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A rough set-based association rule approach for a recommendation system for online consumers

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ABSTRACT

Increasing use of the Internet gives consumers an evolving medium for the purchase of products and services and this use means that the determinants for online consumers' purchasing behaviors are more important. Recommendation systems are decision aids that analyze a customer's prior online purchasing behavior and current product information to find matches for the customer's preferences. Some studies have also shown that sellers can use specifically designed techniques to alter consumer behavior. This study proposes a rough set based association rule approach for customer preference analysis that is developed from analytic hierarchy process (AHP) ordinal data scale processing. The proposed analysis approach generates rough set attribute functions, association rules and their modification mechanism. It also determines patterns and rules for e-commerce platforms and product category recommendations and it determines possible behavioral changes for online consumers.

1. Research background

Most online businesses that are involved in the sales of products/services, such as commercial websites, are aware of the need to acquire knowledge about their online consumers. However, knowledge about online consumers, though available, is not accessible, so it is critical to analyze all of the available knowledge if online users in search for information, products, or services and then highlight potential product promotions and marketing alternatives from online firms. In this regard, recommendation systems are increasingly used by online businesses to suggest options to online consumers (Miao, Yang, Fang, & Goh, 2007). A recommendation system supports users a search for information, products, or services (such as books, movies, music, digital products, Web sites and TV programs) by aggregating and analyzing suggestions from other users, reviews from various authorities and user attributes (Gao, Tang, & Liu, 2015).

As an information technology that supports a personalized service, recommendation systems are widely used by e-commerce practitioners and have become an important research topic in the field of information sciences and decision support systems (Liang et al., 2008; Wu, Kao, Wu, & Huang, 2015). Recommendation systems are decision aids that analyze a customer's prior online behavior and present information on products that match the customer's preferences. By analyzing the consumer's purchase history or communicating with the consumer, recommendation systems employ quantitative and qualitative methods to determine the products that best suit the customer. Most of the current recommendation systems recommend products that have a high probability of being purchased (Bodapati, 2008). They employ content-based filtering (CBF) (Shih, Chen, Chu, & Chen, 2012; Zenebe & Norcio, 2009), collaborative filtering (CF)

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(Herlocker, Konstan, Tervin, & Riedl, 2004; Ortega, Bobadilla, Hernando, & Gutiérrez, 2013), recommendations based on network structure and graph theory (NSGT) (Wang, Dai, & Yuan, 2008), hybrid recommendations (Yin & Peng, 2012), Radio-Frequency Identification (RFID) route recommendation systems (Tsai & Chung, 2012) and other data mining techniques, such as clustering (Kuo, Liao, & Tu, 2005), association rules (Jie, Yong, Wang, & Chu, 2009; Lee & Lee, 2011), rough sets (Su, Wang, Hsiao, & Tseng, 2010) and semantic approaches (Liang et al., 2008). Other studies have determined the effect of recommendation systems on customer's purchasing behavior (Bodapati, 2008; Mandl et al., 2011). These studies argue that the recommendation decision is based not on the probability of a purchase, but rather on the sensitivity of probability of a purchase, as affected by the recommendation action. General practice regards a recommendation system as successful if customers purchase the suggested products (Jiang, Shang, & Liu, 2010).

This personalization of product information is one of the most important factors that effect a customer's product selection and satisfaction in today's competitive and challenging market. A personalized service requires that firms understand their customers and offer goods or services that meet their needs (Aksoy et al., 2011). However, most of the traditional recommendation systems focus on extracting and recommending the common preferences, according to historical data for users. Although common preferences for general users may be a relevant consideration, each individual user also has his/her own personal preferences. He/she may also rely on the domain expert's knowledge to some extent when making decisions (Su et al., 2010). When using traditional recommendation systems, it is often difficult for online consumers to determine whether the items that are presented on a page are actual recommendations or simply the contents of the page displayed indiscriminately to all users.

Currently, personalized recommendation agents are addressing the impersonal nature of integrated recommendations by using technology to assist customers in decision-making and by treating each customer individually (Jiang et al., 2010). However, the key characteristic of e-commerce/business applications is that there is an increasing move towards a customer-centric paradigm, in order to increase competitiveness over other online firms (Liu, Lai, & Lee, 2009). Therefore, consumer preferences and profile building is critical to market segmentation for both online consumers and providers that seek to make personalized recommendations. This study considers that integrate both rough set theory and association rule as a new approach in terms of processing AHP ordinal scale data for developing a recommendation system on electronic commerce.

2. Related research

2.1. Recommendation systems

Since the development of the first recommendation system by Goldberg, Nichols, Oki, and Terry (1992), various recommendation systems and related technologies, such as CBF and CF, have been reported (Herlocker et al., 2004; Zenebe & Norcio, 2009). Of these, user-based CF is considered to be the most successful recommendation technique and is successfully used by many e-commerce systems, such as Amazon.com and Dell.com (Konstan et al., 1997). CF elicits superior preference information from the collaborative transaction logs to assist active users in making a choice from potential items. In other words, the goal of a CF-based recommendation approach is to predict the target item values for active users by learning from a set of users' rating behaviors. It finds a user group that is similar to the target buyer and recommends products that have been rated by users in the reference group that have not yet been viewed by the target buyer.

However, user-based CF has some limitations. It has difficulty in measuring the similarities between users and there is a scalability issue. As the number of customers and products increases, the computation time for algorithms increases exponentially (Hung, 2005). Item-based CF was proposed to overcome the scalability problem by calculating item similarities offline. It is assumed that a user is more likely to purchase items that are similar or related to the items that he/she has already purchased (Deshpande & Karypis, 2004). However, in terms of personalized recommendations, the existing recommender systems suffer from cold-start, first-rater limitations, sparsity and scalability problems. The fusion of rough sets and average-category-rating (FRSA) integrates multiple contents and collaborative information to predict user's preferences according to a FRSA, in order to reduce the gap between the user's preferences and the automated recommendations (Su et al., 2010).

Content-based filtering (CBF) uses content analysis to target items. Target items are described in terms of their attributes, such as color, shape, or material. A user profile is constructed by analyzing responses to questionnaires, ratings for products and navigation history. The recommendation system proposes items that have a correlation with a user's profile. However, a pure CBF system also has limitations, in that users can only receive recommendations that are similar to their earlier experiences and some items, such as music, photographs and multimedia, are difficult to analyze (Cheung, Kwok, Law, & Tsui, 2003). To increase the efficiency of CF and CBF, data-mining techniques that use decision trees, association rules, regression models and Markov chains have been developed to recommend movies and books (Ansari et al., 2000) and to support one-to-one online marketing (Huang, 2012), associative classification (Jiang et al., 2010) and real-time content recommendation in online social communities (Li et al., 2012).

In contrast to the recommendation of products according to the likelihood of purchase, Bodapati (2008) argued that the recommendation decision should also determine a customer's sensitivity to such a recommendation. A model was constructed to measure the role that recommendation systems play in modifying customers' purchase behavior, relative to what the customers would have done without such a recommendation intervention. Although the existing recommendation systems recommend acceptable products to customers, they share a common view that the act of purchasing itself corresponds to the customers' satisfaction, which may not be accurate. Jiang et al., (2010) proposed an associative classification method that predicts a customer's ultimate satisfaction. Depending on the customer's characteristics, a product is recommended to a potential buyer if a recommendation system predicts that a consumers' satisfaction level will be high (Mandl et al., 2011). Therefore, consumers' behavior characteristics, such as their purchasing preference, are critical factors in a recommendation system for online purchase analysis and ordinal data scale processing to determine customer's preference.

2.2. Behavioral change

Watson and Lindsley's initial studies on consumer behavior were inspired from their background as behavioral researchers. These studies led to the role of behavior analytic theory and its application in consumer behavior (Watson & Rayner, 1920; Lindsley, 1962). The applied behavior analysis movement brought operant-based applications into the consumer field, largely focusing on pro-social and social marketing applications. Increased interest in behavioral theory sparked continuing research into the classical conditioning of consumer attitudes and behaviors (DiClemente & Hantula, 2003). In the 1970 s, behavioral consumer research moved from theory-driven laboratory studies to those typified by the new applied behavior analysis movement (Baer et al., 1968). Consequently, research moved into domains such as recycling, gas conservation and electricity conservation, the success of which led Tuso and Geller (1976) and Geller (1989) to propose the increased use of applied behavior analysis in social marketing. A subsequent stream of applied studies used various modeling techniques to change consumer behavior in the context of purchasing goods and services. Winett, Kramer, Walker, Malone, and Lane (1988) used feedback, goal setting and modeling to reduce the purchase of high-fat foods and to increase purchase of foods that are high in carbohydrates. Winett et al., (1991) also used an interactive information system with instructional video programs and feedback to increase the purchase of high-fiber foods and to decrease the purchase of high-fat foods. These studies showed clearly that applied behavioral techniques can change consumer behavior. Also evident in these studies is the finding that sellers can use specific techniques to change the behavior of consumers. In recent years, researchers have used various approaches, such as association rules (Song et al., 2001; Chen et al., 2005; Chang, Hung, & Ho, 2007), machine learning (Shabtai et al., 2012) and fuzzy sets (Huang, 2012), in order to investigate possible approaches to change consumer behavior. The results of these studies show that it is possible to infer the possibility that recommendation plans lead to behavioral changes in online consumers.

2.3. Rough set theory

Rough set theory (RST) was introduced by Pawlak in the 1980 s (Pawlak, 1982; Pawlak, 2002) as a mathematical approach to aid decision-making when there is uncertainty. The rough set approach assumes that for every object there is a certain amount of associated information (data, knowledge), which is expressed by means of attributes that describe the object. Objects that can be similarly described are indiscernible (highly similar) with respect to the available information. The indiscernibility relationship, therefore, generated constitutes the mathematical basis of RST. The universe is partitioned into blocks of indiscernible objects, called elementary sets, which are used to build knowledge about a real or abstract world. This indiscernibility relationship results in the granulation of information (Greco, Matarazzo, & Slowinski, 2001; Singh & Dey, 2006). Pawlak's rough set model is not only the basis for formal reasoning using uncertain information, machine learning and knowledge (Khoo, Tor, & Zhai, 1999; Zhong, 2006), but also for data analysis and autonomous decision-making, and it is used to extract knowledge from datasets (Li et al., 2013). RST classifies imprecise, uncertain or incomplete information that is expressed in terms of data acquired from experience. In RST, a set of similar objects is called an elementary set, which comprises a fundamental atom of knowledge. Any union of elementary sets is called a crisp set and other sets are referred to as rough sets. According to this definition, each rough set has boundary-line elements. For example, some elements cannot be definitively classified as members of the set or its complement. In other words, when the available knowledge is used, boundary-line cases cannot be properly classified. Therefore, rough sets can be considered to be uncertain or imprecise, as illustrated below (Kaneiwa & Kudo, 2001; Darshit Parmar & Blackhurst, 2007).

Firstly, An important issue in RST is about attribute reduction, which is performed in such a way that the reduced set of attributes B, $B \subseteq A$ provides the same quality of classification $\gamma\ B(F)$ as the original set of attributes A. The minimal subset $C \subseteq B \subseteq A$ such that $\gamma B(F)=\gamma C(F)$ is called the *F-reduct* of B and is denoted by $REDF(B)$. A *reduct* is a minimal subset of attributes that has the same classification ability as the whole set of attributes. In other words, attributes that do not belong to a reduct are superfluous in terms of classification of elements of the universe. The *core* is the common part of all reducts. For example, $COREF\ (B)$ is called the F-core of B, if $COREF\ (B)=\cap REDF\ (B)$ (Ou Yang, Shieh, Tzeng, Yen, & Chan, 2011).

Secondly, an attribute, a, is a mapping, $a : U \to Va$, where U is a nonempty finite set of objects (called the universe) and Va is the value set of a. An information system is a pair, $T=(U, A)$, of the universe, U, and a nonempty finite set of attributes, A. Let B be a subset of A. The B-indiscernibility relationship is defined by an equivalence relationship, IB on U, such that $IB=\{(x, y) \in U2 \mid \forall a \in B\ .\ a(x)=a(y)\}$. The equivalence class of IB for each object, $x\ (\in U)$, is denoted by $[x]B$. Let X be a subset of U. The lower and upper approximations of X are defined by $B(X)=\{x \in U \mid [x]B \subseteq X\}$ and $B(X)=\{x \in U \mid [x]B \cap X \neq \emptyset\}$. A subset B of A is a reduct of T if $IB=IA$ and there is no subset B of B where $IB=IA$ (i.e. B is a minimal subset of the condition attributes without losing discernibility). A decision table is an information system, $T=(U, A \cup \{d\})$, such that each $a \in A$ is a condition attribute and $d \notin A$ is a decision attribute. Let Vd be the value set $\{d1, \ldots, du\}$ of the

Table 1
Information system.

U	A Ordinal scale data sets							
	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
x_1	1	5	7	4	3	2	8	6
x_2	1	6	8	2	4	5	3	7
x_3	1	7	2	4	6	5	3	8
x_4	1	2	3	5	7	6	4	8
x_5	1	3	6	2	4	5	8	7

decision attribute d. For each value, $di \in Vd$, there is a decision class, $Ui=\{x \in U \mid d(x)=di\}$, where $U=U1 \cup \ldots \cup U|Vd|$ and for every $x, y \in Ui$, $d(x)=d(y)$. The B-positive region of d is defined by $PB(d)=B(U1) \cup \ldots \cup B(U|Vd|)$. A subset B of A is a relative reduct of T if $PB(d)=PA(d)$ and there is no subset B of B where $PB(d)=PA(d)$. A formula, $(a1=v1) \wedge \ldots \wedge (an=vn)$ in T (denoting the condition of a rule), is defined where $aj \in A$ and $vj \in Vaj$ $(1 \leq j \leq n)$. The semantics of the formula in T is defined by $[[(a1=v1) \wedge \ldots \wedge (an=vn)]]T=\{x \in U \mid a1(x)=v1, \ldots, an(x)=vn\}$. Let ϕ be a formula, $(a1=v1) \wedge \ldots \wedge (an=vn)$ in T. A decision rule for T is of the form, $\phi \rightarrow (d=di)$, and it is true if $[[\phi]]T \subseteq [[(d=di)]]T$ $(= Ui)$. The accuracy and coverage of a decision rule r of the form $\phi \rightarrow (d=di)$ are respectively defined as follows:

$$accuracy(T', r, U_i) = \frac{|U_i \cap [\![\varphi]\!]T'|}{|[\![\varphi]\!]T'|}$$

$$\text{coverage}(T', r, U_i) = \frac{|U_i \cap [\![\varphi]\!]T'|}{|U_i|}$$

In these equations, $|Ui|$ is the number of objects in decision class Ui and $|[[\phi]]T'|$ is the number of objects in the universe, $U=U1\cup \ldots \cup U|Vd|$, that satisfy condition ϕ of rule r. Therefore, $|Ui\cap[[\phi]]T'|$ is the number of objects that satisfy the condition ϕ, restricted to decision class Ui .

An example on describing how rough sets process attribute reduction to core attribute values table on a ranking of non-alcoholic beverages, ordinal scale data sets of information system, from the first to eighth, by, named Tea, Packaged-waters, Sports, Juice, Soda, Others, Coffee and Energy (Liao & Chen, 2014) (shown on Table 1).

Then:

$$f_{a_1} = \{1\} \quad \begin{array}{llll} f_{a_2} = \{2,3,5,6,7\} & f_{a_3} = \{2,3,6,7,8\} & f_{a4} = \{2,4,5\} & \\ f_{a_5} = \{3,4,6,7\} & f_{a_6} = \{2,5,6\} & f_{a_7} = \{3,4,8\} & f_{a_8} = \{6,7,8\} \\ V_{a_1}^{x_1} = 1 & V_{a_2}^{x_1} = 5 & V_{a_3}^{x_1} = 7 & V_{a_4}^{x_1} = 4 \\ V_{a_5}^{x_1} = 3 & V_{a_6}^{x_1} = 2 & V_{a_7}^{x_1} = 8 & V_{a_8}^{x_1} = 6 \end{array}$$

According to specific universe of discourse classification, a similarity relation of the general attributes $a \in A$, denoted by $\frac{U}{A}$. All of the similarity relation, denoted by $R(a_j)$.

$$\frac{U}{A}\{[x_i]_A | x_i \in U\}$$

Example:

$$R(a_3) = \{\{x_1\}, \{x_2\}, \{x_3\}, \{x_4\}, \{x_5\}\}$$
$$R(a_5) = \{\{x_1\}, \{x_2, x_5\}, \{x_3\}, \{x_4\}\}$$
$$R(a_6) = \{\{x_1\}, \{x_2, x_3, x_5\}, \{x_4\}\}$$
$$R(a_7) = \{\{x_1, x_5\}, \{x_2, x_3\}, \{x_4\}\}$$

According to the similarity relation and the fact that $R(a_5) = \{\{x_1\}, \{x_2, x_5\}, \{x_3\}, \{x_4\}\}$ and $R(a_6) = \{\{x_1\}, \{x_2, x_3, x_5\}, \{x_4\}\}$ both belong to the same fundamental set, the ordinal function set is $f_{a_5} = \{3, 4, 6, 7\}$ and $f_{a_6} = \{2, 5, 6\}$. Therefore, a_5 and a_6 are both core attribute values of the ordinal scale data for non-alcoholic beverages and for customer x_1, x_3 and x_4, a_5 always places after a_6, denoted by D_a^+. The pair wise comparison of a_5 and a_6, as shown in Table 2.

2.4. Association rules

Associations in complex data objects, such as data items, occur when one set of attributes is likely to co-occur with another set. A prototypical application is the analysis of supermarket transactions, where associations such as '68% of all customers who buy fish also buy white wine' might be found in a transaction database. To enable knowledge discovery through data mining in databases, an association is a rule that is mined from databases and which infers one attribute set from another. As stated by Agrawal, Imilienski, and Swami (1993), discovering association rules is an important data mining

Table 2
The core attribute values of the ordinal scale data for non-alcoholic beverages.

$R(a_j)$	f_{a_5}	f_{a_6}	D_a
$\{x_1\}$	3	2	D_a^+
$\{x_2, x_5\}$	4	5	D_a^-
$\{x_3\}$	6	5	D_a^+
$\{x_4\}$	7	6	D_a^+
$R(a_j)$	f_{a_5}	f_{a_6}	D_a

problem, and there has been considerable study of the use of association rules in the field of data mining. The algorithm for association rules mainly determines the relationships between items or features that occur synchronously in databases. For instance, during a trip to the shopping center, if people who buy item also buy item Y, there exists a relationship between item X and item Y, and such information is useful for decision-makers. Therefore, the main purpose of an algorithm for association rules is to determine synchronous relationships by analyzing random data and to use these relationships as a reference for decision-making (Sánche et al., 2008). The association rules are defined as follows (Wang, Chuang, Hsu, & Keh, 2004).

Make $I = \{i_1, i_2, ...i_m\}$ the item set in which each item represents a specific literal. D stands for a set of transactions in a database in which each transaction, T, represents an item set, such that $T \subseteq I$. That is, each item set T is a nonempty sub-item set of I. The *association rules* are an implication of the form, $X \to Y$, where $X \subset I$, $Y \subset I$ and $X \cap Y = \Phi$. The rule, $X \to Y$, holds in the transaction set D according to two measurement standards - *support* and *confidence*. Support (denoted as_$Sup(X, D)$) represents the rate of transactions in D that contain the item set X. *Support* is used to determine the statistical importance of D. The higher its value, the more important is the transaction set D. Therefore, the rule, $X \to Y$, which has *support* $Sup(X \cup Y, D)$, represents the rate of transactions in D that contain $X \cup Y$. Each rule, $X \to Y$, also has another measurement standard, called confidence (denoted as $Conf(X \to Y)$). This represents the rate of transactions in D that contain X and also Y. That is, $Conf(X \to Y) = Sup(X \cap Y)/Sup(X, D)$.

In this case, $Conf(X \to Y)$ denotes that if the transaction includes X, the chance that it is also contains Y is relatively high. The measure of confidence is then used to evaluate the level of confidence in the association rules $X \to Y$. Given a set of transactions, D, association rules are mined to generate all transaction rules that have certain user-specified minimum support (called $Min\,\mathrm{sup}$) and confidence (called *Minconf*) (Kouris, Makris, & Tsakalidis, 2005). According to Agrawal et al., (1993), the problem of mining association rules can be broken down into two steps. The first step is to detect a large item set whose support is greater than $Min\,\mathrm{sup}$ and the second step is to generate association rules, using the large item set. These rules must satisfy the following two conditions:

1. $Sup(X \cup Y, D) \geq Min\,\mathrm{sup}$
2. $Conf(X \to Y) \geq Minconf$

To determine association rules, many studies use the Apriori algorithm (Agrawal et al., 1993). In order to reduce the possible biases that are incurred when these measurement standards are used, the simplest way to judge the standard is to use the *lift* judgment. *Lift* is defined as: $Lift = Confidence(X \to Y)/Sup(Y)$ (Wang et al., 2004; Yoon & Lee, 2013).

2.5. Rough set association rules

The primary difficulty that is associated with the maximal association approach is that the generation of the frequent maximal set has an underlying assumption—a taxonomy that exists for the document collections. However, this assumption is feasible only for collections of labeled documents with keywords that are used mainly for training text classifiers, and these can be very expensive to construct, which limits the general applicability of this approach. Bi et al. investigated the applicability of rough set theory to detecting maximal associations, according to ontologies (Bi, Anderson, & McClean, 2003). This work is reported in other papers and shows that by integrating a rough set with association rules, the rules that are discovered are similar to maximal association rules. The rough set and association rule approach is much simpler than the maximal association method in discovering association rules for knowledge discovery and reasoning for different data format/scale problems (Liao & Chen, 2014; Pawlak & Skowron, 2007; Shi, Sun, & Xu, 2012). However, this study proposes a new approach, a rough set-based association rule, which presents as one way to analyze AHP ordinal scale data, while creating predictive if–then rules that generalize data values to the electronic commerce region.

3. Methodology – the rough set-based association rule approach

In terms of developing rough set and association rules for a recommendation system, this study proposes a rough set based association rule approach that is developed from ordinal data scale processing for customer preference analysis. The proposed analysis approach generates rough set attribute functions, association rules and their modification mechanism. The steps for developing the algorithms that are involved in the proposed approach are as follows:

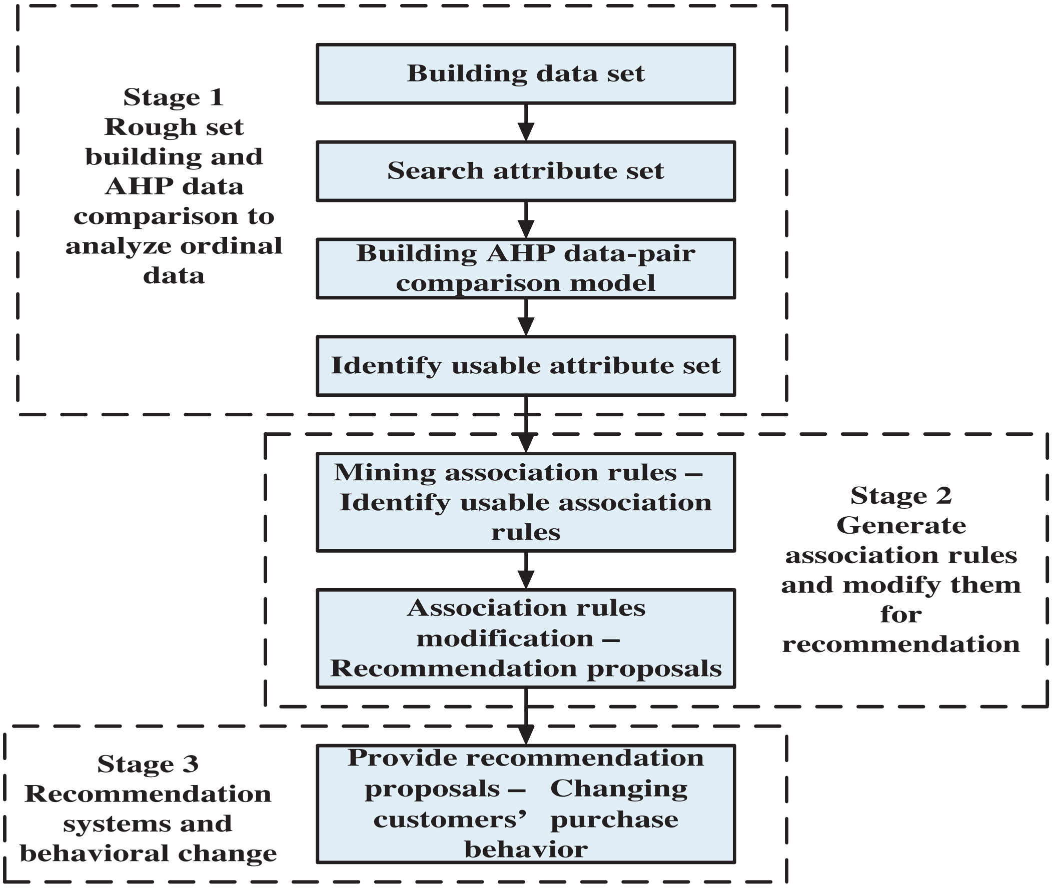


Fig. 1. The research framework.

Step 1: Data processing — create a data set and an information system
Step 2: Implement rough set theory — search for core attribute data
Step 3: Build an AHP model — data-pair comparison
Step 4: Propose association rules — find a usable attribute data set for association
Step 5: Generate usable association rules — find actual association rules using minimum support and minimum confidence for the Apriori algorithm
Step 6: Modify the association rules — find possible recommendation proposals
Step 7: Evaluate the recommendation systems — provide recommendation proposals to customers and determine their intention to change purchasing behavior.

The research framework for the proposed approach is illustrated in Fig. 1.

Preference is a central research issue for personnel recommendation systems because of the nature of customers' tacit intention to purchase and their attitude to purchases. In general, this part of customer tacit knowledge is difficult to study because of the lack of preference condition analysis. In addition to nominal data scales, the ordinal data scale measures customers' preferences by ranking different brands, products and channels. AHP also allows a comparison between the relative weights between two subjective measurements. By doing so, subjective data analysis can be used to determine the relative weakness or strength of customers' preferences and to determine the actual distance between their preferences. Therefore, integrating an ordinal data scale together with the AHP data format on the rough set attribute function gives a better understanding of customers' use of e-commerce platforms and purchasing preferences. Traditional association rules also focus on nominal data and ignore rules that are discovered using ordinal data. Knowledge of some customers' preferences is also hidden in rules that have no precise description of customers' purchasing intention, attitude or behavior. If preference knowledge were discovered, association rules might provide personalized recommendation proposals. Accordingly, this study combines rough sets with association rules to create an application for ordinal scale data. The computation stages for the proposed rough set-based association rule are illustrated below.

The RST is applicable to both qualitative and quantitative research. When combined with association rules from data mining, it can be used to study consumers' ordinal preferences for channels and products. The proportion obtained from

Table 3
Scale of relative importance.

Relative importance	Value (0-9)	Proportion (%)
Equally important	0	0%
Slightly important	2	20%
Fairly important	4	40%
Very important	6	60%
Absolutely important	8	80%

Source: this study

pairwise comparison defines a consumer's degree of preference, which can contribute to changes in purchasing behavior. In this study, two rough set based association rule computation stages – the e-commerce platform recommendation and product recommendation stages – are developed using the mechanisms described below.

Stage 1 – E-commerce platform recommendation mechanisms

There are twelve steps in the development of an e-commerce platform recommendation, as follows.

Step 1: Establish an information system of ordinal scale

Market surveys are widely used in marketing research. In this study, the data collected from a questionnaire survey is transformed into data for the platform information system, $PIS = (U, P)$, where $U = \{x_1, x_2, \ldots, x_k\}, k = 1, 2, \ldots, n$ denotes a nonempty set of finite targets, also known as a set of finite objects, and $p = \{p_1, p_2, \ldots, p_i\}, i = 1, 2, \ldots, m$ represents a nonempty set of path attributes. The complete set of path attributes is p: $U \rightarrow V_p$, $p \in P$, and its information function is $f_p = U \times P \rightarrow V_p$, where V_p denotes the set of values for attribute p, also known as the value field of attribute p. In other words, f_p represents the corresponding value for attribute p of object x_k in set U, and $f(x, p) \in V_p$ is an information set of ordinal scale.

Step 2: Determine the indiscernibility relationship between platform information of ordinal scale

The indiscernibility relationship mathematically determines the relationship between attributes. Attributes of no significance are eliminated by determining the equivalence relationship between attributes in the universe of discourse U. In the platform information system (PIS), B is a subset of the set of attributes, P, i.e., $B \subseteq P$, so the indiscernibility relationship for attribute B is defined as:

$$U/IND(B) = \{p \in B : U/IND(\{p\})\}$$

To determine the indiscernibility relationship between information of ordinal scale, $K = (U, B_1, B_2, \ldots, B_w), w = 1, 2, \ldots, m-1$ is the same as using attribute B to describe the indiscernibility relationship between finite targets of U in the specific domain of discourse. The relationships between attributes are expressed as $B(p_i)$ which is simplified as U/P.

$$B(p_i) = \left\{(p_i, p_j) \in U^2 \middle| \forall p \in B, p(p_i) = p(p_j)\right\}$$

Step 3: Examine the core attribute of ordinal-scale platform information

All data in the information system is arranged in order so there also exists an ordinal relationship between pairs of attributes. If B represents U/P, the relationships between attributes p_i are expressed as:

$$D_p^+ = \left\{x_k \middle| \frac{U}{p}, V_{pi} > V_{pj}\right\}$$

$$D_p^- = \left\{x_k \middle| \frac{U}{p}, V_{pi} > V_{pj}\right\}$$

For any two objects belonging to the same fundament set, there exists a core attribute value for ordinal information p_i and p_j.

$$IND(B) = \left\{[x_k]_p \in U^2 \middle| \forall p \in B, p(p_i) = p(p_j)\right\}$$

Step 4: Establish a mode for comparison between platforms

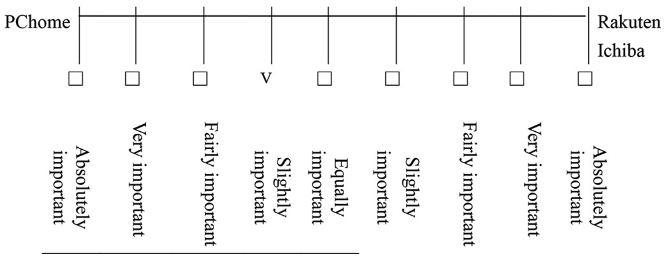
The pairwise comparison between two online shopping platforms is defined as:

$$PCC_{ij} = \{pcc_{12}, pcc_{13}, \ldots pcc_{78}\} i = 1, 2, \ldots 8, j = 1, 2, \ldots 8$$

where $i \neq j$ and $j > i$ is a nonempty platform combination comparison set. Combinations of platforms are in corresponding pairs so there exists between them an upper-triangular value and its opposite lower-triangular value. Pairwise comparison reveals the preference proportion for consumers. Table 3 lists the value and proportion for the relative importance scale that is used for pairwise comparison.

The analytical hierarchy process (AHP) allows the design of a questionnaire using the relative importance scale to probe consumers' preferences for any two platforms. Take, for instance, the two online shopping platforms: PChome and Rakuten Ichiba. The degree of preference for these two platforms is obtained by pairwise comparison, using questions that follow the AHP concepts.

Example: In terms of your online shopping preference, please check the description that best describes the relative importance of PChome compared with Rakuten Ichiba.



A value of 2 for this question implies that PChome is slightly more important than Rakuten Ichiba so the relative importance of PChome to Rakuten Ichiba is 20%. Conversely, the relative importance of Rakuten Ichiba to PChome is -20%.

Step 5: Establish a mode for comparison between products

The results obtained from a pairwise comparison between platforms show different proportional values of relative importance for the two platforms, as perceived by the consumer. These values are then fitted into the regression model to yield the estimated β value for consumer preference. The mathematical mode derived is:

$$Y_l = \hat{\beta}_k PCC_{ij}$$

where Y_l denotes the channel with the core attribute obtained in Step 3 and $PCCij$ denotes the degree of relative importance of platform Pi to platform Pj; $l = 1, 2, \ldots, n$; $k = 1, 2, \ldots, 28$; and $i = 1, 2, \ldots, 8$; $j = 1, 2, \ldots, 8$; $i \neq j$; $j > i$. Using the core attributes obtained in Step 3, platforms are divided into clusters. The β values for each platform in the different clusters are first individually estimated and then summed. This is expressed as:

$$\hat{\beta}_k = \frac{1}{n}\sum_{1}^{n} PCC_{ij}$$

Step 6: Construct a decision table for the platforms

The decision table for different platforms is constructed and is expressed as

$$DT = (U, P = C \cup D)$$

where $U = \{x_1, x_2, \ldots, x_k\}, k = 1, 2, \ldots, n$ denotes a nonempty set of finite targets, also known as a set of finite objects. P usually comprises two elements, C and D; i.e., $C, D \subset P$, where $C = \{c_1, c_2, \ldots, c_s\}, s = 1, 2, \ldots, t$ represents a non-empty set of condition attributes and $D = \{d_1, d_2, \ldots d_j\}, j = 1, 2, \ldots, l$ represents a nonempty set of decision attributes, which are the attribute values obtained in Step 5. The complete set of condition attributes is c: $U \to V_c$, $c \in C$ and its information function is $f_c = U \times C \to V_c$, where V_c denotes the set of values for attribute c, also known as the value field of attribute c. In other words, f_c represents the corresponding value for attribute c of object x_k in set U.

Step 7: Determine the indiscernibility relationship between the decision attribute and consumer behavior

Using the data in the decision table, the indiscernibility relationship is determined; i.e., $K = (U, B_1, B_2, \ldots, B_w), w = 1, 2, \ldots, m-1$. This is the same as using attribute B to describe the indiscernibility relationship between finite targets of U in the specific domain of discourse. In the decision table, B is a subset of the set of condition attributes, C, i.e., $B \subseteq P$, so the indiscernibility relationship for B is expressed as $B(p_i)$, which is simplified as U/P:

$$U/IND(B) = \{c \in B : U/IND(\{c\})\}$$

$$IND(C) = \left\{[x_k]_c \in U^2 | \forall c \in B, c(c_s) = c(c_r)\right\}$$

where $[x_k]_c$ denotes the indiscernibility relationship between corresponding attributes in C.

Step 8: Determine the reduct and the core between decision attributes and consumer behavior

If $c \in C$, then $POS_{(C-\{c\})}(D) = POS_C(D)$ and c can be omitted from DT; otherwise, c cannot be omitted from DT. Attributes c that can be removed from C with no effect are considered to be redundant and are omitted. If $R \subseteq C$ satisfies $\forall c \in R$, then R is a reduct attribute of C. If $DT' = (U, P, R, D)$ and $POS_R(D) = POS_C(D)$, then C is the smallest set of condition attributes.

Step 9: The relationship between the lower approximation and the upper approximation

1. The lower approximation is denoted as: $\underline{C}X = \{x \in U | [x_k]_c \subseteq X\}$.
2. The upper approximation is denoted as: $\bar{C}X = \{x \in U | [x_k]_c \cap X \neq \emptyset\}$. If $C, D \subseteq P$, then $POS_c(D) = U_{x \in U/D}\underline{C}X$ and $NEG_c(D) = U - \cup_{x \in U/D}\bar{C}X$.
3. The boundary region between the lower and the upper approximation is denoted as: $BND_c(D) = \cup_{x \in U/D}\bar{C}X - \cup_{x \in U/D}\underline{C}X$.

Step 10: Calculate the rough support and the rough confidence

The rough support and the rough confidence are calculated by using traditional association rules to replace the accuracy rate that is often used in rough set theory.

1. The rough support is calculated using

$$Sup(IND(B)) = \left| \left| \left\{ IND(B) | \underline{C}X \subseteq \bar{C}X \right\} \right| = \left| \frac{IND(B)\underline{C}X}{\bar{C}X} \right| \right.$$

2. The rough support is calculated using

$$Conf(IND(B) \to d_{c_s}) = |\{IND(B) \cap d_{c_s} | Sup(IND(B))\}| = \left| \frac{Sup(IND(B) \cap d_{c_s})}{Sup(IND)(B))} \right|$$

Step 11: Generate the rules for platform decision-making

$$\frac{\{x_1\}}{c_1 c_4} : c_{1_1} \cap c_{4_1} \Rightarrow d^1_{p_2} = 2$$

$$\frac{\{x_1\}}{c_1 c_2 c_3 c_4} : c_{1_1} \cap c_{2_1} \cap c_{3_1} \cap c_{4_1} \Rightarrow d^1_{p_2} = 2$$

Step 12: Adjust the rules for the platforms

Platforms are recommended according to the estimated β values that are obtained in Step 5 and the decision table. In the recommendation system, external recommendations are targeted to potential customers. In terms of similar items that are preferred by existing customers and the general demands of consumers, recommendation are made on the basis of attributes, in order to increase the purchasing rate through the recommended platform.

Eight online shopping platforms are studied and an external recommendation system is established for each of the platforms, using the condition and decision attributes. The eight online shopping platforms studied are arranged in order of consumer preference, which depends on whether or not an actual purchase is made through the platform. The four most popular online shopping platforms are classified as strong platforms and the remaining four are classified as weak platforms.

Stage 2 – Product recommendation mechanisms

Using the first stage of the development of e-commerce platform recommendation mechanisms, this study uses PChome to illustrate the product recommendation mechanisms. PChome is one of the top four online shopping platforms. Usually, association rules can only find the purchasing behavior for association between items such as "Office Stationery" and "Beauty Care", for possible cross-selling. However, it is difficult to determine which item has a higher purchasing preference and the degree of preference over other product items for a specific purchasing behavior. This degree of preference from customers is important information for product sales and marketing. Therefore, this study considers product recommendation to be a type of customer product preference recommendation. Ordinal data scale processing is the basis for the construction of the recommendation computational steps, as follows:

Step 1: Establish a product information system of ordinal scale

In this study, the data collected from the questionnaire survey is transformed into data for the merchandise information system, $MCIS = (U, M)$, where $U = \{x_1, x_2, \ldots, x_k\}, k = 1, 2, \ldots, n$ denotes a nonempty set of finite targets, also known as a set of finite objects, and $M = \{m_1, m_2, \ldots, m_j\}, j = 1, 2, \ldots, l$ represents a nonempty set of path attributes. The complete set of path attributes is m: $U \to V_m$, $m \in M$ and its information function is $f_m = U \times M \to V_m$, where V_m denotes the set of values for attribute m, also known the value field of attribute m. In other words, f_m represents the corresponding value for attribute U of object x_k in set m, and $f(x, m) \in V_m$ is a product information set of ordinal scale.

Step 2: Determine the indiscernibility relationship between product category information of ordinal scale

By determining the equivalence relationship for attributes in the universe of discourse U, attributes of no significance can be eliminated. In the product information system ($MCIS$), B is a subset of the set of attributes M, i.e., $B \subseteq M$. Therefore, the indiscernibility relationship for attribute B is defined as:

$$U/IND(B) = \{m \in B : U/IND(\{m\})\}$$

To determine the indiscernibility relationship between product information of ordinal scale, $K = (U, B_1, B_2, \ldots, B_W), w = 1, 2, \ldots, m-1$ is the same as using attribute B to describe the indiscernibility relationship between finite targets of U in the specific domain of discourse. The relationships between attributes are expressed as $B(m_j)$, which is simplified as U/M. The indiscernibility relationship between different product categories is described as $[x_k]_{m.}$ The indiscernibility relationship between product category information of ordinal scale is then defined as:

$$B(m_j) = \left\{ (m_i, m_j) \in U^2 | \forall m \in B, m(m_i) = m(m_j) \right\}$$

Step 3: Determine the core attribute of ordinal-scale product information

All data in the information system is arranged in order so there also exists an ordinal relationship between pairs of attributes. If B represents $\frac{U}{m}$, the relationships between attributes m_i can be expressed as:

$$D^+_m = \left\{ x_k | \frac{U}{m}, V_{m_i} > V_{m_j} \right\}$$

$$D^-_m = \left\{ x_k | \frac{U}{m}, V_{m_i} < V_{m_j} \right\}$$

Table 4
The scale of relative importance.

Relative importance	Value (0-9)	Proportion (%)
Equally important	1	4%
Slightly important	3	11%
Fairly important	5	19%
Very important	7	27%
Absolutely important	9	39%

For any two objects that belong to the same fundament set, there exists a core attribute value for ordinal information, m_i and m_j.

$$IND(B) = \left\{[x_k]_m \in U^2 \middle| \forall m \in B, m(m_i) = m\left(m_j\right)\right\}$$

Step 4: Establish a mode for comparison between products

As an example, step 3 shows that core attributes are "Beauty Care" and "Fashion Apparel". In order to propose a possible internal product recommendation, these two items are compared using pairwise comparisons and their relationships are defined as follows:

$MC_i = \{mc_1, mc_2, \ldots mc_5\} i = 1, 2, \ldots 5$ is a non-empty product combination comparison set. Combinations of product category are in corresponding pairs so there exist between them an upper-triangular value and its opposite lower-triangular value. Pairwise comparison reveals customers' preference proportion. Using the AHP setting, the preference proportion is transformed from the scale values, 1, 3, 5, 7 and 9 to the proportion values, 4%, 11%, 19%, 27% and 39% (total 100%). Table 4 lists the values and proportions for the relative importance scale that is used for the pairwise comparison of products.

Step 5: The establishment of a mode for the pairwise comparison of products

Each product item has a specific value and proportion on the relative importance scale because each represents a different strength of customer preference. The mathematical regression mode that is derived for this relationship is:

$$MC_i = \{mc_1, mc_2, \ldots mc_5\},$$

These product values and proportions are then fitted into the regression model to yield the estimated β value for consumer preference, $i = 1, 2, \ldots 5$, and the product strength for a customer preference is determined by providing the mathematical mode derived as:

$$Y_1 = \hat{\beta}_k MC_i$$
$$l = 1, 2, \ldots n; k = 1, 2, \ldots 5; i = 1, 2, \ldots 5$$

The β values for each product for different customers are first individually estimated and then summed. This is expressed as:

$$\hat{\beta} = \frac{1}{n} \sum\nolimits_1^n MC_i$$
$$i = 1, 2, \ldots 5; k = 1, 2, \ldots 5$$

Step 6: Construct a decision table for the products

Using step 5, calculation of the value and the proportion for the relative importance scale shows that customers have the highest preference for the product item, "Beauty Care". A decision table is constructed using beauty care products and this decision table is then extended to generate rough set association rules. The decision table for different products is expressed as:

$$DT = (U, M = E \cup D)$$

where $U = \{x_1, x_2, \cdots x_k\}, k = 1, 2, \ldots, n$ denotes a nonempty set finite targets. M usually comprises two elements, E and D; i.e., $E, D \subset M, E = \{e_1, e_2, \ldots, e_g\}, g = 1, 2, \ldots, v$ represents a nonempty set of condition attributes and $D = \{d_1, d_2, \ldots, d_g\}, f = 1, 2, \ldots, r$ represents a nonempty set of decision attributes, which are the attribute values obtained in Step 3. The complete set of condition attributes is e: $U \to V_e$, $e \in E$ and its information function is $f_e = U \times E \to V_e$, where V_e denotes the set of values for attribute e, also known as the value field of attribute e. In other words, f_e represents the corresponding value for attribute e of object x_k in set U.

Step 7: Determine the indiscernibility relationship between the decision attribute and consumer behavior

Using the data in the decision table, the indiscernibility relationship is determined; i.e., $K = (U, B_1, B_2, \ldots, B_w), w = 1, 2, \ldots, m-1$. This is the same as using attribute B to describe the indiscernibility relationship between finite targets of U in the specific domain of discourse. In the decision table, the indiscernibility relationship is expressed as $B(e_g)$, which is simplified as U/E, where $[x_k]_e$ denotes the indiscernibility relationship between corresponding attributes in E.

$$U/IND(B) = \{e \in B : U/IND(\{e\})\}$$
$$IND(E) = \left\{[x_k]_e \in U^2 | \forall e \in B, e(e_g) = e(e_v)\right\}$$

For example:

$$\begin{aligned}
B_1 &= U/e_1 = \{\{x_1, x_5\}, \{x_2, x_4\}, \{x_3\}\} \\
B_2 &= U/e_2 = \{\{x_1, x_5\}, \{x_2, x_4\}, \{x_3\}\} \\
B_3 &= U/e_3 = \{\{x_1, x_2, x_4\}, \{x_3, x_5\}\} \\
B_4 &= U/e_4 = \{\{x_1, x_2, x_4\}, \{x_3, x_5\}\} \\
B_5 &= U/e_1e_2 = \{\{x_1, x_5\}, \{x_2, x_4\}, \{x_3\}\} \\
B_6 &= U/e_3e_4 = \{\{x_1, x_2, x_4\}, \{x_3, x_5\}\} \\
&\vdots \\
B_{m-1} &= U/E = \{\{x_1\}, \{x_2, x_4\}, \{x_3\}, \{x_5\}\}
\end{aligned}$$

Step 8: Identify the reduct and core between the decision attributes and consumer behavior

If $e \in E$ and e is omitted from DT, then $POS_{(C-\{c\})}(D) = POS_C(D)$, otherwise e cannot be omitted from DT. Attributes e that can be removed from E with no effect are considered to be redundant and are omitted and e is defined as a surplus attribute (not a core attribute). If $R \subseteq E$ satisfies $\forall e \in R$, then R is a reduct attribute of E. If $DT' = (U, M, R, D)$ and $POS_R(D) = POS_E(D)$, then E is the smallest set of condition attributes. If $IND(E)$ represent an indiscernibility relationship searching data E on the decision table, when $IND(E) = IND(E - e_1)$, then e_1 is a reduct attribute of E. However, when $IND(E) \neq IND(E - e_1)$, then e_1 is a core attribute and $CORE(E) = \{m \in E\}$.

For example:

$$\begin{aligned}
U/IND(E) &= \{\{x_1\}, \{x_2, x_4\}, \{x_3\}, \{x_5\}\} \\
U/IND(E - e_1) &= U/(\{e_2, e_3, e_4\}) = \{\{x_1\}, \{x_2, x_4\}, \{x_3, x_5\}\} = U/IND(E) \\
U/IND(E - e_1e_2) &= U/(\{e_3, e_4\}) = \{\{x_1, x_2, x_4\}, \{x_3, x_5\}\} \neq U/IND(E)
\end{aligned}$$

Step 9: The relationship between the lower approximation and the upper approximation

In Step 7, $[x_k]_e$ denotes the indiscernibility relationship between corresponding attributes in E. If $X \subseteq U$, then the relationship between the lower approximation and the upper approximation is described to allow a discussion of the indiscernibility relationship.

1. The lower approximation is denoted as:

$$\underline{E}X = \{x \in U | [x_k]_e \subseteq X\}$$

2. The upper approximation is denoted as:

$$\bar{E}X = \{x \in U | [x_k]_e \cap X \neq \emptyset\}$$

3. If C, $D \subseteq P$, then $POS_e(D) = \cup_{x \in U/D} \underline{E}X$

$$NEG_e(D) = U - \cup_{x \in U/D} \bar{E}X$$

4. The boundary region between the lower and the upper approximations is denoted as:

$$BND_e(D) = \cup_{x \in U/D} \bar{E}X - \cup_{x \in U/D} \underline{E}X$$

For example: If the customer clusters are $\{x_1, x_3, x_4\}$, to a specific cluster, then $\underline{E}(X) = \{x_3\}$, $\bar{E}(X) = \{x_1, x_2, x_3, x_4, x_5\}$ and $BND_e(D) = \{x_1, x_2, x_4, x_5\}$.

Step 10: Calculate the rough support and the rough confidence

In this step, the rough support and the rough confidence are calculated by replacing the accuracy rate that is often used in rough set theory with traditional association rules. A rough set based association rule approach is proposed for the product recommendation mechanism.

1. Rough support

$$Sup(IND(B)) = \left| \left\{ IND(B) \middle| \underline{E}X \subseteq \bar{E}X \right| \right\} = \left| \frac{IND(B) | \underline{E}X}{\bar{E}X} \right|$$

2. Rough confidence

$$\begin{aligned}
Conf\left(IND(B) \to d_{e_g}\right) &= \left| \left\{ IND(B) \cap d_{e_g} | Sup(IND(B)) \right\} \right| \\
&= \left| \frac{Sup\left(IND(B) \cap d_{e_g}\right)}{Sup(IND(B))} \right|
\end{aligned}$$

Table 5
Preference rules for online consumers for {Yahoo, PChome} and {PChome, MoMo} e-commerce platform.

Rule No	$Sup(IND(B))$	$Conf(IND(B) \rightarrow d_{c_s})$	Internet portal preference sorting	Absolute proportion value	Preference rules
1	22.22%	21.10%	{Yahoo = 1} {PChome = 2}	$\hat{\beta}_1 = 31.48\%$	(average monthly income $\geq$ NT$40,001) & (information source = Internet portal) & (purchase reason = product discount) & (purchase frequency = 1-3 times/month)
2	22.22%	21.10%	{Yahoo = 1} {PChome = 2}	$\hat{\beta}_1 = 31.48\%$	(average monthly income $\geq$ NT$40,001) & (information source = friend's word-of-mouth) & (purchase reason = product discount + in demand) & (purchase frequency = 1-3 times/month)
3	11.11%	10.71%	{PChome = 2} {MoMo = 7}	$\hat{\beta}_{10} = 43.64\%$	(average monthly income $\geq$ NT$40,001) & (information source = Internet portal) & (purchase frequency = 4-10 times/month)
4	11.11%	10.71%	{PChome = 2} {MoMo = 7}	$\hat{\beta}_{10} = 43.64\%$	(average monthly income $\geq$ NT$40,001) & (purchase reason = product discount) & (purchase frequency = 4-10 times/month)
5	11.11%	10.71%	{PChome = 2} {MoMo = 7}	$\hat{\beta}_{10} = 43.64\%$	(information source = Internet portal) & (purchase reason = product discount) & (purchase frequency = 4-10 times/month)

Step 11: Generating the product category recommendation rules
Product category recommendation rules are generated as follows:

$$\frac{\{x_1\}}{e_1 e_2} : e_{1_1} \cap e_{2_1} \Rightarrow d^1_{m_2} = 2$$
$$\frac{\{x_1\}}{e_1 e_2 e_3 e_4} : e_{1_1} \cap e_{2_1} \cap e_{3_1} \cap e_{4_1} \Rightarrow d^1_{m_2} = 2$$

Processing ordinal data, it is seen that "Fashion Apparel" and "Beauty care" are the core attribute on the PChome e-commerce platform. In terms of the product recommendation mechanism, possible adjustments to the rules for product categories are then made using the proposed approach.

Step 12: Adjustment of the rules for product categories

For internal recommendations, when a customer profile is determined using customer clusters, that product recommendation can yield possible sales and marketing alternatives, including cross-selling, direct marketing/selling, electronic catalog marketing, product/brand alliance and online shopping, depending on the customers' assigned segment and preferences. Patterns and rules for product recommendation are the basis for recommendation mechanisms. These patterns and rules can be adjusted in order to give further information about alternative recommendations. This mechanism could change customers' purchasing behaviors by providing a particular preferred product mix to a specific customer segment. For example, "Beauty Care" and "Fashion Apparel" are the core attributes on product categories for recommendation.

For this platform recommendation algorithm, the first stage involves establishing rough set association rules and the second stage addresses the problem of product categorization in ordinal scale and the subsequent recommendation mechanism. The first stage in the development of the product recommendation algorithm is the same as that for the computation of the platform recommendation; that is, the core platform is determined by the platform recommendation and then the absolute proportion of products sold on this platform is obtained. These proportions are then converted into values of relative importance for products using the AHP concepts. Finally, when consumer preference has been identified, a variety of products are selected for recommendation to customers. The detailed algorithms are illustrated on the Appendix for further computations reference.

4. Numerical example

4.1. Proposing recommendation system for online shopping platforms

In the regard of experimental design on proposing recommendation system, by using the AHP rough set-based association rule approach, this study implements a recommendation system for Internet shopping portals by determining online consumer purchase preferences using a questionnaire survey. A total of 850 questionnaires were distributed and 720 questionnaires were returned, including 707 effective questionnaires. Nominal and ordinal scale questions were used. The questionnaire contained four parts to determine the demographics of subjects (11 items), recommendations for product categories (8 items), recommendations for Internet portals (8 items) and AHP Internet portal preferences (36 items).

Preference rules of {Yahoo, PChome} and {PChome, MoMo}:

This study includes the eight most popular Internet portals in Taiwan: Yahoo, PChome, Payeasy, Rakuten Ichiba Taiwan, MoMo, ETMall, GoHappy and OKAPI. A total of 36 AHP questions were used for the stage-1 computation. Five preference rules were generated by the proposed computation method and these are illustrated in Table 5.

This study proposes the following two recommendation patterns for an e-commerce platform.

Table 6
Preference rules for Internet consumers for {consumer electronics products, wristwatch} and {beauty care products, group purchase of food}.

Rule No	$Sup(IND(B))$	$Conf(IND(B) \rightarrow d_{c_s})$	Product preference sorting	Proportion value on core product category	Preference rules
1	1.07%	13.64%	{electronics products = 1, watch = 2} {electronics products = 4, watch = 5}	$(\hat{\beta}_1, \hat{\beta}_2) = (25\%, 15.5\%)$	(product = variety) & (transaction mechanism = conveniences)
2	1.07%	13.64%	{electronics products = 1, watch = 2} {electronics products = 4, watch = 5}	$(\hat{\beta}_1, \hat{\beta}_2) = (25\%, 15.5\%)$	(price = allow price comparisons) & (transaction mechanism = conveniences) & (quality = stable)
3	1.07%	13.64%	{electronics products = 1, watch = 2} {electronics products = 4, watch = 5}	$(\hat{\beta}_1, \hat{\beta}_3) = (25\%, 15.5\%)$	(price = allow price comparisons) & (product = Variety) & (quality = excellence)
4	1.60%	5%	{beauty care products = 1, group purchase on food = 2} {beauty care products = 3, group purchase on food = 4}	$(\hat{\beta}_1, \hat{\beta}_4) = (29\%, 19\%)$	(price = allow price comparisons) & (product = Variety) & (transaction mechanism = conveniences) & (quality = stable)

Pattern 1: Recommendation system for consumer behavior between Yahoo, and PChome

In terms of Rule 1, Yahoo and PChome platforms are highly preferred Internet portals and Yahoo has a great competitive advantage. Therefore, this study suggests that these two Internet businesses should maintain and enhance online consumers' loyalty by using Facebook, Line or Twitter for social media marketing. In Table 2, it is seen that the customer profile exhibits specific niche market characteristics for online consumers of Yahoo and PChome: average monthly income ≥ NT$40,001, information source = Internet portal or friend's word-of-mouth, purchase reason = product price discount, frequency = 1-3 or 4-10 times/month. Internet businesses should present complete business/product information on their portals and provide implement discount/cross-selling promotions in order to maintain customer relationships. In addition, to increasing the purchasing frequency, Internet businesses might provide mechanisms such as cash-back, one-stop shopping, a global shopping cart or easy transactions, in order to develop different segments of potential online consumers.

Pattern 2: Recommendation system for consumer behavior between PChome and MoMo

In terms of Rule 3, PChome is a more preferred platform than MoMo. This study suggests that MoMo could change consumers' preferences by implementing social media marketing and broadcasting information using the MoMo TV purchasing channel when there are product discount/cross-selling activities. Consumer purchasing frequency is based on a customer profile segmentation for 4∼10 times/month purchasing with a high frequency. Developing high value-added products for top-level consumers would increase profits for both PChome and MoMo. However, direct selling and marketing is a possible business model for MoMo if TV, internet and catalog business units are integrated in its sales and marketing activities (Liao, Chen, & Hsieh, 2011).

4.2. Proposing recommendation system for internet shopping portals and product categories

In 4.1, Yahoo is shown to have a competitive advantage over different Internet portals. This section also determines a recommendation system for Yahoo's online product category preference.

Preference rules for a strong Internet platform (Yahoo) and a weak Internet platform (MoMo):

Four preference rules are generated using the proposed computational approach and these are illustrated in Table 6.

Accordingly, this study proposes the following two recommendation patterns for product category.

Pattern 3: Recommendation system for product categories on Yahoo

In terms of Rule 1, consumer electronic products and wristwatches are the most popular sale product categories. In this regard, Yahoo might implement cross-selling by extending its product categories and product lines. Greater transaction convenience would also attract more consumers to purchase products on Yahoo. Therefore, Yahoo might consider providing more convenient transaction mechanisms, such as one-stop shopping or a global shopping cart. This is also consistent with Rule 1 {product = variety}. However, its high degree of consumer loyalty means that in addition to product category recommendation, Yahoo could also consider developing a product mix and business alliances for new product development and recommendations.

Pattern 4: Recommendation system for product categories on MoMo

In terms of Rule 4, as a weak online shopping platform, MoMp should consider attracting more online consumers by varying its product categories and product lines to appeal to specific niche markets. In this regard, MoMo might consider defining its market segmentation in order to develop different niche markets. For example, beauty care products and group purchase products are specific niche markets for MoMo. Brand extension is also a by-product of product line extension. MoMo might consider the possibility of owner-branded manufacturing to develop its own Internet product brand. With its established TV purchase channel brand, MoMo could extend its branding development advantage from TV to the Internet channel using product category recommendations.

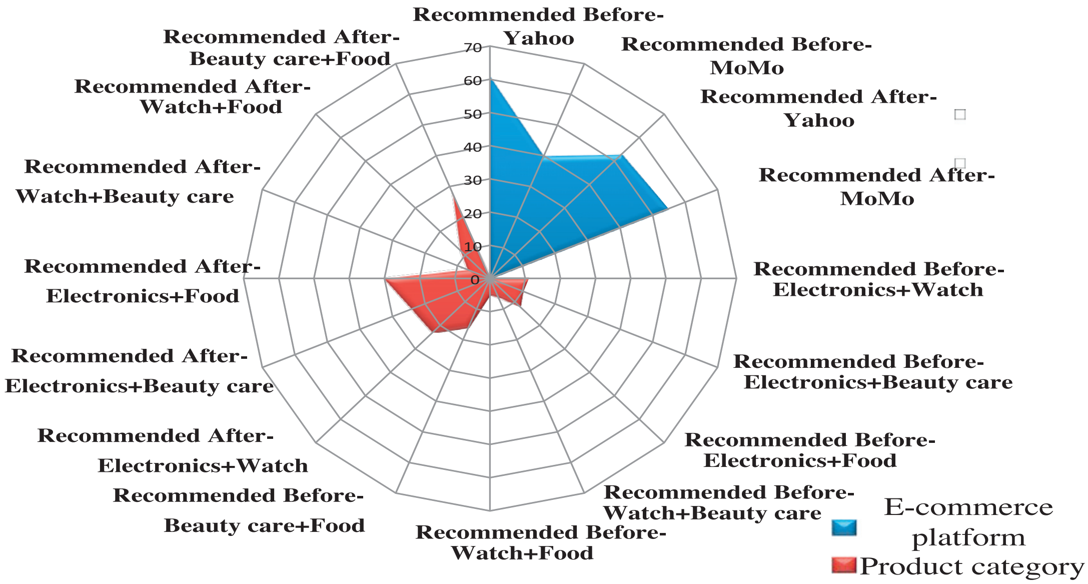


Fig. 2. The effect of the recommendation system on behavioral change.

Table 7
The effect of the recommendation system on behavioral change.

Items/Attributes	Recommendation	Behavioral change
E-commerce platform	1. Yahoo(strong) 2. MoMo(weak)	1. MoMo (enhance users' shopping platform preference) 2. Yahoo (maintain users' loyalty)
Product category	1. Electronics 2. Wristwatch 3. Beauty care 4. Group purchase on food	1. Electronics + group purchase of good 2. Beauty care + group purchase on food 3. Electronics + watch 4. Electronics + beauty care 5. Wristwatch + beauty care 6. Wristwatch + group purchase on food

5. Behavioral change due to recommendation systems

In the regard of experimental design on changing customer behavior, this study also determines whether consumers accept the recommendation results that are generated by the proposed approach and whether they then change their purchase behaviors. Using the same subjects as the previous numerical example, the conditions for acceptance of the recommendations on an Internet portal and product category are determined. A total of 850 questionnaires were sent and 698 questionnaires were returned, including 677 effective questionnaires. Nominal and ordinal scale questions were designed and the questionnaire contained three parts that determined the demographics of subjects (8 items), recommendations for product categories (5 items) and recommendations for online shopping platforms (5 items). The MoMo Internet portal is used as an example to determine whether consumers change their preference from a strong shopping platform to a weak platform and purchase the recommended product category.

5.1. Results of behavioral change

Fig. 2 compares online shopping platforms and product categories for early and late recommendation stages. The following observations of behavioral change can be drawn from the comparison.

1. Behavioral change after platform recommendation from Yahoo to MoMo

In Fig. 2, the section marked in blue denotes a change in the shopping platform used from Yahoo to MoMo, after recommendation. This demonstrates that an Internet business can benefit significantly by analyzing the segmentation of customers in order to determine each group's preferences and thereby improve marketing activities. In this regard, MoMo should consider consumer and market segmentation of electronic commerce, in order to attract new users and maintain the loyalty of regular consumers. Establishing a preference brand image on the Internet is a high priority. Pattern 2 also shows MoMo's possible alternatives for building a recommendation system.

2. Behavioral change after product category recommendation from a single product to a bundled product

In Fig. 2, the section marked in red denotes a change in the acceptance of a specific recommended product category from a single product to a bundled product. This demonstrates that cross-selling and product mixing are ways in which internet businesses can promote sales of their merchandise. In terms of direct marketing and selling, an electronic catalog allows goods/services to be marketed without intermediation (Liao and Chen 2011). Therefore, this study suggests that cross-selling and group purchasing with specific consumer segmentation and the use of an electronic catalog is a possible recommendation system (Liao, Chu, Chen, & Chang, 2012).

Table 7 summarizes the behavioral changes and recommendation systems discussed previously.

6. Conclusion

As business assets, consumers play a vital role in marketing. Most of the parties involved in product sales, such as commercial web sites, retailers and channels, are aware of the need for businesses to acquire and share better customer knowledge. However, the opportunities are limited because knowledge about customers is available but not accessible, and there is little possibility of fully analyzing all of the data that must be collected. The effective processing and use of data has become increasingly important. Therefore, this study develops a recommendation system to analyze knowledge about Internet customer preferences using a data mining approach and rough set based association rules.

The source of information about Internet sales and products for consumers who have never used product information or purchased products through a specific Internet portal/platform, is mostly from inertial behavior or regular purchasing behavior. However, Internet businesses can provide product information and special offers through websites that maintain the existing customer group and support re-intermediation.

This study also suggests that Internet businesses should try to recommend their shopping platform features and increase the amount of bundled product information, to give customers more choices and to encourage one-stop shopping for all products by bundling products and cross-selling. Depending on customer preferences, Internet businesses could then provide customers with appropriate electronic catalogs and increase the attractiveness of these catalogs to customers to promote a recommendation system using direct marketing and selling. Future research could consider further computation and modification of the algorithm or the development of the approach used in this study and the resulting applications.

Finally, this study suggests that customer market segmentation enables a greater understanding of consumers' demands and preferences. The characteristics of these online preferences can also be used to determine whether products are ideal, from the customers' perspective. The analysis of preferences and purchasing behavior gives a better understanding of customers and leads to marketing strategies that allow greater penetration of the online market.

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Appendix. The algorithm.

Algorithm 1: AHP Rough Set Association Rules in the First Stage – E-commerce platform recommendation.

Input:
Paths of Information System (PIS), $PIS = (U, P)$; user's contents x_k, path's attribute contents p_i
Output :
Paths Recommendation (PR); $\{Paths\,Recommendation\}$;
Method :
Begin
  $PIS = (U, P)$;
    for $k \leftarrow 1$ *to* n *do*;
      if $x_1, x_2, \ldots, x_k \in U$ *then*
        for $i \leftarrow 1$ *to* m *do*;
          if $p : U \rightarrow V_p,\ p \in P$ *then* $f_p = U \times P \rightarrow V_p$;
            compute $f(x, p)$, where the paths of information function in *PIS* as described in Step 1;
            end if
      end for
    end if
  end for
$K = (U, B_1, B_2, \ldots, B_w)$;
  for $w \leftarrow 1$ *to* $m - 1$ *do*;
    if $B \subseteq P$ *then* $U/IND(B) = \{p \in B : U/IND(\{p\})\}$;
      $B(p_i) = \{(u, p) \in U^2 | \forall p \in B,\ p(p_i) = p(p_i)\}$;

(continued on next page)

compute $B(p_i)$, where the indiscernibility relation in *PIS* as described in Step 2;
end if
end for
while $IND\,(B) = U/p$ *do*;
if $D_p^+ \equiv D_p^<$ or $D_p^- \equiv D_p^>$ *then*
$B(p_i) = \{[x_k]_p \in U^2 | \forall p \in B,\ p(p_i) = p(p_j)\}$;
compute D_p, where the condition attributes in $B(p_i)$ as described in Step 3;
end if
Find the path comparison combination set using AHP
for each p_i and p_i combination set , also $C_2^8 = 28$ *do*;
for $i \leftarrow 1$ *to* 8 *do*;
for $j \leftarrow 1$ *to* 8 *do*;
if $PCC_{ij} = \{PCC_{12},\ PCC_{13}, \ldots, PCC_{78}\},\ i \neq j \cap j > i$ *then*
compute PCC_{ij}, where customer's path comparison is converted into percentage as described in Step 4;
end if
end for
end for
$\mathrm{DR} = (Y_1, \widehat{\beta}_k PCC_{ij})$;
for $l \leftarrow 1$ *to* n *do*;
if $Y_1, Y_2, \ldots, Y_i \in Y$ *then*
for $k \leftarrow 1$ *to* 28 *do*;
if $\hat{\beta}_k = \frac{1}{n} \sum_1^n PCC_{ij}$ *then*
compute $\widehat{\beta}_k$, where the specific weights of path comparison combination set as described in Step 5;
end if
end for
end if
end for
$DT = (U, P = C \cup D)$;
for $s \leftarrow 1$ *to* t *do*;
if $c : U \rightarrow V_c, c \in C$ *then* $f_c = U \times C \rightarrow V_c$;
compute $f(x,\ c)$, where the information function in *DT* as described in Step 6;
end if
end for
$K = (U, B_1, B_2, \ldots, B_w)$;
for $w \leftarrow 1$ *to* $m - 1$ *do*;
if $B \subseteq C$ *then* $U/IND(B) = \{c \in B : U/IND(\{c\})\}$;
$B(c_s) = \{[x_k]_c \in U^2 | \forall c \in B, c(c_s) = c(c_r)\}$;
compute $B(C_s)$, where the indiscernibility relation in *DT* as described in Step 7;
compute $IND(C)$, where the relative reduct of *DT* as described in Step 8;
compute $IND(C - c_s)$, where the relative reduct of the elements for element *S* as described in Step 8;
end if
end for
for each $[x_k]_c$ *do*;
if $x \subseteq U$ *then*
$\underline{C}X = \{x \in U | [x_k]_c \subseteq X\}$
$\bar{C}X = \{x \in U | [x_k]_c \cap X \neq \emptyset\}$
compute $\underline{C}X$, where the lower-approximation of *DT* as described in Step 9;
compute $\bar{C}X$, where the upper-approximation of *DT* as described in Step 9;
compute $BND_c(D)$, where the bound of *DT* as described in Step 9;
compute $Sup(IND(B))$, where the support as described in Step 10;
compute $Conf(IND(B) \rightarrow d_{c_s})$, where the confidence as described in Step 10;
end if
end for
Output $\{Paths\,Recommendation\}$;
End

Algorithm 2: AHP Rough Set Association Rules in the Second Stage – Product recommendation.

Input:
Merchandise Categories of Information System (MCIS), $MCIS = (U, M)$; user's contents x_k, attribute contents of merchandise category m_i;
Output:
Merchandise Category Recommendation (MCR);
{Merchandise Category Recommendation};
Method :
Begin
$MCIS = (U, M)$;
for $k \leftarrow 1$ *to* n *do*;
if $x_1, x_2, \ldots, x_k \in U$ *then*
for $j \leftarrow 1$ *to* l *do*;
if $m : U \rightarrow V_m,\ m \in M$ *then* $f_m = U \times M \rightarrow V_m$;
compute $f(x, m)$, where the merchandise categories of information function in $MCIS$ as described in Step 1;
end if
end for
end if
end for
$K = (U, B_1, B_2, \ldots, B_w)$;
for $w \leftarrow 1$ *to* $m - 1$ *do*;
if $B \subseteq M$ *then* $U/IND(B) = \{m \in B : U/IND(\{m\})\}$;
$B(m_i) = \{(m_i, m_j) \in U^2 | \forall m \in (m_i) = m(m_i)\}$;
compute $B(m_i)$, where the indiscernibility relation in $MCIS$ as described in Step 2;
end if
end for
while $IND(B) = U/M$ *do*;
if $D_m^+ \equiv D_m^<$ or $D_m^- \equiv D_m^>$ *then*
$IND(B) = \{[x_k]_m \in BU^2 | \forall m \in B,\ m(m_i) = m(m_i)\}$;
compute D_m, where the condition attributes in $B(m_i)$ as described in Step 3;
end if
Find the merchandise categories average weight set based on AHP as described in Step 4;
DR $= (Y_l, \hat{\beta}_k, MC_i)$;
for $l \leftarrow 1$ *to* n *do*;
if $Y_1, Y_2, \ldots, Y_l \in Y$ *then*
for $k \leftarrow 1$ *to* 5 *do*;
if $\hat{\beta}_k = \frac{1}{s} \sum_{1}^{n} MC_i$ *then*
compute β_k, where the average weights of merchandise categories value set as described in Step 5;
end if
end for
end if
end for
$DT = (U, M = E \cup D)$;
for $g \leftarrow 1$ *to* v *do*;
if $e : U \rightarrow V_e, e \in E$ *then* $f_e = U \times E \rightarrow V_e$;
compute $f(x, e)$, where the information function in DT as described in Step 6;
end if
end for
$K = (U, B_1, B_2, \ldots B_w)$;
for $w \leftarrow 1$ *to* $m - 1$ *do*;
if $B \subseteq E$ *then* $IND(B) = \{[x_k]_e \in U^2 | \forall e \in B, e(e_g) = e(e_v)\}$;
$U/IND(B) = \{e \in B : U/IND(\{e\})\}$;
compute $B(E_g)$, where the indiscernibility relation in DT as described in Step 7;
compute $IND(E)$, where the relative reduct of DT as described in Step 8;
compute $IND(E - e_g)$, where the relative reduct of the elements for element $\boldsymbol{g}$ as described in Step 8;
end if
end for
for each $[x_k]_g$ *do*;
if $x \subseteq U$ *then*
$EX = \{x \in U | [x_k]_e \subseteq X\}$
$\bar{E}X = \{x \in U | [x_k]_e \subseteq X \neq \emptyset\}$
compute EX, where the lower-approximation of DT as described in Step 9;
compute EX, where the upper-approximation of DT as described in Step 9;
compute $BND_e(D)$, where the bound of DT as described in Step 9;
compute $Sup(IND(B))$, where the support as described in Step 10;
compute $Conf(IND(B) \rightarrow d_{e_g})$, where the confidence as described in Step 10;
end if
end for
Output {*Merchandise Category Recommendation*};
End

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