldots, a_N\}$.

Let $\Psi(a_s, a_t) = S(a_s) - S(a_t)$, $a_s, a_t \in A$, and define $d(a_s, a_t) = P(\Psi(a_s, a_t) \geq 0)$, where $P(\cdot)$ denotes the probability of $\Psi(\cdot)$ being greater or equal to zero. For a given pair $a_s, a_t \in A$, $\zeta_{\text{min}}(a_s, a_t)$ and $\zeta_{\text{max}}(a_s, a_t)$ are the minimum and maximum values of $\Psi(\cdot)$, respectively. Thus, a measured $d(a_s, a_t)$ denotes the strength of preference, indicating the degree to which the overall evaluation of the menu $a_s$ exceeds that of menu $a_t$, where the measured $d(a_s, a_t)$ ranges in the 1-D interval $[\zeta_{\text{min}}(a_s, a_t), \zeta_{\text{max}}(a_s, a_t)]$. To derive a specific strength of preference, suppose that the distribution $f_{(a_s, a_t)} = (\Psi(a_s, a_t))$ over $[\zeta_{\text{min}}(a_s, a_t), \zeta_{\text{max}}(a_s, a_t)]$ can be approximated by a symmetric triangular distribution with a vertical axis through $\Psi_m$, where $\Psi_m = (\zeta_{\text{max}}(a_s, a_t) + \zeta_{\text{min}}(a_s, a_t))/2$. Then, $d(a_s, a_t)$ becomes [15], [33], [34]

$$d(a_s, a_t) = \begin{cases} 1 - \frac{[\zeta_{\text{min}}(a_s, a_t)]^2}{2[\Psi_m - \zeta_{\text{min}}(a_s, a_t)]^2}, & \text{if } \Psi_m \geq 0 \\ \frac{\zeta_{\text{max}}(a_s, a_t)^2}{2[\zeta_{\text{max}}(a_s, a_t) - \Psi_m]^2}, & \text{if } \Psi_m < 0. \end{cases}$$

For example, suppose that a value interval between menus $a_1$ and $a_2$ is $[\zeta_{\text{min}}(a_1, a_2), \zeta_{\text{max}}(a_1, a_2)] = [-0.21, 0.65]$. Then, the strength of preference for menu $a_1$ can be calculated with (11), which is $d(a_1, a_2) = 0.88$. 

Fig. 4. Proposed HMPSO scheme.

Fig. 5. Learning curves of GA with ranking method, HMPSO, and NM-PSO-C (a) for minimum value estimation and (b) for maximum value estimation.
Phase 4 (Calculating the Customer’s Domination Degree):
All realistic MCDM problems face various uncertainties. Since the alternative evaluations with respect to the criteria are uncertain, we assume them to have a stochastic nature [33], [34]. An $n$-dimensional ordered weighted averaging (OWA) operator assigns a combined goodness measure for each alternative in an MCDM problem based on an $n$-dimensional vector $\mathbf{w} = (w_1, w_2, \ldots, w_n)$ of order weights with $w_j \geq 0$ for all $j$, and $\sum_{j=1}^{n} w_j = 1$, as defined in

$$F(a_1, a_2, \ldots, a_n) = \sum_{j=1}^{n} w_j b_j = w_1 b_1 + w_2 b_2 + \cdots + w_n b_n$$

(12)

where $F : I^n \rightarrow I$ with $I = [0, 1]$, and $b_j$ is the $j$th largest element in the set of $\{a_1, a_2, \ldots, a_n\}$. The input vector components are ordered before multiplying them by the order weights. The OWA method possesses many different options of order weights [35]–[39], where fuzzy quantifiers were used to obtain parameter assessments from the decision maker. A linguistic (fuzzy) quantifier allows for a more flexible quantification than the general and existing quantifiers. A general form of a linguistically quantified statement is $Q(p) = p^\beta$, $\beta > 0$, $0 \leq p < 1$, where $Q$ denotes a linguistic quantifier such as “Most,” “Many,” “A few,” “Almost all,” “About half,” “About 60%,” etc., and, $Q(p)$ denotes a membership. By changing the parameter, $\beta$, one can generate different types of quantifiers and associated operators between the two extreme cases of the “All ($\beta = \infty$)” and “At least one ($\beta = 0$)” quantifiers. For example, the quantifiers $Q(p)$ with $\beta = 0.2, 0.5, 1, \text{ and } 2$ correspond to “At least a few,” “A few,” “Half (identity),” and “Most,” respectively [37].

Given a fuzzy linguistic quantifier $Q$, the OWA weights were generated by the formula $w_i = Q(i/N) - Q((i - 1)/N)$, for $i = 1, \ldots, N$; then, we associate a degree of orness with this quantifier, as indicated in the following:

$$\text{orness}(Q) = \alpha = \sum_{i=1}^{N} \frac{N - i}{N - 1} \left( Q \left( \frac{i}{N} \right) - Q \left( \frac{i - 1}{N} \right) \right)$$

(13)

The DD for each menu, namely, the degree to which each menu dominates the other menus, is calculated as

$$D_{Ds} = F_Q [d(a_s, a_t)] = \sum_{i=1}^{N} w_Q^i \cdot d(a_s, a_t), \text{ for } s \neq t$$

(14)

where $D_{Ds}$ represents the DD of $a_s$ over all the other menus, $N$ represents the number of alternative items, and $F_Q$ and $w_Q^i$ are the OWA operator and the weights guided by the fuzzy linguistic quantifier $Q$, respectively. The DD is used such that the greater the DD of a menu, the more it is preferred.

This study obtains the DD of each alternative over the remaining ones by applying the linguistic quantifier with the type of “Most,” because it has been proven to be effective in many applications [15]. The procedure of the algorithm is performed as follows.

Table III: Criteria Values of an Example with Ten Alternatives and Three Criteria

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>CR-1</th>
<th>CR-2</th>
<th>CR-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$</td>
<td>0.8</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>$a_2$</td>
<td>0.6</td>
<td>0.0</td>
<td>0.4</td>
</tr>
<tr>
<td>$a_3$</td>
<td>0.5</td>
<td>1.0</td>
<td>0.6</td>
</tr>
<tr>
<td>$a_4$</td>
<td>1.0</td>
<td>0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>$a_5$</td>
<td>0.0</td>
<td>0.8</td>
<td>0.3</td>
</tr>
<tr>
<td>$a_6$</td>
<td>0.6</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td>$a_7$</td>
<td>0.5</td>
<td>0.5</td>
<td>0.9</td>
</tr>
<tr>
<td>$a_8$</td>
<td>0.8</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>$a_9$</td>
<td>0.5</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>$a_{10}$</td>
<td>0.4</td>
<td>0.7</td>
<td>1.0</td>
</tr>
</tbody>
</table>

B. Numerical Example

This section illustrates a numerical example to explain how the proposed menu recommender works. An intelligent e-restaurant provides ten alternatives, each of which is characterized by three criteria: price (CR-1), flavor (CR-2), and menu materials (CR-3). The recorded data including price, flavor, and materials of the first five ordered menus were used to construct the PFM model for an individual customer. Using the control criteria of the PFM model, the normalized value of each criterion $v_i(a_j)$ and the value function can be obtained from (1).

Suppose that the normalized criteria values for ten alternatives are obtained from Phase I; an example with ten alternatives and three criteria are shown in Table III. Assume that the customer considers that Criterion 1 is more important than Criterion 2,
TABLE IV
CALCULATED DOMINANCE VALUES BETWEEN PRODUCTS

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>(a_i)</th>
<th>(a_2)</th>
<th>(a_3)</th>
<th>(a_4)</th>
<th>(a_5)</th>
<th>(a_6)</th>
<th>(a_7)</th>
<th>(a_8)</th>
<th>(a_9)</th>
<th>(a_m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_1)</td>
<td>[0.235, 0.265]</td>
<td>[0.17, 0.179]</td>
<td>[0.15, 0.05]</td>
<td>[0.175, 0.628]</td>
<td>[0.04, 0.129]</td>
<td>[0.02, 0.199]</td>
<td>[0.19, 0.05]</td>
<td>[0.05, 0.257]</td>
<td>[0.09, 0.023]</td>
<td></td>
</tr>
<tr>
<td>(a_2)</td>
<td>[0.1, 0.04]</td>
<td>[0.37, 0.31]</td>
<td>[0.278, 0.396]</td>
<td>[0.30, 0.09]</td>
<td>[0.29, 0.21]</td>
<td>[0.45, 0.28]</td>
<td>[0.20, 0.04]</td>
<td>[0.36, 0.029]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_3)</td>
<td>[0.33, 0.06]</td>
<td>[0.335, 0.449]</td>
<td>[0.02, 0.025]</td>
<td>[0.01, 0.195]</td>
<td>[0.23, 0.02]</td>
<td>[0.08, 0.26]</td>
<td>[0.01, 0.104]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_4)</td>
<td>[0.270, 0.78]</td>
<td>[0.001, 0.279]</td>
<td>[0.002, 0.349]</td>
<td>[0.13, 0.009]</td>
<td>[0.165, 0.41]</td>
<td>[0.034, 0.39]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_5)</td>
<td>[0.010, 0.071]</td>
<td>[0.16, 0.335]</td>
<td>[0.115, 0.19]</td>
<td>[0.005, 0.12]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_6)</td>
<td>[0.24, 0.328]</td>
<td>[0.080, 0.295]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_7)</td>
<td>[0.01, 0.078]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Criterion 2 is more important than Criterion 3, and the importance of Criterion 3 is between 0.1 and 0.3; these statements can be summarized as follows:

Since a set of preferences is nonempty and contains more than one element, dominance relations have to be checked via a mathematical program. We apply HMPSO to compute the alternative intervals with a lower bound \(\zeta_{\text{min}}(\cdot)\) and an upper bound \(\zeta_{\text{max}}(\cdot)\). For example, the lower bound and upper bound of paired dominance (PD) relation [17] between \(a_2\) and \(a_3\) can be obtained by minimizing and maximizing (15), respectively

\[
\{(0.6-1.0)w_1 + (0.0-0.4)w_2 + (0.4-0.5)w_3 : w_1, w_2, w_3 \in W\}. \tag{15}
\]

The obtained lower and upper bounds of PD are \(\zeta_{\text{min}}(\cdot) = -0.37\) and \(\zeta_{\text{max}}(\cdot) = -0.31\), respectively. Table IV lists the calculated dominance values between alternatives. The dominance values that are listed in Table IV are further transformed into the strengths of preference using (11), as shown in Table V, which denotes the dominance strength of one menu over the others.

Finally, this system calculates the DD (DD\(_m\), \(m = 1, \ldots, 10\)) of alternatives by employing the Fuzzy OWA operator. Then, the Fuzzy OWA weights \(W = \{w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8, w_9, w_{10}\}\) with orness \(|Q| = \alpha = 2/10\) are generated. The procedure of solving Fuzzy OWA weights is described as follows.

**Step 1:**
Randomly generate \(N + 1\) nonnegative real number \(p_i\) with increasing order as \(P = \{0, 2, 3, 4, 5, 7, 8, 9, 11, 12, 15\}\).

**Step 2.1:**
Calculate

\[
Q = \{q_0, q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, q_9, q_{10}\} = \{0, 2, 3, 4, 5, 7, 8, 9, 11, 12, 15\}
\]

with \(q_N = \sum_{k=0}^{N} p_k\).

**Step 2.2:**
Calculate \(S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}\}\). With \(s_0 = q_0/q_N, s_1 = q_1/q_N, s_2 = q_2/q_N, \ldots, s_10 = q_{10}/q_N\).

\[
\alpha' = \sum_{k=1}^{N-1} \frac{s_k}{N-1} = \frac{1}{N-1} (s_1 + s_2 + \cdots + s_{N-1}) = \frac{1}{N-1} \left( \frac{2}{76} + \frac{5}{76} + \frac{9}{76} + \frac{14}{76} + \frac{21}{76} + \frac{29}{76} + \frac{38}{76} + \frac{49}{76} + \frac{61}{76} \right)
\]

The obtained lower and upper bounds of PD are \(\zeta_{\text{min}}(\cdot) = -0.37\) and \(\zeta_{\text{max}}(\cdot) = -0.31\), respectively. Table IV lists the calculated dominance values between alternatives. The dominance values that are listed in Table IV are further transformed into the strengths of preference using (11), as shown in Table V, which denotes the dominance strength of one menu over the others.

Finally, this system calculates the DD (DD\(_m\), \(m = 1, \ldots, 10\)) of alternatives by employing the Fuzzy OWA operator. Then, the Fuzzy OWA weights \(W = \{w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8, w_9, w_{10}\}\) with orness \(|Q| = \alpha = 2/10\) are generated. The procedure of solving Fuzzy OWA weights is described as follows.

**Step 1:**
Randomly generate \(N + 1\) nonnegative real number \(p_i\) with increasing order as \(P = \{0, 2, 3, 4, 5, 7, 8, 9, 11, 12, 15\}\).

**Step 2.1:**
Calculate

\[
Q = \{q_0, q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8, q_9, q_{10}\} = \{0, 2, 3, 4, 5, 7, 8, 9, 11, 12, 15\}
\]

with \(q_N = \sum_{k=0}^{N} p_k\).

**Step 2.2:**
Calculate \(S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}\}\). With \(s_0 = q_0/q_N, s_1 = q_1/q_N, s_2 = q_2/q_N, \ldots, s_10 = q_{10}/q_N\).

**Step 2.3:**
Let \(\alpha' = \alpha/\alpha' = 0.6\)

\[
s'_i = s_i \times \alpha'^T, (i = 1, 2, \ldots, N - 1)\]

We can get

\[
S' = \{0, 0.0081, 0.0217, 0.039, 0.061, 0.091, 0.126, 0.165, 0.213, 0.265, 1\}
\]

**Step 4.1:**
Let \(\alpha' = \alpha/\alpha' = 0.6\)

\[
s'_i = s_i \times \alpha'^T, (i = 1, 2, \ldots, N - 1)\]

We can get

\[
S' = \{0, 0.0081, 0.0217, 0.039, 0.061, 0.091, 0.126, 0.165, 0.213, 0.265, 1\}
\]

**Step 4.2:**
Calculate \(w_i = s'_i - s'_{i-1}\) to obtain the weighting vector and DD.

\[
W = \{0.0087, 0.013, 0.0173, 0.021, 0.03, 0.035, 0.039, 0.048, 0.052, 0.735\}
\]

Let

\[
W_\Lambda = \{0.0217, 0.0173, 0.021, 0.03, 0.035, 0.039, 0.048, 0.052, 0.735\}
\]

For example, DD of the menu \(a_3\) can be calculated as follows:

\[
\text{DD}_3 = d(a_{10}, a_3) \times W_{A_1} + d(a_6, a_3) \times W_{A_2} + d(a_7, a_3) \times W_{A_3} + d(a_2, a_3) \times W_{A_4} + d(a_9, a_3) \times W_{A_5}
\]


### 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 Microsoft SQL Server 2005 for server management and statistical 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-sized co-located 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) [40] 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 [41].

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 [42]. Wu et al. [43] only adopted two questions (i.e., performance and effectiveness) to test PU and three questions (i.e., learning is easy, easy to get the 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

### TABLE V

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>Alt.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$</td>
<td>0</td>
<td>-</td>
<td>0.53</td>
<td>0.5</td>
<td>0.7</td>
<td>0.88</td>
<td>0.98</td>
<td>0.25</td>
<td>0.88</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>$a_2$</td>
<td>1</td>
<td>0</td>
<td>0.21</td>
<td>1</td>
<td>0</td>
<td>0.367</td>
<td>1</td>
<td>1</td>
<td>0.125</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>$a_3$</td>
<td>0.47</td>
<td>0.79</td>
<td>-</td>
<td>0.098</td>
<td>0</td>
<td>0.96</td>
<td>0.928</td>
<td>0.018</td>
<td>0.665</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>$a_4$</td>
<td>0.50</td>
<td>0</td>
<td>0.902</td>
<td>-</td>
<td>0.439</td>
<td>1</td>
<td>1</td>
<td>0.008</td>
<td>0.093</td>
<td>0.987</td>
<td></td>
</tr>
<tr>
<td>$a_5$</td>
<td>0.30</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0.561</td>
<td>-</td>
<td>1</td>
<td>1</td>
<td>0.002</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$a_6$</td>
<td>0.12</td>
<td>0.633</td>
<td>0.040</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0.946</td>
<td>1</td>
<td>0</td>
<td>0.996</td>
<td></td>
</tr>
<tr>
<td>$a_7$</td>
<td>0.02</td>
<td>0</td>
<td>0.072</td>
<td>0</td>
<td>0</td>
<td>0.054</td>
<td>-</td>
<td>1</td>
<td>1</td>
<td>0.383</td>
<td></td>
</tr>
<tr>
<td>$a_8$</td>
<td>0.75</td>
<td>0</td>
<td>0.982</td>
<td>0.992</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-</td>
<td>0</td>
<td>0.723</td>
<td></td>
</tr>
<tr>
<td>$a_9$</td>
<td>0.12</td>
<td>0.875</td>
<td>0.395</td>
<td>0.907</td>
<td>0.998</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>-</td>
<td>0.956</td>
<td></td>
</tr>
<tr>
<td>$a_{10}$</td>
<td>0.16</td>
<td>0.985</td>
<td>0.010</td>
<td>0.013</td>
<td>0</td>
<td>0.004</td>
<td>0.617</td>
<td>0.277</td>
<td>0.04</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

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 $a_1$ 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.

### TABLE VI

<table>
<thead>
<tr>
<th>Alternatives</th>
<th>DD</th>
<th>Idealized DD</th>
<th>Ranking</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>DD</td>
<td>0.162</td>
<td>0.125</td>
<td>0.1264</td>
<td>0.1263</td>
<td>0.298</td>
<td>0.082</td>
<td>0.052</td>
<td>0.076</td>
<td>0.179</td>
<td>0.045</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Idealized DD</td>
<td>0.778</td>
<td>0.601</td>
<td>0.6077</td>
<td>0.6072</td>
<td>1</td>
<td>0.394</td>
<td>0.25</td>
<td>0.365</td>
<td>0.861</td>
<td>0.216</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ranking</td>
<td>3</td>
<td>6</td>
<td>4</td>
<td>5</td>
<td>1</td>
<td>7</td>
<td>9</td>
<td>8</td>
<td>2</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$$
+ d(a_1, a_3) \times W_{A6} + d(a_8, a_3) \times W_{A7} + d(a_4, a_3) \\
\times W_{A8} + d(a_5, a_3) \times W_{A9} \\
= 0.99 \times 0.0217 + 0.96 \\
\times 0.0173 + 0.928 \times 0.021 + 0.79 \times 0.03 + 0.605 \\
\times 0.035 + 0.47 \times 0.039 + 0.098 \times 0.048 + 0.018 \\
\times 0.052 + 0.0 \times 0.735 \\
= 0.1264.
$$

The experiments are set up as follows. This study included a case study that involves two small- and medium-sized co-located 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.

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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 [44]. 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 [45], [46]. 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 subdimensions, i.e., waiting time, tangibles, and valence [41]. As shown in Table VII, waiting time subdimension is delineated by question D1, whereas tangible and valence subdimensions 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.

1) Limitations:

1) Each customer must visit at least five times to benefit from the customer-centric service that the proposed menu

Fig. 6. (a) Login interface. (b) Menu information. (c) Food inventory level.

Fig. 7. (a) Ordering result. (b) Recommended result. (c) Ordering information displayed in kitchen side.
A1. The interface is user-friendly.
A2. The intelligent e-restaurant has sufficient functions and is easy to operate for customer-centric service.

B1. The intelligent e-restaurant improves the efficiency of the service process.
B2. The intelligent e-restaurant can improve my working efficiency and service quality.

C1. I would like to recommend the e-restaurant system to my friends because of its customer-centric service.
C2. I would like to recommend the e-restaurant system to other affiliated restaurants.

D1. The intelligent e-restaurant can significantly reduce waiting time because it can provide real-time ordering and check out services.
D2. I would like to visit the e-restaurant in the future, because the menu recommender provides appropriate menu choices.

**TABLE VII**

<table>
<thead>
<tr>
<th>Part</th>
<th>Item</th>
<th>Group</th>
<th>Sample number</th>
<th>Mean</th>
<th>SD</th>
<th>P-Value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (Ease of use) (Waiter)</td>
<td>A1. The interface is user-friendly.</td>
<td>e-restaurant I</td>
<td>15</td>
<td>4.00</td>
<td>0.84</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.26</td>
<td>0.79</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>4.13</td>
<td>0.82</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant I</td>
<td>15</td>
<td>4.20</td>
<td>0.56</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.53</td>
<td>0.64</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>4.36</td>
<td>0.61</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>B (Usefulness) (Waiter)</td>
<td>B1. The intelligent e-restaurant improves the efficiency of the service process.</td>
<td>e-restaurant I</td>
<td>15</td>
<td>4.26</td>
<td>0.70</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.60</td>
<td>0.63</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>4.53</td>
<td>0.62</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>B2. The intelligent e-restaurant can improve my working efficiency and service quality.</td>
<td>e-restaurant I</td>
<td>15</td>
<td>4.60</td>
<td>0.51</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.73</td>
<td>0.45</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>4.66</td>
<td>0.48</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>C (Behavioral Intentions) (Waiter)</td>
<td>C1. I would like to recommend the e-restaurant system to my friends because of its customer-centric service.</td>
<td>e-restaurant I</td>
<td>15</td>
<td>3.93</td>
<td>1.03</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.13</td>
<td>0.99</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>4.03</td>
<td>0.99</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>C2. I would like to recommend the e-restaurant system to other affiliated restaurants.</td>
<td>e-restaurant I</td>
<td>15</td>
<td>3.73</td>
<td>0.46</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>15</td>
<td>4.00</td>
<td>0.64</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>30</td>
<td>3.86</td>
<td>0.62</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>D (Quality of Service) (Customer)</td>
<td>D1. The intelligent e-restaurant can significantly reduce waiting time because it can provide real-time ordering and check out services.</td>
<td>e-restaurant I</td>
<td>45</td>
<td>4.00</td>
<td>0.56</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>D2. I would like to visit the e-restaurant in the future, because the menu recommender provides appropriate menu choices.</td>
<td>e-restaurant II</td>
<td>45</td>
<td>4.51</td>
<td>0.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>90</td>
<td>4.25</td>
<td>0.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant I</td>
<td>45</td>
<td>4.20</td>
<td>0.58</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e-restaurant II</td>
<td>45</td>
<td>4.36</td>
<td>0.54</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>pooled</td>
<td>90</td>
<td>4.27</td>
<td>0.56</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

*One-sample t-test.

recommender provides. Customers who visit less than six times are recommended with the most frequent ordered menus that are similar to those of new customers.

2) Customers do not receive the customer-centric service if they have privacy concerns.

3) This preliminary work explores the feasibility of applying intelligent e-restaurants. A larger scale and more elaborate work is required to confirm the effectiveness of the proposed system in a wide variety of restaurants and different retailing shops.

4) The outcome of the preliminary phase of prediction is more suitable for small and medium-scaled restaurants than for large-scale restaurants.

5) Despite an apparently inefficient current HR of only 65.41%, the HR is expected to rise given the increasing number of customers and visiting records. Undertaking a full-scale experiment with more restaurants is currently underway.

6) When new menus or new criteria are introduced, the recommender system needs to collect enough data to retrain and rebuild the system. The PFM model must be modified if new criteria are introduced, which in turn will affect PWD relationships, dominance values, strength of preference, and customer’s dominance degree.

7) In general, validity can be verified by comparing the results with an external value. In our study, there is no external value to indicate the overall quality of service; hence, the subjective impression was taken as basis of quality of service by asking the waiters and customers their impression on the functions and quality of service provided by the proposed system. The validity of the proposed system is weak needing further improvement.

2) **Lessons Learned:**

1) Each step of the service procedure must be identified carefully before developing the e-restaurant. Moreover, user interface of the proposed recommending system must be designed based on the viewpoints of waiters to ensure ease of use.

2) Traditional restaurant can easily be upgraded by following the framework of the intelligent e-restaurant with inexpensive equipment.

3) The proposed recommending system is highly promising for other areas, such as 3C (computer, communication, and consumer) product sales, livelihood-related industries, and department stores, via proper adjustment.

4) Most waiters agree that the proposed system is able to accelerate the service process and improve working efficiency; however, some argue that it will also deprive their opportunities to have close interaction with customers. The social dimension induced by the introduction of this system should not be underestimated.

V. **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 membership card to pay bills instead of using cash. The proposed system 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 redeploymenst 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.

REFERENCES

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