Expert Systems with Applications 38 (2011) 12128–12141

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A PSO-based intelligent service dispatching mechanism for customer expectation management

Yen-Hao Hsieh [a,*], Soe-Tsyr Yuan [b], Ruei-Lin Kuo [c]

[a] Department of Information Management, Chia Nan University of Pharmacy and Science, Tainan, Taiwan
[b] Department of Management Information Systems, National Chengchi University, Taipei, Taiwan
[c] Value-Added Service, Department of Data Communication, Business Group, Chunghwa Telecom, Taipei, Taiwan

ARTICLE INFO

Keywords:
Particle swarm optimization
Customer expectation management
Service experience design
Service science

ABSTRACT

In the era of experience economy, service providers have to provide customers with high quality service experience in order to attract more customers and achieve higher customer satisfaction. Managing customer expectation is a critical approach for service providers to consider. Although customer expectation has been discussed across different research disciplines, to our knowledge, there is still no systematical and feasible way to apply customer expectation management into real environments. This study attempts to establish an intelligent service dispatching mechanism by using particle swarm optimization for customer expectation management. This mechanism can help service providers design and deliver satisfactory service experience to customers. In order to evaluate the effectiveness and robustness of this mechanism, this study employs micro- and macro-simulation experiments to confer and analyze its performance. The simulation results show service providers can gain benefit and raise customer satisfaction by managing customer expectation during service experience delivery. Meanwhile, customers can also receive memorable experiences and have positive responses to service providers and other customers. Consequently, a high performance ecosystem within service providers and customers can be formed.

1. Introduction

The service industry has been key to driving economic growth. Businesses need to pay attention to customer feedback to better provide service (Berry, Carbone, & Haeckel, 2002; Meyer & Schwager, 2007). A memorable service experience could improve customer loyalty and reputation of service providers leading to greater profit. The experience the consumer has during a service encounter significantly influences their assessment of the service provider (Lewis & Entwistle, 1990; Soloman, Surprenant, Czepiel, & Gutman, 1985). Svensson (2006) indicated previous research is seldom from service provider perspective (mainly emphasizing customer perspective), thus no sophisticated approach to dynamic service encounters exists for service providers to ensure effective services. How to provide high quality experiences for customers is critical.

Parasuraman, Berry, and Zeithaml (1991) noted that service providers must recognize customer needs in order to fulfill expectations to achieve high customer satisfaction during the service experience. Managing customer expectation is an important approach to enable customers to have a satisfactory experience (Kurtz & Clow, 1992–93; Pitt & Jeantrout, 1994; Clow & Beisel, 1995; Coye, 2004). Service providers can provide customers with appropriate services according to their expectations. Competent service providers can raise customer expectations in order to achieve a customer franchise and build a threshold that competitors must achieve to enter the market (Parasuraman et al., 1991). For instance, FedEx uses information technology to offer tracking of packages, where customers can use computers for real time tracking of their package. Consequently, customer expectation management is a strategic way to deliver a high quality service experience and enhance the service provider's competence.

Previous research suggests understanding customer expectation is essential for the service experience. These investigations have been collected by empirical methods, such as conducting surveys. There are potential biases from customers who may not have a clear memory of their experience (Homer, 1993). Lessons learned from the survey method may be insufficient to provide the most current and accurate knowledge required to guide the service practices. We argue that there is a need for a systematic and quantitative approach to understanding customer expectations with adequate service during delivery, especially in real time environments. However, the context of the interaction is complex and variable; service providers can encounter many difficulties in managing customer expectations, offering sufficient service and creating a satisfying experience in a dynamic environment (Ho &

* Corresponding author. Tel.: +886 229393091x85024; fax: +886 2 29393754.
E-mail addresses: yhhsiehs@mail.chna.edu.tw (Y.-H. Hsieh), yuans@mis.nccu.edu.tw (S.-T. Yuan), sunnysray@cht.com.tw (R.-L. Kuo).

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doi:10.1016/j.eswa.2011.03.007

Zheng, 2004; Hubbert, Sehorn, & Brown, 1995). For example, service providers should first consider customer needs, resource arrangement and market reports to make appropriate decisions for delivering existing services within a dynamic service context. Moreover, service providers should also collect customer responses, especially for satisfaction compared with expectations after the interaction. This study attempts to explore the following research questions and thereby set the stage for future service research.

- What kinds of approaches can help service providers effectively design and deliver high quality service experience within the dynamic service contexts?
- How can service providers systematically combine customer expectation management with service experience delivery in practice?

To examine these questions, this study employs the particle swarm optimization (PSO) approach to intelligently and effectively select appropriate services for managing customer expectations and offering high quality service in a dynamic environment. The particle swarm optimization approach can simulate human behaviors underlying different requirements and goals. To maximize value for customers from the perspective of expectations and minimizing costs of service providers, the PSO-based mechanism is utilized. We propose an intelligent service dispatching mechanism which can ensure a high quality service experience and select suitable services for customers by analyzing and computing customer expectations, service encounter situations and strategic goals of service providers. The objectives of this study are to: (1) provide a PSO-based approach that can select appropriate services for customers in different situations through calculations to maximize expectation-based customer value and by minimizing service costs of the provider, (2) to study in detail the feasibility and process of implementing customer expectation management in a real time and dynamic environment.

This paper is structured as follows. Section 2 describes the conceptual framework of customer expectation management. Section 3 further delineates the PSO-based service dispatching mechanism. Section 4 then details the simulation experiments and the result analysis. Finally, the conclusion remarks are provided in Section 5.

2. A conceptual framework for customer expectation management

This study proposes a conceptual framework of customer expectation management (as shown in Fig. 1) to delineate how service providers can employ particular tactics to influence customer expectations during the encounter to achieve high quality service experience. The conceptual framework will serve as the basic foundation for building the PSO-based intelligent service dispatching mechanism. The details of the framework are provided in Section 2.2.

2.1. Theoretical foundations

2.1.1. Expectation theory

The nature of customer expectations concerns what customers expect and determines what should be happening during the service encounter (Zeithaml, Berry, & Parasuraman, 1993; Boulding, Kalra, Staelin, & Zeithaml, 1993). Customer expectations can also be viewed as the anticipation of how excellent the service can be offered by service provider. Parasuraman et al. (1991) proposed that customer expectations have two levels: the desired expectation and the adequate expectation. Desired expectations represent the level of service a customer hopes to receive, defined as the level at which a customer wants the service performed. It is a combination of what the customer believes "can be" and "should be", while adequate expectations, a lower level of expectation, are considered to be customer's acceptable level of performance. This relies on the customer's assessment of what the service "will be" (Zeithaml et al., 1993).

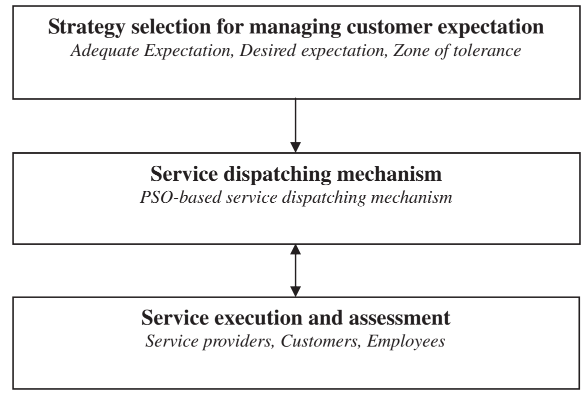

Fig. 1. Conceptual framework of customer expectation management.

The zone of tolerance for customers is influenced by several complex factors during the encounter (Zeithaml et al., 1993). Zeithaml et al. (1993) proposed a comprehensive framework of service expectations and defined eleven antecedent factors which could affect the desired and adequate expectations (as depicted in Fig. 2). Parasuraman et al. (1991) specified that service providers with higher competence can raise customer expectations to narrow the zone of tolerance by providing proper services in order for achieving the customer franchise. Consequently, recognizing these determinants can lead to an operational design strategy to achieve customer expectations.

This study attempts to propose a PSO-based intelligent service dispatching mechanism to provide effective services at the right time and in the right situation, which can influence the adequate expectation, the desired expectation and the zone of tolerance of customers. In this way expectation-based values can be maximized for customers while minimizing cost for providers.

2.1.2. Particle swarm optimization

Particle swarm optimization (PSO) is inspired by the social behavior of natural swarms. By computing patterns in nature, results can be applied to complex optimization domains, and provide an alternative to conventional evolutionary computation approaches.

Each solution is referred to as a "particle" and each moving particle in the multi-dimensional solution space with its own fitness value through mapping the fitness function. Each particle also has a velocity to determine distance of movement and next direction. Consequently, moving each particle in a multi-dimensional solution space is decided by the local best value and global best value. In other words, each particle selects the next direction based on the best value of its own experience (Cognition-only Model), simultaneously comparing the best value for the whole swarm (Social-only Model). Each particle is constantly updated for best values to decide the appropriate direction find an optimized solution (Kennedy & Eberhart, 2001).

The steps of the PSO algorithm are:

(1) *Initiation:* Choosing the position and velocity of each particle randomly.
(2) *Evaluation:* Calculating the fitness value for each particle according to the fitness function.

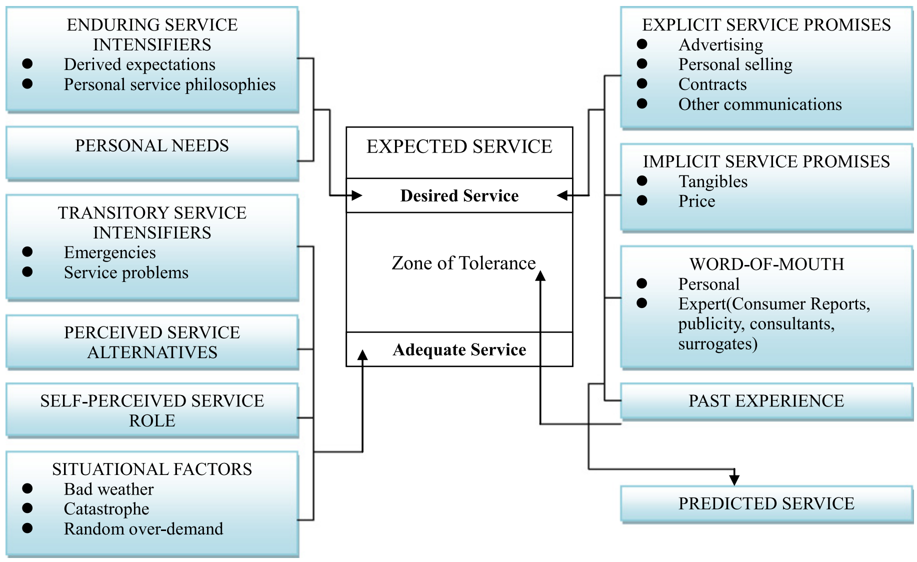

Fig. 2. Nature and determinants of customer expectations of service (Zeithaml et al., 1993).

(3) *Find the Pbest:* Finding the best position of each particle from its own experience.
(4) *Find the Gbest:* Finding the best position of each particle from the experience of the whole particle.
(5) *Updating velocity:* Updating the position and velocity of each particle with the following two formulas:

$$V_i^k = W v_i + C1\text{rand}() * (\text{Pbest}_i - \text{particle}_i) + C_2 * \text{rand}() * (\text{Gbest}_i - \text{particle}_i) \quad (1)$$

$$\text{particle}_j^k = \text{particle}_i + v_i^k \quad (2)$$

Table 1 shows the definitions of PSO parameters. This study utilizes the PSO algorithm which has an advantage of searching efficiency to find the optimal solution by minimizing service costs and maximizing service value for customers. The PSO algorithm can be applied to customer expectation management by considering the benefits to providers and customers according to swarm intelligence in dynamic surroundings.

2.2. Descriptions of the conceptual framework of customer expectation management

There are three phases of the conceptual framework for customer expectation management: (1) strategy selection of customer expectation management, (2) service dispatching mechanism and (3) service execution and assessment.

Table 1
The definitions of PSO parameters.

Parameters	Definition
W	Inertia weight
v_i	The previous velocity of ith particle
v_i^k	The new velocity of ith particle
C_1, C_2	Constriction factor
rand()	The random function that generate a value between 0 and 1
Pbest_i	The best fitness value considering the experience of ith particle
Gbest_i	The best fitness value considering the experience of whole particles
particle_j^k	The new position of ith particle

2.2.1. Strategies for managing customer expectations

Service providers have to classify their objectives into a strategy for customer expectation management (Hsieh et al., 2008; Parasuraman et al., 1991). Each type of strategy is associated with the status of an expectation. For instance, stabilizing adequate expectations and raising desired expectations of customers is a strategy for low-capability service providers. These are defined by employing expectation determinants; low-capability service providers achieve objectives and satisfy customers. When a secondary service provider promotes a new product, customer expectations may be too low, lowering adequate service level anticipated by customers. However, if customers experience service failures during encounters owing to poor delivery, their expectations become higher. In these cases, instead of expending a lot of resources to fulfill high end services, low-capability service providers can apply strategies based on different conditions to manage customer expectations and achieve high quality service experience delivery.

To demonstrate the PSO-based intelligent service dispatching mechanism, we examine raising desired expectations and stabilizing adequate expectations in order to expand the zone of tolerance. Widening the zone of tolerance can increase opportunities to meet customer expectations. For doing so, an example could be that customers aid service providers to raise other customers' desired expectation by pushing the information to interact with each other (e.g. word-of-mouth) after being served by the service providers. In other words, customers can be the promoters to enable service providers to arise customers' desired expectation.

2.2.2. Service dispatching mechanism

With a strategy type of customer expectation management, the service dispatching mechanism is used to compile a set of expectations determinants that can effectively influence customer expectations. This set of expectation determinants can then be used to identify relevant service encounters and useful expectation-based service tactics. There is no need for service providers to employ all possible expectation determinants as shown in Fig. 2. Service providers could combine several into a particular portfolio (a service tactic) (Hsieh & Yuan, 2009a). A service tactic is an operational means for service providers to affect customer expectations by combining helpful tactics to deliver high quality service to customers.

Particle swarm optimization (PSO) is used to find effective expectation determinants (e.g. those that maximize value for customers and minimize costs for providers). A PSO-based intelligent service dispatching mechanism is proposed to provide customers with appropriate service experiences by exercising dynamically selected determinants and corresponding tactics. Service providers and customers can co-create value and gain profit through the proposed mechanism to create a high performance ecosystem.

2.2.3. Service execution and assessment

According to the service encounter triad (Fitzsimmons and Fitzsimmons, 2006), there are interactions between the three players: service providers, employees and customers. The three players are accounted for in the service dispatching mechanism for adjustment and modification of the processing logic and rules according to the results of implemented services. For example, the service dispatching mechanism sets up relevant knowledge databases (encounter data, implementation of expectations and customer patterns) to collect feedback from the three players. The mechanism can then continuously derive useful and critical information to select, design and deliver appropriate services. The service dispatching mechanism can be refined gradually and help service providers deliver high quality service to customers.

This study implements customer expectation management for better service experience according to the conceptual framework. Low-capability service providers are taken as an example and a suitable strategy of customer expectation management is chosen for these providers (raising desired expectations and stabilizing adequate expectations). A PSO-based method is employed, which is defines suitable parameters and objective functions for aforementioned providers, to establish the service dispatching mechanism to deliver a high quality service experience. The feasibility of customer expectation management by employing above examples and settings is examined. According to different targets (e.g. high-capability service providers) and other possible strategies (e.g. decreasing desired expectations and raising adequate expectations), researchers can still define appropriate approaches (parameters or functions) and utilize suitable methods (such as agent-based approach) to build a feasible service dispatching mechanism by following our proposed conceptual framework.

3. The PSO-based intelligent service dispatching mechanism

This study proposes a PSO-based intelligent service dispatching mechanism which includes six modules (as depicted in Fig. 3) to deliver high quality service experiences by embedding the notion of customer expectation management. Firstly, the preference identification module automatically gathers customer preference information and defines the strategy for customer expectation management. Next, the PSO-based determinant selecting module chooses effective expectation determinants and arranges service encounters through a series of precise and systematic computations according to customer preference information, provider cost and existing resources. The contextualized journey decision module selects proper service encounters. The expectation measurement module can calculate values for adequate and desired expectations in order to dynamically ensure appropriate services are selected. Accordingly, the service component execution module can help to provide customers with high quality service and a satisfactory experience during the encounter. The proposed mechanism continuously collects data in real time and examines historical data to refine the logic rules of dispatching services to suit the actual situations from the knowledge database systems (e.g. encounter data, implementation of expectations and customer patterns).

Our investigation integrates this PSO-based intelligent service dispatching into an exhibition service system (Hsieh & Yuan, 2009a) characterized by the assurance of exquisite service experience delivery when interfacing the exhibition stakeholders (including visitors, exhibitors and organizers) within a location-based service enabled exhibition environment. Each stakeholder type has various purposes and can influence others.

3.1. Preference identification module

The preference identification module collects customer (e.g. visitors) preference information by identifying visitor profiles, needs and service preferences through their input; the mechanism can specify service requirements for visitors and reflect on real opinions. The preference information includes visitor profile, selected

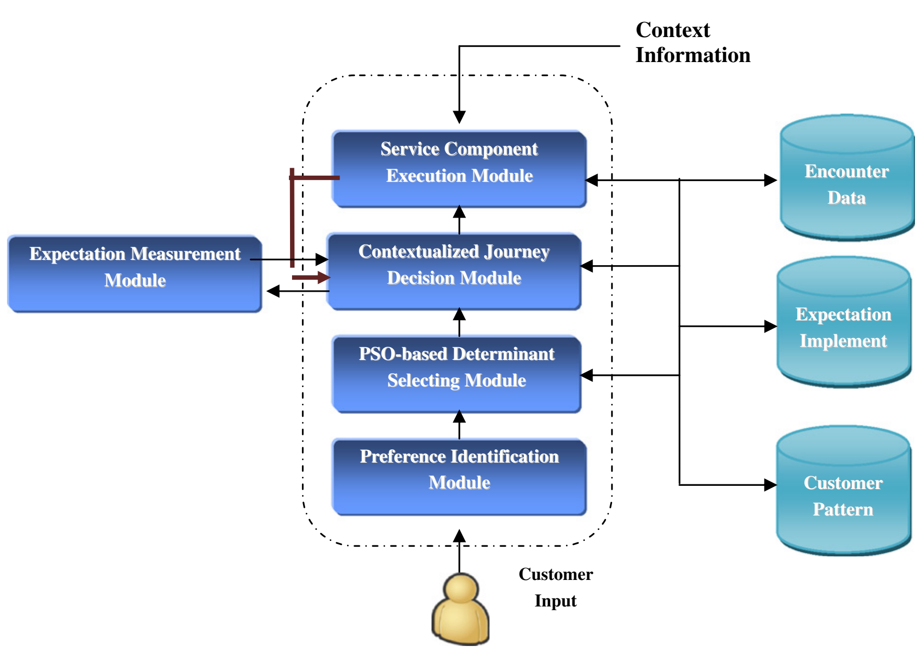

Fig. 3. Conceptual framework of customer expectation management.

service type, target product type, preferred service vendors, and willingness to spend time on service journey after visitor input. This module also automatically defines a suitable strategy for managing customer expectations for specific customers based on the preference information. The following module (PSO-based determinant selecting module) can then select suitable candidate determinants that can effectively control visitor expectations. Table 2 shows that data items from customer preference information.

3.2. PSO-based determinant selecting module

The PSO-based determinant selecting module employs particle swarm optimization to simulate the environment of service experience delivery in order to select effective expectation determinants and assist service providers to manage customer expectations.

The module uses service operation inputs (including equipment, staff and materials) from service providers and service outcomes (including value and emotions) from customers (as depicted in Fig. 4). Intangible aspects are considered in nature compared with customer experience and service outcome. Customer experience is part of the service operation process. Customer processing operations are offered by service providers and used by customers (Morris & Johnston, 1988). Fig. 4 exemplifies how the service operation process and customer experience overlaps in terms of service productivity (Johnston & Clark, 2001). The operation of the module utilizes PSO to find the effectively-controlling expectation determinants based on service productivity (Johnston & Clark, 2001). The optimization problem for PSO to be resolved is the multi-objective function (as shown in Formula (3)) that maximizes customer value (value extraction objective) and minimizes service provider cost (cost extraction objective):

$$\text{Maximize Productivity} = \text{Value}/\text{Cost}. \tag{3}$$

To further define the multi-objective function, *Productivity(X)* comprises two objective functions (as shown in Fig. 5). One is the expectation-based-value (X) which explores how to choose the expectation determinant by maximizing customer value (e.g. service outcome). The other is Cost(X), which explores how to choose the expectation determinant by minimizing cost. X is the determinant condition variable. Consequently, the PSO-based determinant selecting module selects appropriate expectation determinants by maximizing function productivity (X).

The objective function Cost(X) indicates expectation determinants that can minimize the cost of service (e.g. material, equipment and staff cost). Values obtained by customers also influence how to select effective expectation determinants by customer expectation management. The objective function expectation-based-value (X) in value extraction represents values that can influence expectation determinants and should be maximized by considering past customer patterns, expectation determinant knowledge, and real time performance of expectation determinants. The PSO-based determinant selecting module takes into account the cost and value extraction in order to select effective expectation determinants and maximize service productivity for customer expectation management.

3.2.1. Cost extraction

Service cost is an important factor which directly influences service offered. The module considers three cost types (e.g. staff, equipment and materials) and utilizes the PSO optimization method to choose the expectation determinants to minimize total cost of offering services. The objective function shows as follows:

$$\text{Minimize}\quad \text{Cost}(x) = \sum_{i=1}^{n} X_1 * (C_{Si} + C_{Ei} + C_{Mi}) \tag{4}$$

$$\text{Subject to}\quad \sum_{i=1}^{n} C_{Si} + CEi + C_{Mi} \le S_B$$

In Formula (4), the C_{Si}, C_{Ei}, and C_{Mi}, respectively represent staff cost, equipment cost and material cost of each expectation determinant to offer services to customers; n represents the total number of determinants at the exhibition, and $X_i = 1$ means the determinant i should be used in the collaborative interaction mechanism for serving visitors in terms of the cost objective. Furthermore, the restriction Eq. (4) represents the total cost (e.g. staff, equipment and materials) which cannot exceed budget of service providers (S_B).

Table 2
Customer preference information.

Information	Data items
Customer profile	Customer name Customer ID Customer register ID Customer occupation Customer target products Customer email Customer phone number Customer address
Selected service type	Selected service type number Selected service type name
Target product type	Product category information
Preferred service vendor	Preferred vendors list
Willing spending time	Spending hour

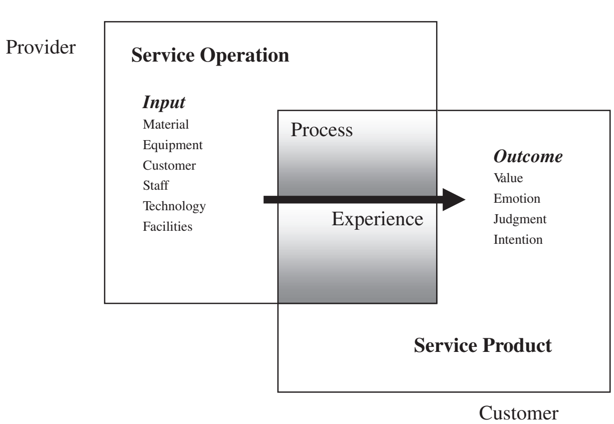

Fig. 4. The relationship between service operation and service product (Johnston & Clark, 2001).

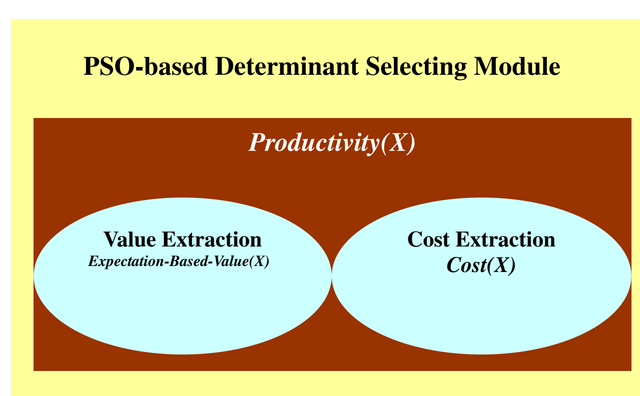

Fig. 5. The objective functions in PSO-based selecting module.

3.2.2. Value extraction

Expectation-based-value (X) is based on the degree of influence of expectation determinants from the viewpoint of customer expectation management. This can reveal the value obtained from services according to determinant identification. The total value obtained by customers (degree of determinant influence) is made up of three types of data. The objective function of value extraction is represented as Formula (5):

$$\text{Maximize expecatation-based-value}(X) = \sum_i$$
$$= 1^n X_i * (V_{Pi} + V_{Ki} + V_{Di}) \tag{5}$$

In Formula (5), n represents the total number of determinants in the exhibition environment, where $Xi = 1$, i represents serving visitors in terms of value objectives. The V_{Pi} is represented as the ith determinant's degree of influence on a specific customer from his past exhibition journey, V_{Ki} is represented as the ith determinant's degree of influence on the key performance indicator (KPI) of service providers (exhibition organizer). Each expectation determinant has an influence weight according to the KPI setting by service providers. V_{Di} is represented as the ith determinant's degree of influence on the real time determinant control performance. Control variation for the word of mouth (WOM) determinant for visitor A, B, and C are 4, 5, and 6, and real time control performance of WOM is 5:

$$\text{Real-time control performance}$$
$$= \frac{\sum_{i=1} n\text{Determinant vontrol variation}_i}{N}. \tag{6}$$

In Formula (6), N represents the expectation measurement by distance, and utilizes the moving average approach to calculate the control performance for a specific determinant.

3.2.3. Particle swarm optimization approach

This module utilizes the PSO approach to choose appropriate expectation determinants according to aforementioned multi-objectives; the services offered derived from these determinants could bring benefits to service providers (exhibitors and organizers) and customers (visitors).

The PSO approach is an evolutionary computation derived from the foraging of birds. It utilizes a swarm of candidate solutions (called particles) to continuously adjust vector locations to find local and global optimal solutions according to past experience.

Initial particles are generated randomly, and each particle represents a set of candidate solutions. In Fig. 6 of the particle representation, the ith solution vector can be represented as a particle i which shows possible determinants. Where $\text{particle}_{i,1}$ is 1, determinant one is selected. On the contrary, where $\text{particle}_{i,3}$ is 0, determinant 3 is not chosen by the ith solution vector in terms of the aforementioned service productivity objective.

For particle i calculate the velocity V_i according to the best solution $Pbest_i$ and the global best solution $Gbest_i$ in each iteration. Thus, V_i is added to calculate the vector value of the particle in the next iteration. The equation is based on the parameter dimension j, as follows:

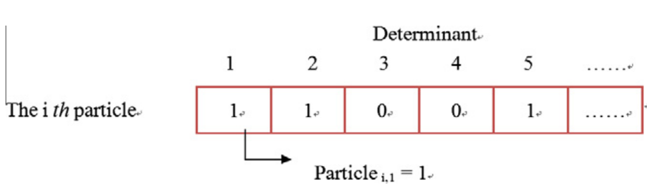

Fig. 6. The particle representation.

$$V_{ij} = 0.729 * v_{ij} + 1.494 * \text{rand}() * (\text{Pbest}_{ij} - \text{particle}_{ij}) + 1.494 * \text{rand}() * (\text{Gbest}_{ij} - \text{particle}_{ij}) \tag{7}$$

$$\text{particle}_{ij} = \text{particle}_{ij} + v_{ij} \tag{8}$$

where rand() is a random function to generate scores from 0 to 1, and the coefficient in Formula (7) is chosen by constriction factor analysis (Shi & Eberhart, 1998) to guarantee convergence. Formula (8) employs the stochastic quantity to avoid local optimal solutions in order to match the balance of exploitation and exploration searches. Fig. 7 shows the flow chart of the PSO algorithm.

This module uses the selected determinant information in the contextualized journey generation module to arrange interaction points in the service journey of the customer.

3.3. Contextualized journey decision module

The contextualized journey decision module aids service providers in selecting appropriate service encounters using contextual factors which consider the distance between encounter points, time spent by visitors, vendor preference, target product and expectation measurement outcome from the expectation measurement module. In this study, it is assumed that each determinant can associate a list of possible expectation-based service tactics which are implemented in each service encounter.

This module then arranges the service journey based on the three main steps as shown in Fig. 8. First, the encounter points that should be arranged in the service journey are filtered by the chosen determinants decided by the PSO-based determinant selecting module, the preferred service vendors and target product type by preference.

Second, the module calculates the distance between filtered encounter points which are candidates for arranging in the service journey, and then arranges the service journey that allows the

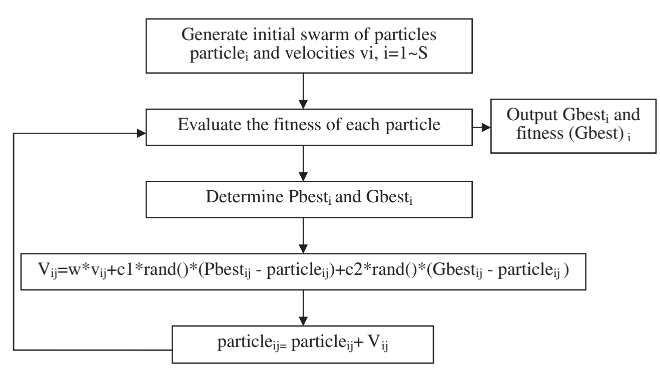

Fig. 7. The flowchart of the PSO algorithm (Shi & Eberhart, 1998).

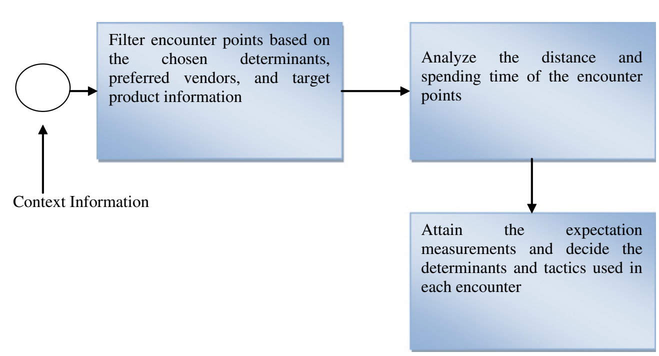

Fig. 8. The journey arrange process.

smallest distance for customers to walk between all encounter points. The module utilizes the nearest neighbor algorithm to find the minimum distance for each component to generate a sequence of encounter points. This step determines the summation of the average serving time of accumulated encounter points in the service journey generated by first step, and adjusts the sequence of encounter points if the summation of the average serving time exceeds time spent willingness of the customer. The assumption is that the encounter points of preferred vendors must be input into the journey.

Third, for a service encounter in the journey, the contextualized journey decision module inputs associated determinants in the expectation measurement module to ensure if the influence of the determinants works in line with the selected strategy for managing customer expectations (e.g. customer desired expectations increase and the adequate expectations are stabilized). The expectation measurement module provides values of adequate and desired expectations and feasible service tactics which are put into the contextualized journey decision module by a quantitative approach (detailed in Section 3.4). Fig. 9 then exemplifies an interactive operation between the contextualized journey decision module and the measurement module to produce control actions based on managing customer expectations. Consequently, the contextualized journey decision module provides tactics to the service component execution module to select appropriate service components for service experience delivery and customer expectation management.

The module also chooses service tactics which are sent from the expectation measurement module for each encounter and then provides information for the tactics service component execution module.

3.4. Expectation measurement module

The expectation measurement module (Hsieh & Yuan S.T., 2009b) determines the likely performance of selected determinants delivered by the contextualized journey decision module by calculating measurable indicators (e.g. numbers of determinants, average variation of customer expectations and provider capability). The expectation measurement module generates two outputs, which include scores for customer expectations and feasible service tactics, to be used in the contextualized journey decision module. The contextualized journey decision module delivers results from the expectation measurement module and information in the context in service encounters to the service component execution module, to create a high quality service experience. Thus, the expectation measurement module is a critical function for understanding customer thinking, and ensures the integrity and effectiveness of service delivery of the proposed mechanism.

The measurement used for expectations is a mathematical model based on Fechner's law (Thurstone, 1929) and operational risk (Basel Committee on Banking Supervision, 2001). Fig. 10 represents the reasoning process of the expectation measurement model, which involves three separate stages: expectation determinants, expectation measurement model and customer expectations. The measurement model also contains feedback which can continuously update a real time database to measure customer expectations.

3.4.1. Expectation determinants stage

The input for the expectation measurement model comprises combinations of determinants obtained from the contextualized journey decision module. According to Zeithaml et al. (1993), these determinants include enduring service intensifiers, personal needs, transitory service intensifiers, perceived service alternatives, customer perceived service role, situational factors, expected service, explicit service promises, implicit service promise and word of mouth communications (Zeithaml et al., 1993).

3.4.2. Expectation measurement model stage

This step calculates scores for desired and adequate expectations, while the customer remains exposed to external stimuli.

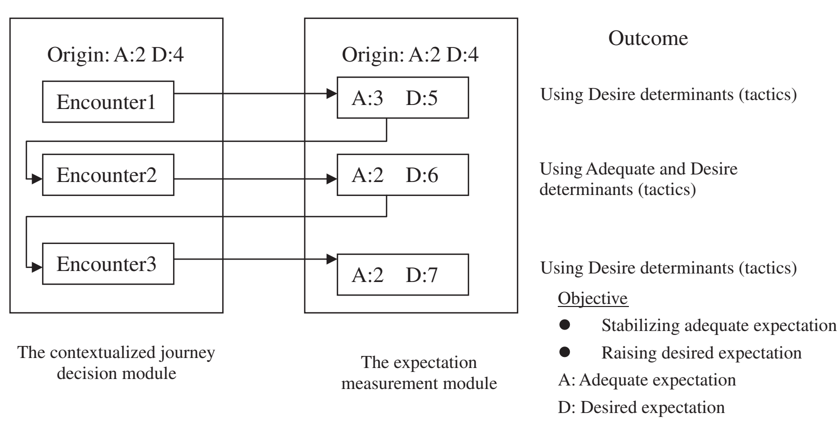

Fig. 9. The interactive operation between the contextualized journey module and the expectation measurement module.

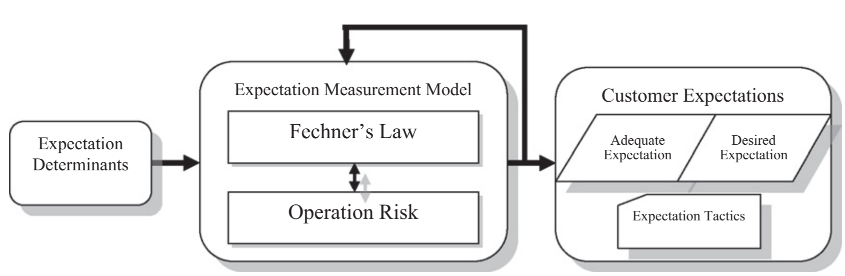

Fig. 10. The process of expectation measurement module.

The primary objectives of managing customer expectations are raising adequate expectations, adequate expectation abatement, raising desired expectations and desired expectation abatement. This study aims to stabilize the adequate expectation and increase the desired expectation. According to the management objectives and combinations of determinants, stimuli can be computed using a stimulus intensity formula based on analogical mapping between factors considered by operational risk and stimulus intensity factors regarded in dynamic service context. After obtaining stimuli values, the expectation measurement model calculates the adequate or desired expectation scores based on Fechner's Law (e.g. the magnitude of sensations can be calculated based on the magnitude of external stimulus).

3.4.3. Customer expectations stage

Accordingly, outputs of the expectations measurement model include scores for adequate expectations, desired expectations and a list of recommended service tactics. The service tactics list, which is derived from the real time database, provides a reference. This list of appropriate expectation tactics can be mapped to specific service components to influence customer expectations through the solution selection module. After implementing service tactics (service components), the contextualized journey decision module should store the values of expectation variation and capabilities indicators in a real time database. The expectation measurement model can then use the feedback control to reflect actual customer expectations.

3.5. Service component execution module

According to service tactics proposed by the contextualized journey decision module, this module selects and executes components during service encounters. The module further employs the social exchange relationship value between service providers and customers who become promoters and value co-creators during service delivery (Bettencourt, 1997). In other words, the exchanged value obtained by customers during a service encounter can make them more willing to play the partial employee role by promoting the service provider.

The module defines the relative compensation calculation that can be represented as the exchanged value of the service from the view of customers. With regard to the exhibition service surroundings, there are four parameters in the relative compensation calculation; O_c represents the service value for visitors, and I_c represents the effort by visitors using the service and purchasing the product; both parameters form the service outcome and income from the visitors' point of view. O_p represents the benefits to service providers, and I_p represents the costs to offer different kinds of services; both parameters form the service outcome and income from service providers' point of view. The relative compensation calculation for O_c/I_c and O_p/I_p are represented as in Formula (9) and (10):

$$O_C/I_C = \frac{\text{Number of Recommendations fo Services Component}}{\text{Average Customer Paid for Service Component}}, \tag{9}$$

$$O_p/I_p = \frac{\text{Number of Transations fo Services Component}}{\text{Service Component Cost/Number of Serving Customers}}. \tag{10}$$

In Formula (9) and (10), the volume of recommendations for services resulting from visitors experiencing a good experience, and the unit visitor serving cost is calculated from the service cost divided by the total number of visitors served. The module utilizes the average paid concept to measure the average visitors paying for services and weight concepts to measure how services aid transactions in service encounters.

In order to involve customers during the service experience delivery, this module selects appropriate service components to meet customer needs and generate greater benefit to customers rather than service providers. For instance, by choosing a service component that can make, $O_c/I_c > O_p/I_p$, the service is beneficial to customers, creating customer satisfaction. The module treats the exchanged value obtained leaves customers with a feeling of relative compensation for social equity. The service component is selected to serve customers if the relative compensation calculation is beneficial to the customer.

4. PSO-based mechanism evaluation

In order to evaluate the effectiveness and robustness of the proposed mechanism, this study uses micro and macro simulation experiments to confer and analyze the performance of the proposed mechanism. The micro perspective aims at the appropriate initial values of parameters used in the PSO approach to be simulated for improved performance of finding solutions according to the best fitness values. In order to provide pertinent service performance, customer stereotypes are employed to compare the performance of possible parameters. The macro perspective evaluates the effectiveness for customer expectation management and examines service productivity and overall performance of the ecosystem (service system, service providers and customers). Four simulation experiments are addressed, including evaluation of parameters of particle swarm optimization, performance of customer expectation management, service productivity and a high performance service ecosystem.

4.1. Evaluation of parameters of particle swarm optimization

This set of experiments is focused on parameter adjustment to achieve performance competence when offering service. Parameters include the upper and lower boundaries of inertia weight, default particle numbers and evolutionary iteration times. The inertia weight value should be set at 0.95 for improved performance finding solutions. The objective of the experiments is to test different sets of parameters and obtain the best performance of finding solutions according to the best fitness values. Experiments obtain average best fitness values and adjust parameters of evolution iteration times and default particle numbers by fixing other parameters (e.g. MinPosition is 0, MaxPosition is 1, and inertia weight is 0.95).

4.1.1. Evolution of iteration times

Evolution iteration times are set at 1000, 2000, and 2500 to evaluate the efficiency of PSO algorithm by fixing the other parameters (e.g. inertia weight 0.95). The *Y*-axis represents the best fitness value which indicates the performance of finding the solution in PSO. The *X*-axis represents execution times (each time collaborative interaction mechanism represents a user in a journey) of the algorithm. There were 3 runs, each with 10 service executions to test different parameters of evolution iteration times.

Figs. 11–13 show three runs to demonstrate performance. The blue[1] line represents the best fitness value tendency for 1000 iteration times, the red line represents the best fitness value tendency for 2000 iteration times, and the green line represents the best fitness value tendency for 2500 iteration times. The simulation results of the average best fitness value for the three runs are

[1] For interpretation of colour in Figs. 11–16, the reader is referred to the Web version of this article.

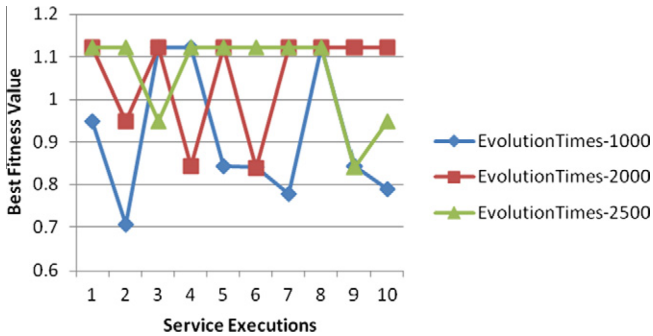

Fig. 11. First run for evolution.

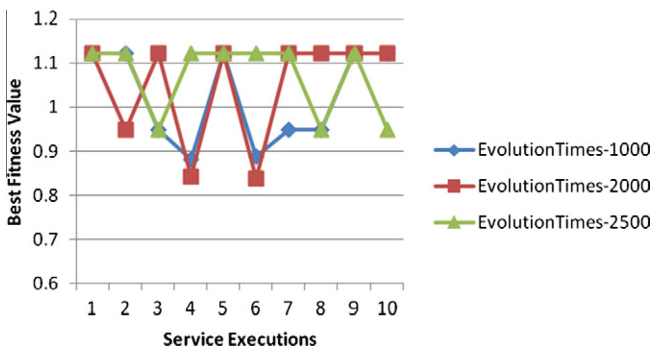

Fig. 12. Second run for evolution times.

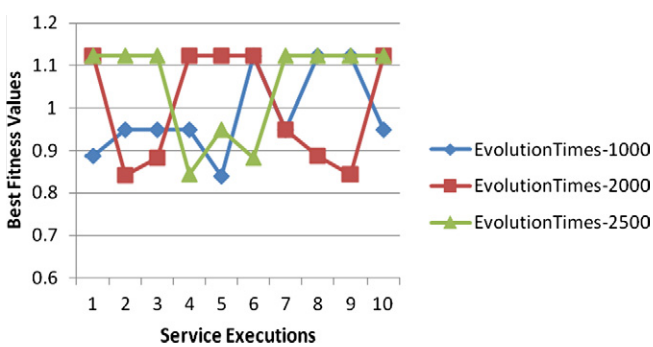

Fig. 13. Third run for evolution times.

described in Table 3. The performance of 2000 evolution times is the best. The parameter of evolution iteration times is set at 2000 times in the PSO algorithm owing to efficiency and computing cost.

4.1.2. Default particle numbers

After adjustment for parameter of evolution iteration times, evolution iteration times are set at 2000, also fixes other parameters (e.g. inertia weight 0.95) to test different sets of parameters for default particle numbers to increase efficiency of the algorithm. The *Y*-axis represents the best fitness value which indicates the performance of finding the best solution in the PSO algorithm. The *X*-axis represents the execution times (each time the mechanism serves a user in a journey) of the algorithm. The experiments measure the best fitness values for 3 runs, each with 10 service executions to test an alternative parameter of default particle numbers. Since the range of the default particle numbers is 50–300, the appropriate parameter of default particle numbers is set by selecting 150, 200 and 250 default particle numbers.

Figs. 14–16 show three runs to demonstrate performance. The blue line represents the best fitness value tendency for 150 default particle numbers, the red line represents the best fitness value tendency for 200 default particle numbers, and the green line represents the best fitness value tendency for 250 default particle numbers. The simulation results of the average best fitness value for three runs are described in Table 4.

According to simulation results, the red line (200 default particle numbers) increases the efficiency of the algorithm that has

Table 3
The average performance of evolution iteration times.

	1000 Iteration times	2000 Iteration times	2500 Iteration times
Average performance	9.647022	10.64373	10.45889

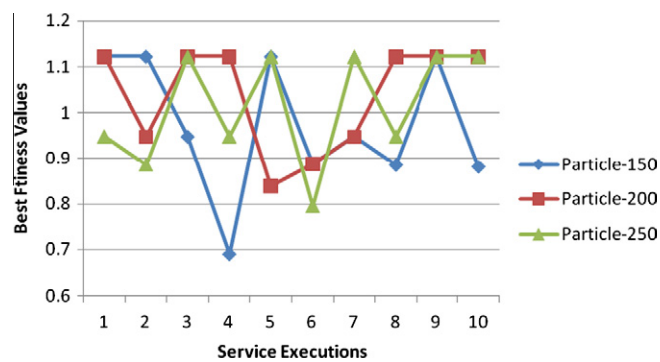

Fig. 14. First run for the parameter of default particle numbers.

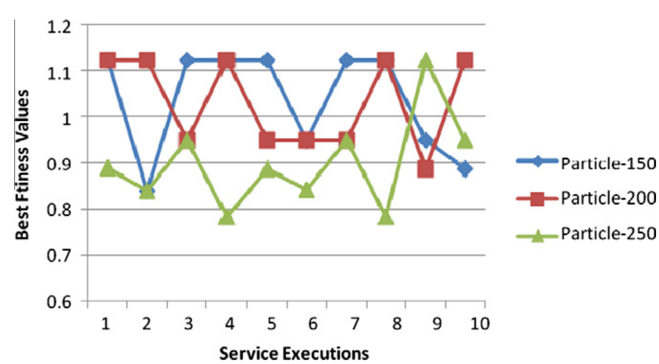

Fig. 15. Second run for the parameter of default particle numbers.

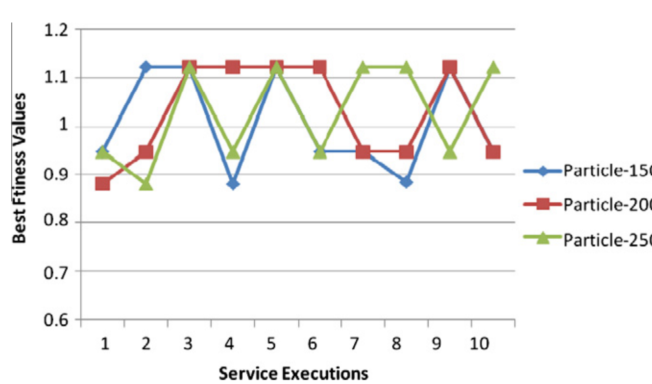

Fig. 16. Third run for the parameter of default particle numbers.

Table 4
The average performance comparison of default particle numbers.

	150 Particle numbers	200 Particle numbers	250 Particle numbers
Average performance	10.04501	10.31076	9.358024

more combinations of expectation determinants solutions than the others (e.g. 10.04501 for the blue line, 10.31076 for the red line and 9.358024 for the green line). The 250 default particle numbers may have more unanimous solutions greatly reducing the efficiency of the PSO algorithm. Consequently, the default particle numbers are set at 200 for better performance.

Two experiments are supported for parameters of evolution iteration times and default particle numbers to adjust parameter settings owing to better performance finding solutions. Table 5 depicts the values of five main parameters in the PSO algorithm.

4.2. Evaluation of performance of customer expectation management

This set of experiments attempts to use three customer stereotypes to validate whether the proposed mechanism can effectively manage expectations based on the objectives of stabilizing adequate expectations and raising desired expectations for customers. According to Frei (2006), there are five types of attributes that can characterize customer behavior: (1) arrival (e.g. how often do the customers arrive at service environments? Does this imply the strength of needs?), (2) capability (e.g. customer capabilities such as knowledge, skill, physical abilities, or resources), (3) effort (e.g. how much effort are customers willing to evert for the task?), (4) request (e.g. requirement of three aspects – existence, relationship, growth), (5) subjective preference (e.g. original expectations of each customer).

Table 6 describes the settings for appropriate customer stereotypes in detail. The experiments simulate the processes of the proposed mechanism five times. Three customer stereotypes include: the *appropriate serving stereotype* that is a suitable type of customer for the current strategy of managing customer expectations (e.g. stabilizing the adequate expectations and increasing the desired expectations), *extreme opposed serving stereotype* that is opposite to the appropriate serving stereotype, and *other stereotype* which differs from above two stereotypes, selected randomly. Table 7 shows initial values of parameters for evaluating customer expectation management.

Table 5
The initial values of the PSO algorithm parameters.

Parameters	Values
Evolution iteration times	2000
Default particle numbers	200
Inertia weight	0.95
Minimum position	0
Maximum position	1

Table 6
The settings of customer stereotypes.

Indicators	Appropriate serving stereotype	Extreme opposed serving stereotype
Arrival	Seldom	Often
Capability	Medium	High
Effort	Much	Medium
Request	Relation	Growth
Subjective preference	Medium and low	Medium and low

Table 7
Initial values of parameters for evaluating customer expectation management.

Items	Values
Number of experiment user stereotypes	3
Sample of each stereotype	3
Number of service executions	10
Number of experiment runs	3

The objective of this experiment is to evaluate the performance of customer expectation management through the proposed mechanism. The progressions of adequate and desired expectations of three customer stereotypes are depicted in the Figs. 17 and 18. Adequate (1) and Desired (1) represent the appropriate serving stereotype (e.g. blue line), the Adequate (2) and Desired (2) stands for the extreme opposed stereotype (e.g. red line), and the Adequate (3) and Desired (3) present the other customer stereotype (e.g. green line).

According to simulation results in Fig. 17, the progression lines for adequate expectations are nearly stable by continuously and dynamically managing by the proposed mechanism. For example, when the variation of adequate expectation value in one run is over threshold value (0.5), the mechanism will utilize the appropriate expectation determinants to increase/decrease the adequate expectation value for stabilization. Although three different customer stereotypes are involved in experiments, the simulation results are significant indicators of good performance of customer expectation management using the proposed mechanism in terms of stable adequate expectations.

Fig. 18 shows the progression lines of desired expectations continuously increase. The simulation results show that variations of desired expectation values of the appropriate serving customer stereotype (Adequate(1)) are better than the other two stereotypes, since the appropriate serving customer stereotype has high-

Fig. 17. The progression of adequate expectation.

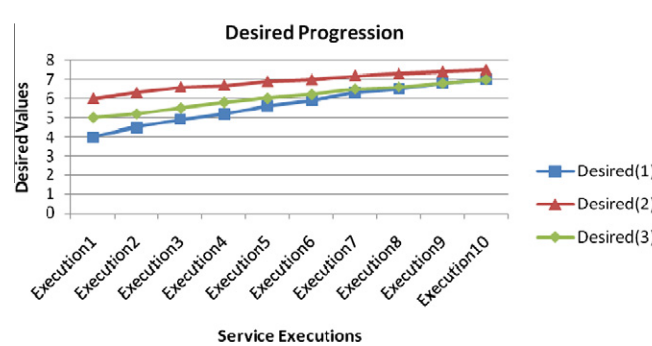

Fig. 18. The progression of desired expectation.

er willingness to make an effort to be involved in service encounters. However, the extreme opposed stereotype and the other customer stereotype still can be managed by the proposed mechanism based on the progressive tendencies.

The current strategy of customer expectation management is to stabilize customer adequate expectation and increase customer desired expectations to widen the zone of tolerance. Table 8 shows the analysis of customer expectations in detail which the proposed mechanism can achieve objectives. Z represents the initial value of the zone of tolerance, and Z' represents the value of the zone of tolerance after determinants have influenced customers. The Z' value of the appropriate serving customer stereotype is larger than other two stereotypes (e.g. Z': appropriate stereotype 5.5 > opposed stereotype 3.7, or appropriate stereotype 5.5 > other stereotype 4.4). Consequently, the results can exemplify good performance of customer expectation management with the proposed mechanism by increasing desired expectations.

4.3. Evaluation of service productivity

Service productivity is an important issue for service providers to consider. Although service providers can deliver high quality service to customers without efficiency, customers may be not satisfied with service owing to additional time spent. This set of experiments attempts to measure the efficiency of service productivity with the proposed mechanism. Service productivity can be represented as the service outcome divided by service inputs (Johnston & Clark, 2001). In the experiments, the number of recommendations (SCs_Recom) and transaction weight (SCs_TransWeight) of service components represent the service outcome. When customers recommend services and make transactions, delivered services influence customer thinking significantly. Similarly, the service cost (SCs_Cost, e.g. staff, materials and equipment needed to offer services) represents service inputs. In Formula (11) the equation of the service productivity can be depicted as follows:

$$\textbf{Service productivity} = (\mathbf{SC_s\_TransWeight} + \mathbf{SC_s\_Recom})/\mathbf{SC_s\_Cost} \tag{11}$$

The experiments attempt to evaluate the performance of service productivity using three strategic conditions. There are 3 runs, each with 10 service executions to test service productivity. Table 9 shows the description of parameters in detail. *A* condition represents transaction benefits and number of recommendations of service components during service delivery. *B* condition represents transaction benefits of service components and *C* condition represents number of recommendations of service components during service delivery.

Figs. 19–21 describe the variation of service productivity for the three strategic conditions. Results for service productivity are in Table 10. The results show strategic condition A has better performance on service productivity than the other two conditions in 3 runs (e.g. 1st Run: $\sum_{i=1}^{10} A_i 0.431541 > \sum_{i=1}^{10} B_1 0.37258$). B and *C* conditions take only one factor (e.g. number of recommendations, or transaction weight) into account which generates less performance of service productivity. The results support consideration of number of recommendation and transaction weight of service components is extremely critical for service productivity. High service productivity results from the efficient mechanism by considering the total benefit to providers and customers.

Table 8
The analysis of customer expectations.

Stereotype	Expectation			
	Adequate	Desired	Z	Z'
Appropriate stereotype	1 → 1.5	4 → 7	3	5.5
Opposed stereotype	4 → 3.8	6 → 7.5	2	3.7
Other stereotype	2 → 2.6	5 → 7	3	4.4

Table 9
The parameters of service productivity evaluation.

Items	Values
The number of journey	3
The number of service executions	10
The number of experiment runs	3
A (blue line)	Considerations of transaction benefits and numbers of recommendations
B (red line)	Only consideration of transaction benefits
C (green line)	Only consideration of numbers of recommendations

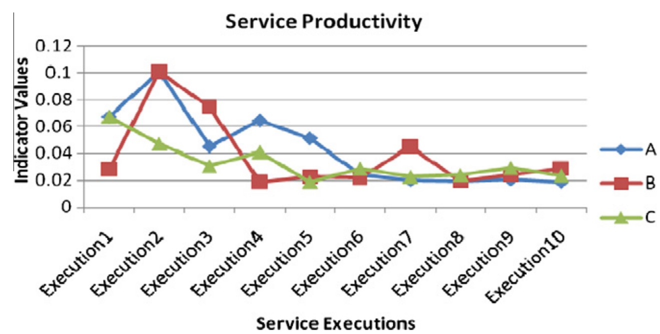

Fig. 19. First run of service productivity.

Fig. 20. Second run of service productivity.

Fig. 21. Third run of service productivity.

4.4. Evaluation of high performance service ecosystem

Based on the macro viewpoint, this set of experiments validates the robustness and effectiveness of the proposed mechanism for a

Table 10
The performance analysis of service productivity.

	Service productivity analysis		
	$\sum_{l=1}^{1}0A_i$	$\sum_{l=1}^{1}0B_i$	$\sum_{l=1}^{1}0C_i$
First run	0.431541	0.373258	0.331364
Second run	0.463449	0.394470	0.343720
Third run	0.444541	0.366718	0.325244

$\sum_{l=1}^{1}0A_i$: The summation of service productivity values from *A* condition.
$\sum_{l=1}^{1}0B_i$: The summation of the service productivity values from *B* condition.
$\sum_{l=1}^{1}0C_i$: The summation of the service productivity values from *C* condition.

high performance service ecosystem that can create value for providers and customers. This experiment utilizes the surplus value theory (Carlsson & Davidsson, 2002; Marx, 1952) to evaluate the performance of the proposed mechanism by assessing value perceptions of providers and customers. The equation of surplus value is shown in Formula (12):

$$S = P - (C + V), \tag{12}$$

where **S** denotes surplus value, **P** represents total value, **C** is total spending on investments and materials, V denotes spending on labor, and **(C + V)** represents total cost.

This study seeks to maximize both service provider and customer surplus value. The objective functions of surplus value for a high performance service ecosystem are shown in Formula (13) and (14):

$$\text{Maximum} \quad S_p = P_p - (C + V)_p, \tag{13}$$

$$\text{Maximum} \quad S_c = P_c - (C + V)_c. \tag{14}$$

P_p represents the total value obtained by service providers deploying our mechanism (e.g. how to manage customer expectations), the proportion of zone variation to the original zone P_p. $(C+V)_p$ indicates the effort service providers are willing to make in service encounters, and can be represented as the utilization degree of service components. P_c represents the total value for customers by employing the degree of the customer satisfaction. Customers get greater satisfaction if there is more service components selected, more closely matching their preferences. $(C+V)_c$ represents the total cost and effort of customers making recommendations. For example, a customer making a higher effort might recommend services 5 times, which can be considered a threshold in the experiments; if the mechanism wants the customer to recommend services an additional 2 times, this is the effort by the customer in service encounters. This experiment simulates 15 customers, 15 journeys, and 10 service executions which leads to the computation of the values of $\boldsymbol{S_p}$ and $\boldsymbol{S_c}$ to analyze that if these solutions can achieve the equilibrium of pareto optimal solutions (Hochman & Rodgers, 1969; Sawaragi, Nakayama, & Tanino, 1985). Table 11 shows definitions of above parameters.

The pareto optimal solution is one where the improvement in one objective does not lead to a simultaneous degradation in one or more of the remaining objectives. According to Baumgartner, Magele, and Renhart (2004) and Krieger and Green (1991), "a pareto optimal solution is, by definition, the best that can be achieved for one objective without disadvantaging at least one other objective". Many previous research findings support the pareto optimal solution as the best solution in the multi-objective function which has a trade off relationship between different objectives. When the pareto optimal solution is attained, the equilibrium state will emerge, which can be regarded as an appropriate performance situation within multi-objective purposes (Burke, 1995).

In order to ensure pareto optimality, the randomized method is utilized to generate solutions to represent other possible situations created by other mechanisms (e.g. mechanisms delivers services without considering customer expectation management). The parameters of the randomized method are defined according to a service domain expert and market surveys data from Taiwan.

Table 11
The parameters of evaluation for the high-performance service ecosystem.

Parameters	Definition/value
S_p	Surplus value of service providers
P_p	(Zone of tolerance after expectation management)/ (zone of tolerance before expectation management)
$(C+V)_p$	The utilization degree of service components
S_c	Surplus value of customers
P_c	The degree of the customer satisfaction
$(C+V)_c$	The recommendation effort degree of service components
The number of customers	15
The number of journeys	15
The number of service executions	10

In Fig. 22, the *x*-axis represents the S_p and *y*-axis represents the S_c. The 15 solutions (rhombus pots) are generated by the collaborative interaction mechanism are clustered into a group and the other solutions (circle pots) are attained by the randomized method (other allocation strategies) also clustered into a group; therefore, the pots of the rhombus group have better performance for S_c (customer surplus value) than the pots of circle group. None of the pots of the circle group have performance S_p (provider surplus value) better than the pots of rhombus group. Moreover, for any pot of the rhombus group, if there are any pots in the circle group that have better performance in S_c, then those pots in the circle group must have worse performance in S_p. Solutions generated by the collaborative interaction mechanism conform to the definition of the pareto optimal solution, when one objective has improvement, the others are not negatively affected.

4.5. Discussion

According to the simulation results of the above four experiments, evaluation and insights are summarized:

(1) *Initial values of key parameters for better performance:* The parameters of evolution iteration times and number of particles have significant influence on the performance of the PSO algorithm. This study refers to previous research findings to determine the appropriate settings of key parameters (e.g. runs: 3, evolution iteration times: 2000, and particles: 200) to get the better performance for the other three experiments.
(2) *Exploration of customer expectation management:* The simulation results show that the proposed mechanism can successfully manage customer expectations (adequate expectations, desired expectations and the zone of the tolerance) to achieve the target strategy (e.g. stabilizing adequate expectations and raising desired expectations) by testing three customer stereotypes. The results support the idea that customer expectation management is feasible in a real time and dynamic service system.
(3) *Exploration of service productivity:* In the experiments, we test the three strategies (benefit to service providers, benefit to customers, and both considerations to providers and customers) for the performance of service productivity. The simulation results show that delivering services by considering both benefits to customers and providers has better performance than the other two strategies, considering

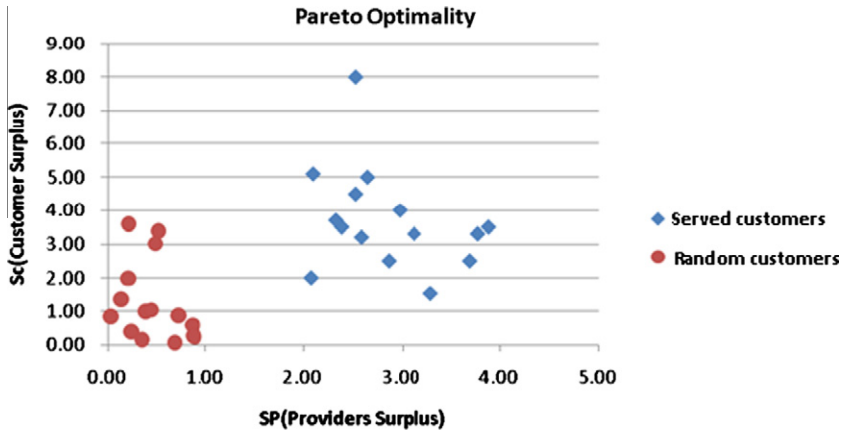

Fig. 22. Pareto optimality for served customers and random customers.

one-party value. Service providers should create valuable services that customers can also be involved in. Thus, service providers can acquire and co-create values with their customers.

(4) *High performance service ecosystem:* Delivering services to customers by different service providers within different service encounters can be regarded as a service ecosystem. The main objective of the proposed mechanism is to aid service providers to intelligently and dynamically deliver high quality services to customers. The simulation results demonstrate that solutions generated by the proposed mechanism are better than the solutions generated by the random mechanism (e.g. implicitly representing any other solution mechanisms) in terms of the pareto optimal concept. Accordingly, both service providers and customers can get value from service encounters underlying the proposed mechanism. For instance, service providers can gain profit and have repeat customers; customers can be satisfied with expected services.

5. Concluding remarks

This study utilizes the concept of customer expectation management to build a PSO-based intelligent service dispatching mechanism. The proposed mechanism can effectively design and deliver high quality service by managing customer expectations and employing the PSO approach to maximizing value to providers and customers, while minimizing the cost to providers. The proposed mechanism can help to create a high performance ecosystem, since target service values can be attained. The feasibility of implementing customer expectation management is supported by positive evaluation results. Service providers can be empowered with a systematic approach of integrating existing services into customer expectation management in real time environments to deliver a high quality service experience.

In summary, this research proposes a PSO-based intelligent service dispatching mechanism to ensure delivery of high quality services to customers by adopting customer expectation management. The proposed mechanism can enable service providers to achieve customer satisfaction and result in memorable experiences. Accordingly, this study conducts four experiments (evaluation of parameters of particle swarm optimization, evaluation of performance of customer expectation management, evaluation of service productivity, and evaluation of a high performance service ecosystem) to evaluate the proposed mechanism.

The contribution of the PSO-based intelligent service dispatching mechanism is twofold:

(1) *Managing customer expectations and behavior in real time environments:* Previous research only analyzes the importance of customer expectations, yet there is no mechanism to implement the notion in practice. This study proposes a PSO-based intelligent service dispatching mechanism which is developed based on customer expectation management. The proposed mechanism can dynamically select and deliver appropriate services to customers in different situations according to expectation values which are calculated by an expectation measurement module. Service providers can immediately understand customer thinking and provide appropriate services to fulfill customer needs.

(2) *Building a high performance ecosystem:* In the traditional mindset, since service providers only deliver immutable services which must be beneficial for them rather than the consideration of customers, customers must accommodate these services. However, service-dominant logic changes this during service delivery (Vargo & Lusch, 2004). Service providers can design the service delivery process which customers can be involved and co-create value together. The PSO-based intelligent service dispatching mechanism adopts surplus value to examine the benefits between providers and customers. Significant evidence shows that both considerations of providers and customers will lead to a high performance ecosystem.

Although this research provides support of feasibility for customer expectation management during service encounters, there are still limitations and possible directions for further research. First, the service delivery process which can be influenced by many other factors (e.g. service recovery, or internal service quality) is extremely complicated and dynamic. This study proposes a PSO-based intelligent service dispatching mechanism which is mainly based on customer expectation management. The proposed mechanism may not be fully applied to all occasions of dynamic service delivery. Second, only the proposed mechanism is demonstrated by conducting four simulation experiments. Hence, the values of parameters should be adjusted and modified to fit in with the practical and real world situations.

There are also limitations in our resolutions that are potential directions of future research. First, while designing delivery for service encounters, aforementioned factors should be taken into consideration to build a faultless service dispatching mechanism based on the results of this study. Second, another important direction is to apply the proposed mechanism into a real environment to collect practical data for further modification. For instance, an exhibition is a dynamic and real time environment to implement the PSO-based intelligent service dispatching mechanism. Third, customer thinking is extremely complex and difficult to analyze by considering customer expectations. Subsuming customer emotions and perceptions to further research should be an essential direction in order to understand customer psychology and behavior.

Acknowledgments

The authors would like to thank the Sayling Wen Culture & Educational Foundation for their financial support of this research. We also acknowledge the valuable help of the members of the Service Science Research Center in NCCU for their insightful comments and suggestions.

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