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Segmenting online game customers – The perspective of experiential marketing

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ABSTRACT

In this paper, we developed measurement scales for five experiential modules of the SEMs for online game players and the three attributes that are repurchase desire, public praise and recommendation desire and cross-purchase desire to set up the decision trees from the collected questionnaires of existence players. Accounting to the online games consumers attributes' literatures, we located and modified the important influential factors for each experiential module. Then, by applying the technique of decision tree data mining, we explored the potential relationship between the important influential factors and customer loyalty. The major contribution of this paper is to integrate data mining and experiential marketing to segment online game customers. These results can help firms to predict and understand the new consumers' purchase behavior. According to this understanding, online games' manufactures could draw up the different market strategies to increase the more purchase for the new different attributes' consumers.

1. Introduction

With the advancement of Internet technology, online games have become a major part of leisure activities for many people. As the online games consumers are growing, companies worldwide produce new games to attract and please customers. For example, the American company Electronic Arts Inc. launched the first-ever Internet-based game "Ultima Online" in 1997, a first 3D online game "Ever Quest" was released in Japan soon. After 1997 Asian financial crisis, Korean manufacturers devoted themselves to develop the industry of online games that rescued successfully the crash economy of Korea and then become a trend-setter in this industry. The topic of online games is so important that scholars and practitioners are interested in how gamers react to other online gamers, and how games should be designed (Choi & Kim, 2004; Lo, Wang, & Fang, 2005).

Online games provide a virtual reality for participants. Every player could act as a role or control a role to conduct any expedition or fighting, or to form a communal link through interaction or dialogue with other players. A variety of games bring the players different experiences. For example, a player could experience a totally different life; the battlefield created by multi-media technology generates visual and audible amusement and satisfaction; the good result from the games may alleviate you from actual frustration and failure; many players could obtain identification and ethnicism from cooperation and competition by building a virtual community. Since the experience of players has immediate influence on their consumption desire, the key to improve the marketing effect for online game manufacturers is how to create deep-going and satisfactory experience for the players. That is, from the perspective of experiential marketing, the perceived experience will significantly influence the future consumption decision of online game customers.

The realization that customers concern not only the practical functions of products, but also the consumption experience has substantially changed the concept of production and marketing. That is, customers may focus on subjective recreational experience (Addis & Holbrook, 2001). Therefore, the enterprises are obliged to create individual experience for the customers in order to satisfy customers and then improve their loyalty (Prahalad & Ramaswamy, 2000).

Experiential marketing is a methodology, a concept that moves beyond the traditional "features-and-benefits" marketing. Experiential marketing connects consumers with brands in personally relevant and memorable ways. Schmitt (1999) proposed the strategic experiential modules (SEMs) as the assessment items of customer experience. He classified customer experience into sense, feel, think, act, and relate experiential modules. Each experience is analyzed in different forms to design appropriate experiential modules. The modules then lay a basis for experiential marketing policy. The experiential marketing is so popular that many companies are eager to practice it. Five experiential modules of the SEMs are defined as follows:

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1. Sense experiential module: aimed at individual senses, such as: good-tasting food, magnificent game images and pleasing game music. The sensory pleasure or stimulation aids in the customer's positive evaluation, stimulates their desire of consumption and improves the value of products.
2. Feel experiential module: stirring up the customers' feeling on a specific brand name or product. The experience provider intends to link closely the experience, products and customers by various means, such as: creating a slogan, e.g., Nike's ''Just Do It", highlighting the sports sprit without fear of failure.
3. Think experiential module: aimed at activating the innovative thinking of the customers. In so doing, it is required to understand what the customers are thinking and what they are interested in order to arouse resonance. For instance, many rare treasures in the online games could be obtained only through successful thinking of or obstacle-breaking by the players.
4. Act experiential module: aimed at interaction with the others and physical experience, e.g. interaction of the service staff and players in online games.
5. Relate experiential module: including all the above-specified experiences. The individuals are related to other individuals and things through personal experience, rather than individual personality and feeling.

In this paper, we would like to construct the method that how to forecast the purchase behavior of new online games' consumers through the consumer attributes' data of existence players to increase the sales revenue for the firms. There are many data mining methods, and decision tree is one of the most used. Data mining technology has been widely applied to management, marketing, medicine and finance, and so on. Data mining can help enterprises efficiently analyze customer behavior and obtain a further insight into the customer demands (Nemati & Barko, 2003). Unlike typical statistics calculating only the data distribution, decision tree can be used to analyze the potential association rules among data attributes, and then predict the classification results of unknown data samples through these rules. Therefore, decision tree is an efficient tool to analyze customer behavior. In this paper, we argue that the decision tree data mining is a powerful method to segment customers. ID3 algorithm developed by Quinlan (1979) is one of most commonly used and efficient decision tree algorithms. We modified it and then established a new algorithm called Improved-ID3. The major reformation of the Improved-ID3 is to avoid excessively unnecessary partition of nodes, and simplify the complexity of decision trees through preventing from useless branching.

The five experiential modules of the SEMs are used to develop measurement scales for online game players. Accounting to the online games consumers attributes' literatures, we located and modified the important influential factors for each experiential module. Then, by applying the technique of decision tree data mining, we explored the potential relationship between the important influential factors and customer loyalty. In short, the major contribution of this paper is to integrate data mining and experiential marketing to segment online game customers. In this paper, we developed the three attributes that are repurchase desire, public praise and recommendation desire and cross-purchase desire to set up the decision trees from the collected questionnaire data of existence players. These results can help firms to predict and understand the new consumers' purchase behavior. According to this understanding, online games' manufactures could draw up the different market strategies to the more purchase for the new different attributes' consumers.

This paper is organized as follows. Section 1 describes intention of this research. Section 2 discusses the research framework of this paper. Section 3 first describes the procedure of ID3 decision tree data mining and then details our proposed Improved-ID3 algorithm. Section 4 shows the results of performing Improved-ID3 data mining on the behavior data of online game customers. Section 5 concludes this paper.

2. Research design

In this paper, the five experiential modules of the SEMs are used to establish the measurement scales for segmenting the online game customers. The main goal is to get a better understanding of online game customers from the perspective of experiential marketing.

2.1. Loyalty of online game players

Customer loyalty is an important concept in marketing, but the definition is not universally accepted. For example, Dick and Basu (1994) defined customer loyalty as the strength of relationship between consumption attitude and repurchase behavior. Jones and Sasser (1995) regarded customer loyalty as the repurchase desire of a customer for certain products or services. Some researchers stressed that customer loyalty is aroused by the strong preference of a customer on a certain brand (Assael, 1992). Oliver (1997) considered customer loyalty as deeply held commitments to rebuy or repatronize products or services in the future. Bhote (1996), however, defined customer loyalty as the willingness of a customer to positively promote the satisfactory products or services.

There exist different ways to measure customer loyalty. For instance, Jones et al. (1995) indicated that customer loyalty could be evaluated in three aspects: (1) intent to repurchase; (2) primary behavior; and (3) secondary behavior. Kristensen, Martensen, and Gronholdt (2000) argued that, customer loyalty is composed of four indexes: (1) repurchase desire; (2) recommendation desire; (3) price tolerance; and (4) cross-purchase desire. Combined the above measurements, we evaluated customer loyalty by the following three criteria: (1) repurchase desire; (2) public praise and recommendation desire; and (3) cross-purchase desire.

(1) Repurchase desire: a customer will repurchase certain products or services, when he has such a requirement within a certain period of time.
(2) Public praise and recommendation desire: if a customer is satisfied with certain products or services, he is willing to recommend them to his relatives and friends, and positively promote the brand or image in any manner.
(3) Cross-purchase desire: if a customer is satisfied with certain products or services, he will show a desire of purchasing the relevant products or services, peripheral products or services as well as other irrelevant ones.

In this research, these three criteria are taken as *target attributes* to discuss which *important influential factors* in the behavior data of players are related to them.

2.2. Analysis of constructs of online game players' behavior

It is well recognized that customer satisfaction has significant influence upon purchase behavior and decision-making. That is, customer satisfaction plays a key role in marketing policy. As mentioned above, the behavior of online game customers is described in terms of five strategic experiential modules: sense, feel, think, act and relate experiential modules. Each experience is evaluated from the viewpoint of customer satisfaction. The evaluation process establishes the constructs of online game customer behavior. In the following, we discuss the definitions of *customer satisfaction*.

Howard and Sheth (1969) considered customer satisfaction to be the cognition of a customer as whether the benefit is worth the cost. Oliver (1981) argued that customer satisfaction is considered as the assessment of customers for pleasantly amazement during the process of purchase. Tes and Wilton (1988) indicated that customer satisfaction is a perceptive difference between a customer's expectation and actually perceived experience. Hauskn-echt (1990) pointed out that customer satisfaction would be involved with many reactions, such as: joyful, pleasant, satisfied emotion. Woodruff, Cadotte, and Jenkins (1983) argued that customer satisfaction means the emotional reaction of customers on the benefits obtained from products. Besides, it is also believed by Fornell (1992) that customer satisfaction means the degree of gratification for products or services, which is conveyed in the form of consumption desire. According to the above definitions, it is clear that customer satisfaction is deemed as an overall attitude toward consumption experiences.

It is well known that customers may evaluate different products or services from different angles. Thus, it is important to take product features into consideration when evaluating customer satisfaction. There exist many influential factors corresponding to product features to the customer satisfaction of online games, such as: linking speed, quality of server connectors, feel experience, services, challenge of games and interpersonal relationship (Choi & Kim, 2004; Hsu, Lee, & Wu, 2005; Lo et al., 2005). The hardware factors could be improved with the technological progress. However, good personal experience and feeling rely on the game designers' innovative ideas and the sellers' excellent services. It is evident that personal experience and feeling play vital roles in evaluating customer satisfaction.

As mentioned before, we develop the measurement scales from the five modules of strategic experiential modules. The selected *important influential factors* for each experiential module are described below.

1. *Sense experiential module:* This module focuses on the quality of game-related designs perceived by players, such as image design, sound design, 3D sounds effect, characters design, incidental music, and animation design. Since the virtual cyberspace of online games without smell and taste senses, the following two factors are considered as the important influential factors to the players' sense experience: (A) image design: involving the quality of characters design, image design, and 3D effect design and so on; and (B) sound effect design: involving the quality of incidental music design, 3D sound effect design, and so on.
2. *Feel experiential module:* In this module, the satisfaction is evaluated based on whether the games make the players delighted or relaxed. The following two factors are considered as the important influential factors: (A) emotional delight: whether the players could take delight and satisfaction during the game process; and (B) psychological relaxation: whether the players could feel relaxed or released from mental nervousness through the game process.
3. *Think experiential module:* This module checks whether the games possess the features of challenge, interest, difficulty and so on. These features could stimulate the players' emotions of curiosity, surprise, thinking, delight, amusement, and challenging desire. The following two factors are considered as the important influential factors: (A) difficulty and challenge: whether the game could stir up the players' emotion for challenging something; and (B) brainstorm: whether the players will search for the best ways to play games.
4. *Act experiential module:* This module focuses on game-related services or staffs, such as: customer service, official website, dedicated phone line for customer service, game manger, and so on. The following two factors are considered as the important influential factors: (A) quality of service: the handling speed and attitude of game manager and customer service staffs, as well as provision of multiform channels for data inquiry or troubleshooting; and (B) security-related services: the guarantee of the rights and interests from being damaged, such as emergency measures when a user's account was stolen.
5. *Relate experiential module:* This module stresses the acquisition of confidence from the interaction with other players during the game process. The following two factors are considered as the important influential factors: (A) interaction and interpersonal relationship: personal interaction with other players; and (B) sense of fulfillment: the approbation from other players and the acquisition of self-confidence.

2.3. The concept of research design

The major purpose of this paper is to segment online game customers via decision tree data mining. As mentioned above, repurchase desire, cross-purchase desire and recommendation desire are taken as the target attributes. The selected important influential factors of the five experiences are treated as *decision attributes*. Besides, demographic variables (e.g. gender, income, and age) are also taken as decision attributes. The proposed Improved-ID3 algorithm detailed in Section 3 can easily build a decision tree which schematically shows the potential association rules between the target attributes and the decision attributes. Recall that the three target attributes (three criteria) are used to measure customer loyalty in this paper. The concept of research design is shown in Fig. 1.

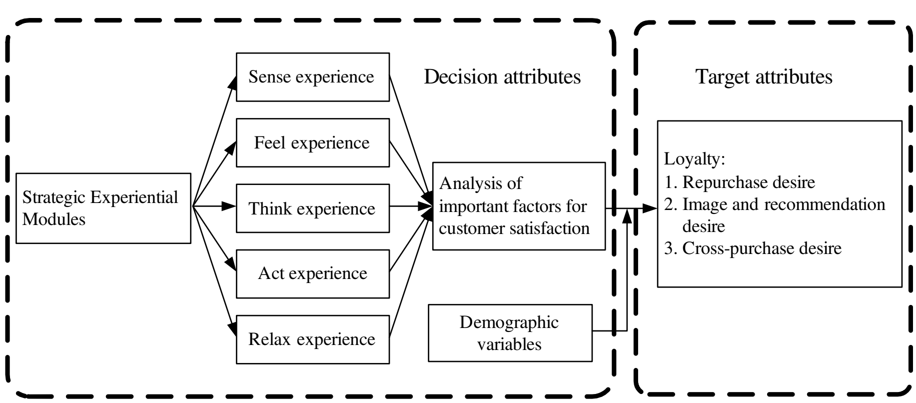

Fig. 1. The concept of research design.

3. An improved decision tree data mining method: Improved-ID3

The decision tree is one of the most popular classification algorithms in data mining. With simple computation, it can generate straightforward association rules. Fig. 2 depicts an example of a tree, wherein the nodes in the upper levels are the *parent nodes* of those connecting to them in the lower levels, and vice versa, the nodes in the lower levels are the *children nodes* of those connecting to them in the upper levels. For instance, node A is the parent node of node B, and node B is the children node of node A. The node without parent node is the *root node*; that is, the starting point of a tree. For example, node A is the root node of the tree in Fig. 2. The nodes without children nodes are *leaf nodes*, e.g. nodes C, D, and E. The *internal nodes* are referred to all non-leaf nodes. The *ancestors nodes* of a node indicate all nodes along the path from the root node to its parent node, e.g. nodes A and B are ancestors of node D.

Among various decision tree algorithms, Iterative Dichotomiser 3 (called ID3 for short) (Quinlan, 1979) was one of the most well-known and effective decision tree algorithms. Katharina and Dirk (1999) studied the behavior of ID3 and pointed out that ID3 was better than other decision tree methods, such as C4.5, CHAID, and CART. As compared with the improved methods (for example, C4.5) based on ID3, Ohmann, Moustakis, Yang, and Lang (1996) indicated that the number of association rules worked out by ID3 was not as numerous as that of C4.5. Thus, considering the simplicity of rule number, ID3 algorithm possessed the superior characteristic. Therefore, we chose ID3 as the data mining technique for this study.

Assume the collected data consist of n attributes. The users, based on their research objectives, select one from the n attributes as the *target attribute*, and treat the remaining $(n-1)$ attributes as *decision attributes*. It has been shown that ID3 can efficiently locate the association rules between the decision attributes and the target attribute by establishing a decision tree. Assuming the target attribute has t kinds of values, the decision tree will be able to identify t *classes*. For example, let "Catching a cold" be the target attribute with two possible attribute values "True" and "False". Then the ID3 will identify two classes: "Catching a cold = True" and "Catching a cold = False". Each leaf node of a decision tree is associated with one class which is labeled as the corresponding value of the target attribute.

The ID3 algorithm establishes a decision tree starting from creating a root node C comprising all data patterns, and marking all decision attributes as "unselected". The algorithm will mark the one with the optimal classification effect from the unselected decision attributes as "selected". Then, all data patterns associated with node C are split into different clusters according to their values corresponding to the selected attribute. Each cluster is corresponding to a children node of C. Repeat the same procedure to branch each children node until one of the stopping criteria is met.

There exist two common stopping criteria: (1) all decision attributes are labeled as "selected"; and (2) all data patterns in current node belong to the same class, i.e., the attribute values of the data patterns corresponding to the target attribute are the same. When any of the stopping criteria is reached, the ID3 algorithm will label the current node as a leaf node, label the class of this leaf node as the target attribute value including most data patterns, and stop.

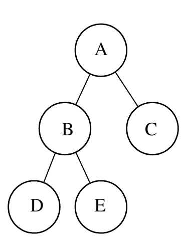

Fig. 2. An example tree.

In the resulted decision tree, the class associated with each leaf node represents the result of a sequence of classifications based on the selected decision attributes along the path from the root node to this leaf node. Therefore, each path from the root node to a leaf node forms an "if-then" type association rule between the decision attributes and the target attribute. Let all decision attributes are "unselected" at the beginning, the ID3 algorithm is summarized as follows:

Step 1. Create a root node C containing all data patterns.
Step 2. **If** all data patterns associated with node C belong to the same class, **then**
label node C as this class, set C to be a leaf node, and **stop**;
else go to step 3.
Step 3. **If** all decision attributes are "selected" **then**
Check all classes of the data patterns associated with node C by means of majority voting, and select the class with maximum data patterns;
Label node C as this class, set C to be a leaf node, and **stop**;
else perform step 4.
Step 4. Calculate *Entropy* $E(C)$ of node C by using the following formula:

$$E(C) = -\sum_{i=1}^{t} \frac{p_i}{n} \times \log_2 \frac{p_i}{n}$$

where t is the total number of classes associated with C, p_i is the total number of data patterns corresponding to the ith class in C, and n is the total number of data patterns in C.
Step 5. For each "unselected" decision attribute, say A, calculate its *Entropy* $E^+(A)$ and *Information Gain* $G(A)$ by using the following formulas:

$$E^+(A) = \sum_{j=1}^{k} (n_j/n) \times E(C_j)$$

$$G(A) = E(C) - E^+(A)$$

where k is the number of possible attribute values of A, C_j (for $1 \leqslant j \leqslant k$) is a subset of C including the data patterns corresponding to the jth possible attribute value of A, and n_j is the total number of data patterns contained in C_j.
Step 6. Label the decision attribute with maximum Information Gain as "selected". Assume the selected attribute has m kinds of values. Duplicate m children nodes of C denoted as $C_1, C_2, \ldots, C_m$. Each C_i, $1 \leqslant i \leqslant m$, contains data patterns with the ith value of the selected attribute.
Step 7. Treat each children node C_i, $1 \leqslant i \leqslant m$, as node C, and **go to** step 2.

Although ID3 algorithm is an efficient method, there is still a room for improvement. The remaining paragraphs of this section give description of a revised ID3 algorithm. Let S be a node of a decision tree, Class(S) be a function used to find the class of maximum data patterns in node S, N be the total number of data patterns, |Class(S)| be the number of data patterns in Class(S), and |S| be the number of data patterns in S. The proposed ideas used to improve the ID3 algorithm are described below:

1. *PURITY*(S): The PURITY of a node S, PURITY(S), is defined as: PURITY(S) = (|Class(S)|/|S|) $*$ 100%. A higher purity means a

higher tendency of data patterns concentrating on the same class. This definition is commonly used in data mining literature.

2. *SUPPORT(S)*: The SUPPORT of a node S, SUPPORT(S), is defined as: SUPPORT(S) = $(|S|/N) * 100\%$. A higher support indicates a higher degree of representation of node S. This definition is also commonly used in data mining literature.
3. *Sufficient Node*: Since each path of a decision tree from the root node to a leaf node represents an association rule, it is clear that the PURITY of relevant nodes influence the degree of representation of this rule. The higher PURITY means the higher degree of representation of this rule. We define a node as a Sufficient Node if its PURITY greater than or equal to a predetermined threshold. Here we set the threshold as 80%.
4. *Weak Node*: We set a "minimal_SUPPORT" and a "minimal_PURITY" as thresholds. If both SUPPORT and PURITY of a node are less than the above thresholds, we define this node as a Weak Node. The minimal_SUPPORT is set as 10%, and minimal_PURITR is set as 70%.

The original ID3 method may develop a copious and complex decision tree. Thus, the main idea of the revised ID3 algorithm is to apply some pruning concepts to avoid excessive branching of a decision tree. The example shown in Fig. 3 is used to illustrate the pruning procedure. Assume that node C with PURITY(C) of 88%. After separating the data pattern in node C, the tree creates two children nodes C_1 and C_2, of which PURITY(C_1) is 100% and PURITY(C_2) is 83%. Assume C, C_1, C_2 belong to the same class.

Since C_1, C_2 and parent node C are Sufficient Nodes and belong to the same class, any branching from node C cannot yield any more useful rules, but only increases the branches and the height of the decision tree. Thus, the algorithm can stop here. Moreover, a branching criterion can be used to further prune a decision tree; that is, branching a node is allowed only if the node meet the minimal_SUPPORT. The proposed algorithm is called Improved-ID3. The first five steps of the Improved-ID3 are the same as those of the ID3. The last two steps of the ID3 are, however, replaced with the following step:

Step 6. Label the decision attribute with maximum Information Gain as "selected". Assume the selected attribute has m kinds of values. Duplicate m *candidate* children nodes of C denoted as $C_1, C_2, \ldots, C_m$. Each C_i, $1 \leqslant i \leqslant m$, contains data patterns with the ith value of the selected attribute.

6.1 **If** node C is a Sufficient Node **and** Class(C_i) = Class(C) for $1 \leqslant i \leqslant m$, **then**
  set C to be a leaf node and discard all C_i for $1 \leqslant i \leqslant m$,
  set the class of node C as Class(C),
  and **stop**.

6.2 For each C_i, $1 \leqslant i \leqslant m$:
 If SUPPORT(C_i) $\geqslant$ minimal_SUPPORT **and** C_i is not a Weak Node **then**
  set C_i to be a children node of C,
  treat node C_i as node C,
  and **go to** step 2.
 else discard C_i.
 If all C_i for $1 \leqslant i \leqslant m$ are discarded **then**
  set C to be a leaf node,
  set the class of node C as Class(C),
  and **stop**.

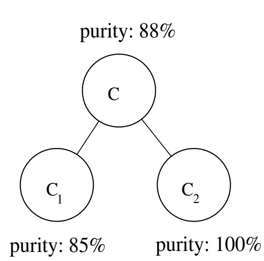

Fig. 3. An example of purity.

4. Data analysis and results

According to the analysis of constructs of online game players' behavior and concept of research design of Section 2, a web-based questionnaire was designed and 310 questionnaires were collected. Samples (286 of 310) were valid.

4.1. Reliability analysis

A test with good *reliability* should generate consistent scores in different settings. In general, higher consistency of scores means smaller effect of errors. The most common metric used to measure the reliability of questionnaire is Cronbach's α reliability coefficient. A reliability coefficient of .70 or higher is generally considered acceptable in most research. The values of Cronbach's α in Table 1 show a high reliability of our questionnaire.

4.2. Analysis of decision tree

It is quite often that different attributes have different measure scales. Therefore, to perform data mining analysis, the original data need to be normalized. In this paper, the average score of each attribute was normalized based on a Likert scale of low, medium and high, with "low" denoting "not important at all" and "high" denoting "very important".

Eventually, three measurement indexes, "repurchase desire", "public praise and recommendation desire" and "cross-purchase desire", are selected as three target attributes. The rest of measurement indexes in Table 1 and some demographic variables are taken as the decision attributes. The Improved-ID3 decision tree algorithm is used to locate the association rules between the decision attributes and the three target attributes. The rules are schematically illustrated as decision trees. The value associated with a leaf node represents the value of the corresponding target attribute. A path from the root node to a leaf node forms an association rule; namely, an "if-then" rule between all internal nodes (selected decision attributes) and the leaf node (target attribute).

Table 1
Reliability of variables.

Variables	Subvariables	Reliability
Loyalty	Repurchase desire	0.739
	Public praise and recommendation desire	0.77
	Cross-purchase desire	0.772
Sense experience	Image design	0.785
	Sound effect design	0.766
Feel experience	Emotional delight	0.755
	Psychological relaxation	0.764
Think experience	Brainstorm	0.76
	Difficulty and challenge	0.715
Act experience	Quality of service	0.82
	Safety-related services	0.714
Relate experience	Interaction and interpersonal relationships	0.818
	Sense of fulfillment	0.81

The results of decision tree data mining are separately discussed below according to three target attributes: "repurchase desire", "public praise and recommendation desire" and "cross-purchase desire". It should be important and interesting to know the distributions of age and gender in each decision tree. The survey data show that 71.3% of the respondents are men, and 28.7% are women. As for the age structure, 20.6% of the respondents are under 18 years, 68.5% are between 19 and 24 years old, and 10.4% are over 25 years old. The gender and age distributions of customers are also analyzed in accordance with every output rule. Based on the above information, we can check if the demographic variables play roles in the decision trees.

4.2.1. The decision tree with the target attribute of "repurchase desire"

The decision tree with "repurchase desire" as the target attribute is illustrated in Fig. 4, wherein there are seven paths (association rules) from the root node to leaf nodes. The seven association rules are detailed below:

A. **If** the service level is high, **then** the repurchase desire is high. The purity of this rule is 84%, and the support is 19.6%. That is, 84% of samples associated with this leaf node match this rule, accounting for 84% $*$ 19.6% = 16.46% of total samples.
B. **If** the service level is medium, the degree of interaction and interpersonal relationship is high, the degree of brainstorm is high, and the degree of difficult and challenge is high, **then** the repurchase desire is high. The purity of this rule is 83.5%, and the support is 15.3%.
C. **If** the service level is medium, the degree of interaction and interpersonal relationship is high, and the degree of brainstorm is low, **then** the repurchase desire is low. The purity of this rule is 82.1%, and the support is 9.8%.
D. **If** the service level is medium, the degree of interaction and interpersonal relationship is low, and the degree of emotional delight is high, **then** the repurchase desire is high. The purity of this rule is 80%, and the support is 11%.
E. **If** the service level is medium, the degree of interaction and interpersonal relationship is low, and the degree of emotional delight are low, **then** the repurchase desire is low. The purity of this rule is 87.5%, and the support is 8.4%.
F. **If** the service level is low, and the degree of psychological relaxation is high, **then** the repurchase desire is high. The purity of this rule is 80%, and the support is 5.8%.
G. **If** the service level is low, and the degree of psychological relaxation is low, **then** the repurchase desire is low. The purity of this rule is 78.7%, and the support is 16.2%.

From the perspective of rule A, the quality of service is the most important influential factor to the repurchase desire of online players. Good quality of service enables 16.46% players to generate higher repurchase desire. From the perspective of rules B, C, and D, if online players are grouped into two groups with either high or low degree of interaction and interpersonal relationship under moderate quality of service, the players with high degree of interaction and interpersonal relationship will have high repurchase desire once the brainstorming and challenge are increased. On the other hand, the players with low degree of interaction and interpersonal relationship pay much attention to the degree of emotional delight. Thus, in the event of delight, the repurchase desire is high, otherwise the repurchase desire is low. It is worthy to note that if the games could deliver enough challenge, brainstorming, psychological relaxation, and delightful experience, the online players will be attracted even if the quality of service is barely satisfactory.

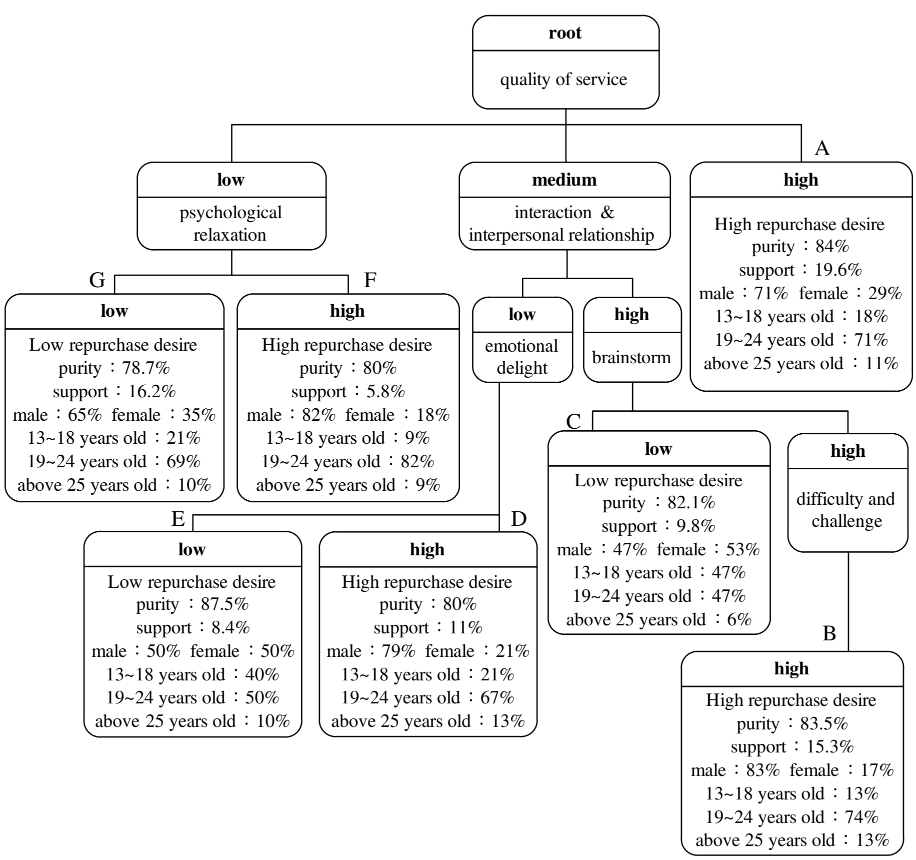

Fig. 4. Decision tree of repurchase desire.

The gender distributions of rules B, C and D differ appreciably from the average value. The distributions show that compared to men, woman players care more about the quality of service. Namely, under unsatisfactory quality of service, the repurchase desire of man players may increase due to the increasing of satisfactory interaction and interpersonal relationship, brainstorming, and difficulty and challenge; however, this is not the case for woman players. Moreover, according to rule C, the variation of the repurchase desire of players under 18 years old is similar to that of women described above.

4.2.2. The decision tree with the target attribute of "public praise and recommendation desire"

The decision tree with the "public praise and recommendation desire" as the target attribute is illustrated in Fig. 5, wherein there are five paths (association rules) from the root node to leaf nodes. The five association rules are detailed below:

A. **If** the degree of difficulty and challenge is high, **then** the recommendation desire is high. The purity of this rule is 86%, and the support is 19.2%. That is, 86% of samples associated with this leaf node match this rule, accounting for 86% $*$ 19.2% = 16.5% of total samples.
B. **If** the degree of difficulty and challenge is low, **then** the recommendation desire is low. The purity of this rule is 86.3%, and the support is 18.2%.
C. **If** the degree of difficulty and challenge is medium, and the degree of quality of service is high, **then** the recommendation desire is high. The purity of this rule is 87.1%, and the support is 10.8%.
D. **If** the degree of difficulty and challenge is medium, and the degree of quality of service is low, **then** the recommendation desire is low. The purity of this rule is 78%, and the support is 17.3%.
E. **If** the degree of difficulty and challenge is medium, the degree of quality of service is high, and the degree of interaction and interpersonal relationship is low, **then** the recommendation desire is low. The purity of this rule is 74.7%, and the support is 15.4%.

Association rule A indicates that 16.5% of total samples will generate high recommendation desire due to the high degree of difficulty and challenge. Rule E indicates that insufficient difficulty and challenge will lead to poor image and recommendation desire. However, according to rules B and D, in the case of medium degree of difficulty and challenge, good quality of service could lead to obvious recommendation desire.

Rules A and B indicate that men are prone to recommend to the others due to high degree of difficulty and challenge; interestingly, if the degree of difficulty and challenge is lowered, a higher percentage of women is reluctant to recommend to the others. The players under 18 years old are willing to recommend to the others

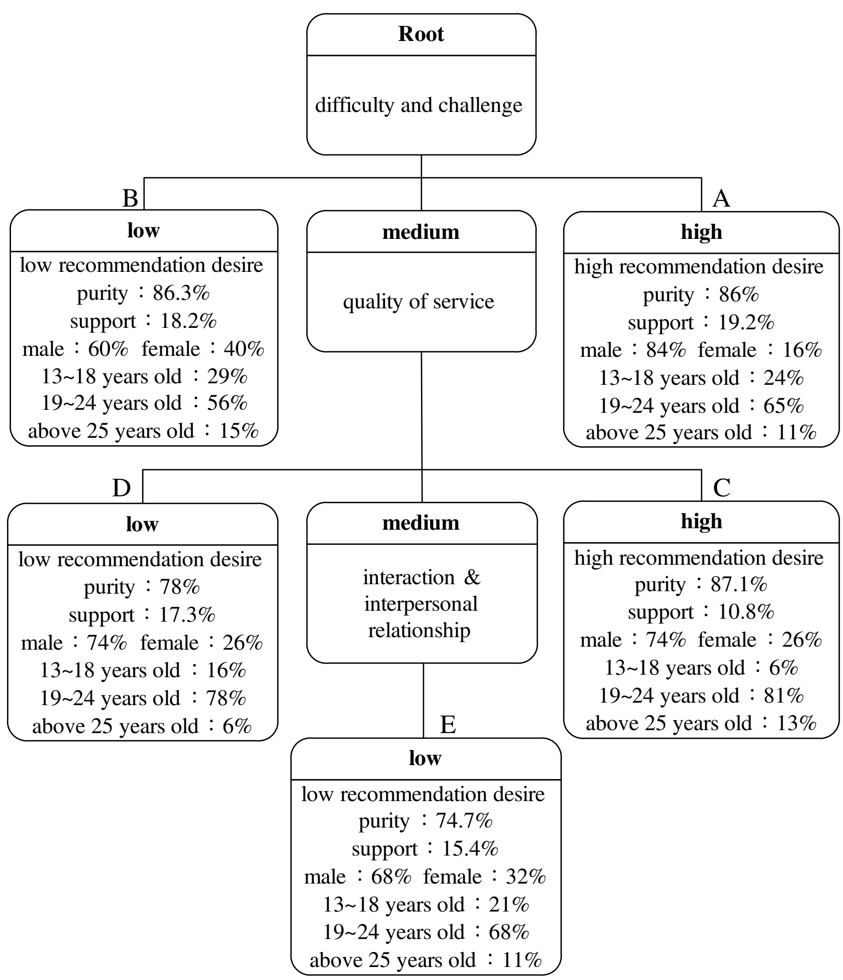

Fig. 5. Decision tree of public praise and recommendation desire.

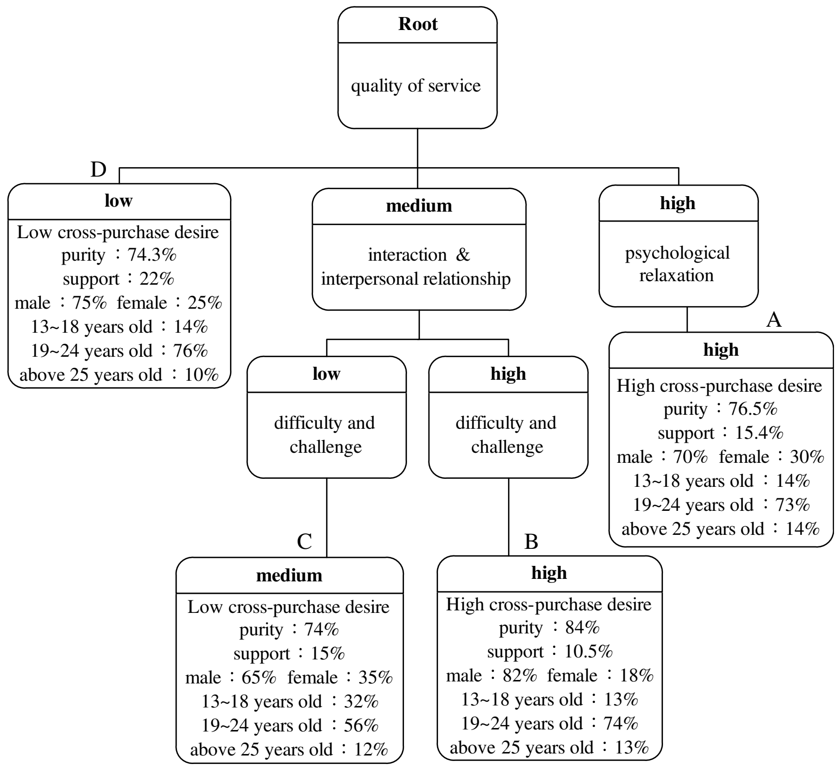

Fig. 6. Decision tree of cross-purchase desire.

due to high degree of difficulty and challenge; however, the willingness significantly declines due to the low degree of difficulty and challenge. Rule C indicates that the players of 19–24 years old are more willing to recommend to the others due to satisfactory quality of service, but only few players under 18 years old are willing to recommend to the others due to satisfactory quality of service.

4.2.3. The decision tree with the target attribute of "cross-purchase desire"

The decision tree with the cross-purchase desire as the target attribute is illustrated in Fig. 6, wherein there are four paths (associated rules) from the root node to leaf nodes. The four association rules are detailed below.

A. **If** the degree of quality of service is high, and the degree of psychological relaxation is high, **then** the cross-purchase desire is high. The purity of this rule is 76.5%, and the support is 15.4%. That is, 76.5% of samples associated with this leaf node match this rule, accounting for $76.5\% * 15.4\% = 11.78\%$ of total samples.
B. **If** the degree of quality of service is medium, the degree of interaction and interpersonal relationship is high, and the degree of difficulty and challenge is high, **then** the cross-purchase desire is high. The purity of this rule is 84%, and the support is 10.5%.
C. **If** the degree of quality of service is medium, the degree of interaction and interpersonal relationship is low, and the degree of difficulty and challenge is medium, **then** the cross-purchase desire is low. The purity of this rule is 74%, and the support is 15%.
D. **If** the degree of quality of service is low, **then** the cross-purchase desire is low. The purity of this rule is 74.3%, and the support is 22%.

The cross-purchase desire indicates the purchase desire to other extended products, services and peripheral products. If the customers have insufficient loyalty or confidence to the enterprises, they often show a conservative attitude to the unknown products or services due to the high uncertainty. Rule D clearly indicates that poorer quality of service will directly make the customers lose confidence. In other words, the customers will refuse to purchase the extended products because of the low quality of service. Rules A and B show that in the case of moderate quality of service, the customers will have higher cross-purchase desire once they have better experience of leisure and game.

Men and women have quite different desires to rules C and D. For example, a higher percentage of men support the conclusion of rule C, namely, good interaction and positive challenge results in higher cross-purchase desire. Contrarily, the cross-purchase desire of women will significantly decline in the case of poor interaction and negative challenge.

5. Conclusions

The marketing activities have now turned to create pleasing experience for the customers in the age of "Experience Economy". The features of online games make it important to apply experiential marketing to the online game industry. It is then crucial to segment online game customers from the perspective of experiential marketing.

This research refined ID3 decision tree to segment online game customers from the perspective of experiential marketing, and the results showed that quality of service, difficulty and challenge, and interaction and interpersonal relationship have most significant influential on customers' loyalty. Quality of service had the most impact on the repurchase and cross-purchase desires. However, difficulty and challenge is the most influential on the image and recommendation desire. The distributions of age and gender in each decision tree explicitly show the roles that the demographic variables matter.

The contribution of this research is to integrate data mining and experiential marketing for online game customers. The results show that the proposed method can efficiently and effectively explore the behavior of online game customers. This customer information can definitely help service or product providers improve their services or products, and most important excel in the highly competitive market. We strongly believe that our proposed integrated approach can also be successfully applied to other industries that can benefit from experiential marketing.

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