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Mobile Phone Recommender System Using Information Retrieval Technology by Integrating Fuzzy OWA and Gray Relational Analysis

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Abstract: With the advancement and diversification of information retrieval technology, such technology has been widely applied in recent years in personalized information recommender systems (RSs) and e-commerce RSs in addition to data-mining applications, especially with respect to mobile phone purchases. By integrating the weights of fuzzy ordered weighted averaging (OWA) and gray relational analysis, this research calculated the recommended F1 indices of three weight calculation methods to be 20.5%, 14.36%, and 16.43% after an examination by 30 experimenters. According to the operational results attained by the 30 experimenters, the recommended products obtained by the fuzzy OWA and gray relational analysis calculation method covered the products recommended by the other two weight calculation methods with a higher recommendation effect.

Keywords: information recommender systems; fuzzy order weighted averaging; gray relational analysis

1. Introduction

As the information on the Internet becomes increasingly vast, users need tools to help them find the information they need. Thus, information retrieval technology has become more advanced and diversified. In recent years, such technology has been widely used in personalized information recommender systems (RSs) and e-commerce RSs, as well as in data-mining applications. Traditional RSs are only capable of comparing similar objects in a database and then recommending items based on the description or information regarding the target product provided by the user. However, most comparison methods use the explicit value of the attribute, and sometimes, when consumers do not fully understand the level or degree of certain attributes, consumers may not be able to describe very precisely the objects in which they are interested. In such cases, the recommendation results of the traditional RS will inevitably be inflexible and low-quality. Moreover, the traditional RS does not include the concept of attribute weights, so each product attribute is regarded as having equal weight. Because different users in fact emphasize attributes differently, without the concept of attribute weights, users cannot accurately express their personal preferences.

This research integrated the concepts of fuzzy ordered weighted averaging (OWA) and gray relational analysis, making it easier for users to express their preferences, needs and priorities when products are recommended online. The models of fuzzy OWA, normalized fuzzy weight and experienced preference weight were introduced into the RS to provide multiple attribute weight calculation methods so that the distribution of attribute weight was more in line with user needs and provided users with more objective and reasonable recommendations. In addition, a mobile product RS that meets market demands helped verify the technology proposed in this research. Finally, the conformity ratio of the recommended products, the F1 index [1], and a satisfaction questionnaire that queried users' satisfaction with the RS of this research were used to verify the practicability of the RS established herein [1,2].

2. Literature Review

In the defuzzification literature, Bobyr et al. [3] presented a new method for defuzzifying the output parameters of the Mamdani fuzzy controller based on fuzzy rules. The method is characterized by using general equations to calculate the area of a geometric shape. During the realization process of the language terms of the fuzzy inference, the structure changes from triangle to trapezoid. This is the reason general equations are used. However, this method is finite and can only be used for triangular and trapezoidal membership functions. Gaussian functions can also be used to modify the proposed method. The error of the traditional defuzzification model also leads to a decrease in the precision of the fuzzy system, because the root-mean-square error increases during the training period. One of the reasons for the error is that the partially-activated fuzzy rules are excluded from the fuzzy inference. The precision of the fuzzy system can also be improved by the continuity attribute. The proposed method guarantees that the nature of the continuity can be realized, because when parameterized membership functions are used, the intersection of the adjustment language items equals 0.5.

The method proposed in this paper eliminates the inherent errors in the traditional and non-traditional defuzzification models. A comparative analysis of the defuzzification method for the traditional and non-traditional models shows the effectiveness of the proposed model. Rouhparvar and Panahi [4] established a new method of generalized fuzzy number defuzzification, which uses the center point of a triangle with three bisectors of its angles intersecting. The coordinates of the center point can also be calculated by Mathematica to solve the problems of defuzzification and the ranking of fuzzy numbers. This paper presents some numerical examples to illustrate the utility of the proposed method.

In the literature on OWA, Nguyen et al. [5] considered the scenario of a chairperson and the committees of a conference assigning papers to reviewers. Assigning paper reviewers is a multi-agent problem that requires understanding the reviewers' expertise and the paper topics involved in the matching process. Nguyen et al. presented a detailed description of some of the characteristics used to calculate the reviewers' expertise and summarized several factors relevant to finding the most suitable combination of reviewers for each paper. The reviewers' expertise were implicitly collected from public information and automatically populated into reviewer profiles. The OWA aggregation function was used to aggregate the information from different sources and rank the candidate reviewers for each paper.

Fernández et al. [6] considered the problem of multiple viewpoints or scenarios with multi-objective combinatorial optimization. When the number of solutions becomes considerable or a single meaningful solution is needed, the problem of aggregating multiple criteria to obtain globalized objective functions is particularly challenging. Fernández et al. studied the OWA optimization problem from the perspective of modeling. Alternative integer programming formulae for these problems were proposed, and their respective value ranges were studied and compared. In addition, their related polyhedrons were studied, and some viewpoints of effective inequalities were proposed. The proposed formulae were specifically aimed at two well-known combinatorial optimization problems (i.e., the perfect combination of the shortest path and minimum cost), and the results of the computational experiments were presented and analyzed.

In the RS literature, Inan et al. [7] adopted a RS to obtain user preferences and constructed a user model to recommend related items to users. Similar to any RS, the main purpose of this system was to match the most suitable item for the constructed user model based on the user's preferences. RSs that use current technologies are limited by processing data sparsity. To address this issue, the proposed

RS combines the content information of cinematic features and collaborative filtering methods. The proposed system is superior to others in the literature, and the experimental results showed that when the collaborative filtering method was used to intensify the content information, the overall system performance improved. Osadchiy et al. [8] studied recommendation systems based on methods such as collaboration and content-based filtering and evaluated them using historical data; however, this method cannot be performed for real-time data and different attribute data. Jakomin et al. [9] stated that the recommendation system is an important tool for modern e-commerce, streaming services, search engines, social networking, and many other areas, including the scientific community. This document is capable of simulating a set of variable flows and is useful for evaluating various recommendation systems. However, this method still uses data to simulate relevant conditions and cannot immediately reflect the immediate status and diversity of the data. Colace et al. [10] focused on two case studies, including the first system to help users select upcoming movies, using a well-known database as the primary source of data and a second system to help users find travel packages with certain characteristics, using TripAdvisor as the research database. Different from previous literature, this research used mobile phones as the research commodity and actual interview-related users as the object; therefore, the data is more realistic and the information considered is more diverse. The relevant feedback mechanism developed by Pouli et al. [11] allows users to participate in the evaluation of the initial relevance search for the results of the original query and to provide feedback on the most relevant results list based on one or more generations of calculus. The proposed framework implements a similar learning program to improve multimedia content retrieval and increase the user experience. The proposed performance and effectiveness framework are based on extensive evaluation and proof of the experimental research, utilizing interactive multi-modal computing and multimedia selection based on network RS. Zoidi et al. [12] described a method for extracting the facial image from a person's identity tag in a stereoscopic video. The final data representation is an optimized linear combination of projections for all data representations. The multi-site retention performance proposed in this document evaluates facial images extracted from stereo images based on an optimized prediction method for cluster-based label propagation. The experimental results showed that the method is more efficient than other methods. The rapid increase in the preconditions for advertising companies and online publishing companies to enrich multimedia content shows an undeniable need for innovative ways to effectively create rich multimedia content. Based on this need, in this document, the focus was on the design of a framework consisting of personalization, relevance feedback and recommendation mechanisms. The main contribution of this paper was the introduction of an overall framework that provides personalized rich multimedia content. This reference integrates the proposed recommendation framework in the MECANEX streaming media platform to enable usability research in a real-world environment [13]. This reference includes implicit assistance in the form of editorial supervision and in the form of recommended services. Electronic media offers new opportunities to create referral services that are constantly changing over time. Fab is a well-known RS protocol for the Web, and several versions have evolved [14]. RS is considered to be based on demographics, content and collaborative analysis. This document describes the RS protocol and related algorithms, explains the key processes of evolution, and explains the important directions for its future development [15].

Bobadilla et al. [16] presented a visual RS utilizing a Java framework that facilitated the following: (1) Associating the item and user; (2) providing the tree-diagram structure containing the most correlated relationship between the items and users; (3) using the visualization and resulting tree diagram; (4) choosing the most balanced visualization and the tree-diagram structure that is the easiest to navigate; (5) making a choice between various collaborative filtering similarity measures; (6) using the centrality measure to measure the result quality; and (7) embedding the new similarity index and quality measure easily. A visual RS can be used (1) as the analysis tool of an RS (2) to provide the visual tool related to an item and a user for both users and technical managers and (3) to promote research into collaborative filtering graphical representation and information navigation fields.

The online social network (OSN) of Terán et al. [17] has received great attention from researchers and can be used for different purposes such as event detection, crisis management and prediction. More and more social network research studies have utilized the trend classification method in this field. Such works exclude all kinds of social networks and focus on analyzing microblogs and using them as the data source underlying an RS. The aim is to provide the authors with insight into the comments and trends of the academic literature relating to the proposed background and to provide a comparison of different research methods. The general classification proposed in such works is used to describe the most advanced social network recommendation methods used for microblogs. This kind of work can be extended to include the new methods and trends in microblogging RSs.

Han et al. [18] considered a RS that uses social tag information to deal with the problem of data sparsity. Most people believe that the relationship between user/item and tag has improved the recommendation methods. However, the sparsity of tag information is challenging for most such existing methods. In this paper, a kind of extension tag has been proposed to support the matrix decomposition technique that uses the correlation between tags exported by tag co-occurrence to improve the RS's performance. The same is true in spite of the sparsity of tag information. The proposed method has integrated the coupling similarity between tags, and its calculation has been achieved through tag co-occurrence in the same item to extend the tag of each item. In the end, the item similarity of the extension tag has been used as a regularization term of the item relationship to restrain the process of matrix decomposition. The MovieLens dataset and Book-Crossing dataset were adopted to evaluate the performance of the proposed algorithm.

The RS based on distrust proposed by Xu et al. [19] has attracted much attention and has been widely accepted in recent years. A previous work investigated the use of trust information to establish a better rating prediction model, but any method where the distrust relationship is used to obtain a more accurate ranking-based model is lacking. In this paper, a new model named trust neutral distrust Bayesian personalized ranking (TNDBPR) has been developed, which uses the relationship between trust, distrust and neutrality for item ranking. The experimental results using the Epinions dataset showed that TNDBPR can improve the performance evaluation through the relationship between trust and distrust.

In regard to research into information retrieval, Chen [20] noted that similarity networks include important topological characteristics and models which are of great importance to understanding the interaction between samples in large datasets. To set up an interactive, comprehensive view in a dataset, he proposed to integrate the Similarity Network Fusion (SNF) technology into a full spectrum of similarity networks based on them having different data types. This paper has proposed a revised version of SNF called contextual information-based SNF (CI-SNF). In CI-SNF, first, the revised Jaccard distance is executed in terms of the SNF's fusion similarity to make use of the contextual information contained in the fusion similarity network. Second, the regional homogeneity of the samples coming from the same category, based on the Jaccard distance, is intensified by speculating over the highly ranked sample source under a specific inquiry and inquiring about the category. Third, the inverted index technique is introduced to use the sparsity of the regional homogeneity to improve the calculation efficiency.

Lai et al. [21] considered a private information retrieval agreement to allow users to retrieve the chosen data items (or k items) from a database containing N data items, instead of showing user choices from the server. In order to avoid the leakage of information relating to the data items in the private information retrieval system, Lai et al. put forward a new kind of private information retrieval agreement based on attributes, which can strengthen data privacy. In such a new agreement, each data item is related to a set of attributes, and these attributes are not disclosed to the users, who have only been exposed to a general attribute set that does not show information related to individual data items.

Munir and Anjum [22] suggested that the sharp increase in the use of knowledge discovery applications requires the end user to craft a complex search request to retrieve the information. Such users expect to master both the structural complexity of the complex database and the semantic relationship between the data stored in the database and the search inputs. In order to overcome these difficulties, the researchers focused on generating the knowledge representation and interactive query through ontology, especially stressing the interface between data on improved results as search requests change to move the results set closer to a user's research demand. Based on Munir and Anjum's results, they suggested that additional research can close the gap between ontology and the relational model to use ontology to generate an accurate search request. Information retrieval results based on ontology, conversion from a database to ontology, and a comparison of the mapping methods of ontology have provided a reference to strengthen the search ability of an information management system loaded on a large scale.

This research integrated fuzzy OWA and gray relational analysis to design an intelligent RS structure to measure the factors affecting the target, such as quantification (cost, profit, etc.) and semantic level (satisfaction). The research has also considered the fuzzy theory generally in different decision-making situations [8–10,23,24]. The normalized fuzzy weight method [25] and modified Delphi method [2,26] only consider the degree of semantics and cannot specifically quantify specific consideration factors, including cost, profit, etc., so the integration method of this research is both specific and practical.

3. Integration Technique of Fuzzy Weight and Information Retrieval

This research integrates fuzzy OWA and gray relational analysis to design an intelligent RS structure. First, the users provide the information to be retrieved through attribution selection. Second, the weight selected by the users is used to express the preference for this attribute, and the weight calculation of the attributes selected by the users is integrated to gain the fuzzy comprehensive scores of each product in the target product cluster. In the end, the attributes are ranked according to the degree of conformity with the retrieval conditions, and the recommendation results are sent back to the users [10,24].

This RS can be divided into two modules: The preference attribute selection module and the information integration operator module. The preference attribute selection module can also be divided into two stages: The categorical data attribute selection and the numerical data attribute selection. The information integration operator module contains three kinds of different attribute weight operation methods: integrating fuzzy OWA and gray relational analysis method, normalized fuzzy weight method, and experienced preference weight method (a modified Delphi method). The calculation program of this research is introduced below, as shown in Figure 1 [10,24].

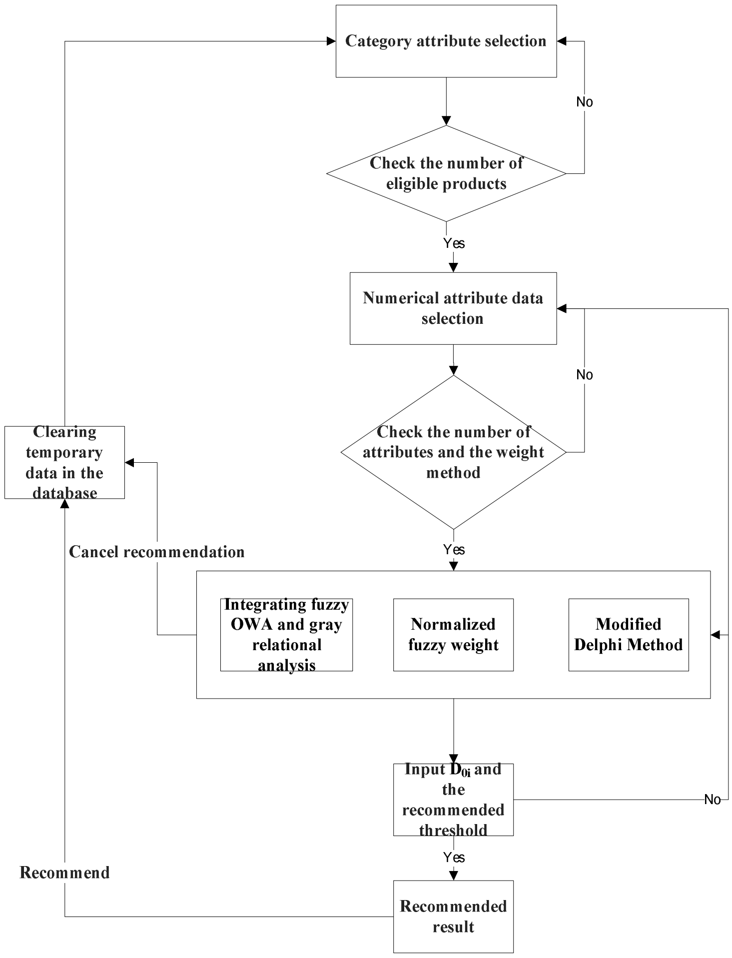

Figure 1. The research process. OWA, ordered weighted averaging.

3.1. Preference Attribute Selection Module

In the preference attribute selection module, the attribute selection occurs in two stages: (1) categorical data attribute selection and (2) numerical data attribute selection. In the categorical data attribute selection stage, each user can select product attributes independently according to personal preference to distinguish the user's target product cluster. Next, the user enters the stage of numerical data attribute selection. This research fuzzifies the numerical data attribute, uses the fuzzification method for the cumulative probability distribution approach (CPDA), and refers to experts' opinions to revise the interval end point of the individual scale to establish a membership function with a suitable attribute. Each numerical data attribute is classified into high-order (H), middle-order (M), and low-order (L) on the semantic scale. Such a classification method captures the users' general impressions of the products, and the users can then select the attribute and weight from the numerical data attribute based on their personal preferences, which is used to calculate the fuzzy comprehensive score when subsequent products are recommended [27].

3.2. Information Integration Operator

When the user's product information retrieval and preference are integrated, the user's personal preference for different attributes are accorded different weights. This research provides three kinds of different weight calculation methods: the integrating fuzzy OWA and gray relational analysis weight method, normalized fuzzy weight method, and experienced preference weight method (a modified Delphi method). These methods are introduced below [1,2].

3.2.1. Gray Relational Analysis

The gray system theory conducts regional analysis between the factors of a research system when the complex system model is uncertain and adopts a decision-making calculation method to analyze the system. Gray relational analysis is the key influencing factor in the ranking [23].

Step 1: Normalize the research data, shown as:

$$R_i(g) = \frac{y_i(g)}{\sum\limits_{g=1}^{N} \frac{y_i(g)}{N}}, i = a, \ldots, dg = A, \ldots, N \tag{1}$$

Step 2: List the research standard as the base; the calculation of difference sequence is shown as:

$$\Delta_{0i}(g) = |R_0(g) - R_i(g)|, i = 1, 2, 3, \ldots g = A, \ldots, N \tag{2}$$

Step 3: Gain $\Delta_{\max}$ and $\Delta_{\min}$ in all of the data, as shown in Equations (3) and (4):

$$\Delta_{\max} = \underset{i,g}{Max} \Delta_{0i}(g) \tag{3}$$

$$\Delta_{\min} = \underset{i,g}{Min} \Delta_{0i}(g). \tag{4}$$

Step 4: Calculate the gray correlation coefficient $\gamma_{0i}(g)$ in all of the data, as shown below:

$$\gamma_{0i}(g) = \frac{\Delta_{\min} + \varsigma \cdot \Delta_{\max}}{\Delta_{0i}(g) + \varsigma \cdot \Delta_{\max}}. \tag{5}$$

Step 5: Calculate the data's gray relational degree D_{0i} in each column and standard column as:

$$D_{0i} = \sum_{g=A}^{N} \frac{\gamma_{0i}(g)}{N}. \tag{6}$$

Step 6: Sort the importance factors according to the gray relational degree.

3.2.2. Integrating Fuzzy OWA and Gray Relational Analysis Weight

In the calculation process of fuzzy OWA, only the condition parameter (D_{0i}) and the number of attributes (n) are required to be given. The attributes are arranged in order as $y_1, y_2, \ldots, y_n$ according to their respective degrees of importance. For Equations (1)–(6), the numerical analysis method is adopted, and the Newton location of the root is used to calculate the relative weight value of each attribute. Each attribute's degree of membership of product materials is then multiplied by the attribute's fuzzy OWA weight value for integration. The calculation steps are shown below [1,2].

Step 1: Set the number of attributes as n and the condition parameter as D_{0i}.

Step 2: Rank the attributes according to the degree of importance.

Step 3: Calculate the maximum attribute weight w_1 through: $w_1[(n-1)D_{0i} + 1 - nw_1]^n = [(n-1)D_{0i}]^{n-1}\{[(n-1)D_{0i} - n]w_1 + 1\}\, w_1$.

Step 4: Substitute the maximum attribute weight w_1, the number of attributes n, and condition parameter D_{0i} into $w_n = \frac{[(n-1)D_{0i} - n]w_1 + 1}{(n-1)D_{0i} + 1 - nw_1}$ to gain the minimum attribute weight w_n.

Step 5: Substitute w_1 and w_n into $w_j = \sqrt[n-1]{w_1^{n-j} w_n^{j-1}}$ to gain the fuzzy OWA weight of attributes $w_2, \ldots, w_{n-1}$.

Step 6: Multiply the attribute's degree of membership times the corresponding fuzzy OWA weight value for integration according to the attribute's importance ranking and substitute the calculation result into $I = y_1 \tilde{w}_1' + \ldots + y_n \tilde{w}_n'$ to gain the fuzzy comprehensive score.

Step 7: Substitute the fuzzy comprehensive score into $H_i = \frac{I_i}{Max(I_i)}$ to calculate the conformity ratio H_i of each product.

Step 8: Rank the target product according to the level of the conformity ratio and select the product greater than the threshold value set by the users independently as the recommended product.

3.2.3. Normalized Fuzzy Weight

The normalized fuzzy weight method is aimed at the weight value of the fuzzy semantic quantifier. The users apply the semantic quantifier to preset the degree of importance of individual attributes. The semantic quantifier is represented by the corresponding fuzzy number, and then the fuzzy number is normalized. For the convenience of calculation and processing, the normalized fuzzy number is defuzzified to be the weight of this attribute. The weight normalization allows the users to have consistent judgment while setting the threshold value [2,25].

Referencing the proposal by Miller [25] that a human's optimal short-term memory ability is in the range of 7 ± 2 under Miller's grading system, this research sets the weight's semantic quantifier as five semantic scales: very important, important, ordinary, unimportant, and very unimportant (VI, I, M, UI, and VUI, respectively). The calculation steps of the normalized fuzzy weight method are shown below [2,25].

Step 1: Set the number of attributes selected by the users as n.

Step 2: Convert the semantic quantifier of an attribute's degree of importance into the corresponding fuzzy numbers $\widetilde{k}_1, \widetilde{k}_2, \ldots, \widetilde{k}_n$.

Step 3: Normalize the fuzzy numbers $\widetilde{k}'_i = \frac{\widetilde{k}_i}{\sum\limits_{i=1}^{n} \widetilde{k}_i}$.

Step 4: Defuzzify the normalized fuzzy numbers and use them as the weight of the applicable attribute $w_i = z\left(\widetilde{k}'_i\right)$.

Step 5: Multiply the degree of membership of each attribute by the normalized fuzzy weight value for integration and substitute it into $I = y_1 w_1 + \ldots + y_n w_n$ to calculate the fuzzy comprehensive score, for which the ranking of an attribute's degree of importance is $y_1, y_2, \ldots, y_n$.

Step 6: Substitute the fuzzy comprehensive score into $H_i = \frac{I_i}{Max(I_i)}$ to calculate the suitable proportion of each product.

Step 7: Rank the target product according to the level of the conformity ratio and select the product greater than the threshold value set by the users independently as the recommended product.

3.2.4. Modified Delphi Method

Expert consistency is assessed based on whether there is a consensus among expert opinions regarding a given subject. Therefore, if the evaluation result of the Delphi method has achieved a concentrated distribution, then it exhibits consistency; if the result is distributed on both extremes (mostly located in a high-score region and low-score region), then it shows inconsistency; and when the result lies between the two extremes, then it denotes uncertainty. This paper defines consistency as the proportion of people for whom the median score of all the experts is equal to or greater than 7, and this proportion varies with different criteria and with rounds of the Delphi method. In the first round of the Delphi method, the proportion of experts whose median score is equal to or greater than 7 must be equal to or greater than 55% with respect to the importance and equal to or greater than 50% with respect to the evidence (validity) and the improvability. If these three conditions are met, then this index presents consistency. The index presents inconsistency if the score of at least 1/3 of the experts is 1–3 and the score of at least 1/3 of the experts is 7–9. If this index presents neither consistency nor inconsistency, then it exhibits uncertainty. In the second round of the Delphi method, it is the same as the scoring standard of the questionnaire in the first round, but the standard for consistency increases so that the proportion of experts whose median score is equal to or greater than 7 must be equal to or greater than 70% [2,26].

4. Implementation and Verification of the RS

Based on the fuzzy weight determined as described above, the information retrieval integration technique can be used to develop the RS applied in fields such as mobile phone selection and purchase recommendations. In evaluating the efficiency of a RS, the recall, precision, F1 index [1], and satisfaction [28] are usually used as the measurement indices. Therefore, this research also adopted the abovementioned indices to illustrate the practicability of our prototype system of mobile phone recommendation in addition to using the conformity rate of the recommended product as the experimental description.

After the users log into the system, they select the type of operational system, the internal processor (CPU) speed, the built-in camera's automatic focus ability, and the built-in storage capacity of the mobile phone on their own.

Step 1: Choose the preference attributes from the numerical data attribute and gain the number of attributes.

Step 2: Judge the weight methods chosen by the users as integrating fuzzy OWA and gray relational analysis weight, normalized fuzzy weight, or experienced preference weight.

Step 3: If using the integrating fuzzy OWA and gray relational analysis method, then the attribute importance and condition parameter (value) increase in rank. Calculate the score whereby the semantic membership of an individual attribute is multiplied times integrating fuzzy OWA and gray relational analysis weight.

Step 4: If using the normalized fuzzy weight method, then calculate the degree of importance of each attribute after normalization and multiply the score from the semantic membership degree of the individual attribute times the normalized fuzzy weight.

Step 5: If using the experienced preference weight method, then the experienced preference weight corresponding to the attribute will be gained. After normalization, calculate the score whereby the semantic membership degree of an individual attribute is multiplied times the new weight.

Step 6: Integrate and add up the score of each attribute and calculate the fuzzy comprehensive score and conformity ratio of the individual mobile product.

Step 7: The mobile phone product materials whose conformity ratios are greater than the threshold values set by the users independently are selected and ranked, and the results are recommended to the users. Because the end-users' personal characteristics are different from other research, this research had higher requirements for product functions, and therefore the threshold values were set to 85%, as shown in Table 5.

4.1. Experiment on the Conformity Ratio of the Recommended Product

The three kinds of attribute weight calculation methods proposed by this research were verified empirically, and their experimental results were recorded and analyzed. To make the experimental results comparable, it is necessary to carry out the individual experiments under the same experimental environment under the same conditions. The following three points were important conditions of the experimental design in this research:

(1) In calculating the integrating fuzzy OWA and gray relational analysis weight, it is necessary to rank the attributes according to the degree of importance; thus, the linguistic variable of an attribute's degree of importance with a normalized fuzzy weight cannot be designated repeatedly.

(2) In calculating the experienced preference weight when users have not preset the attribute degree of importance, the weight value collected by this research is used as the basis for an attribute's degree of importance (e.g., a higher weight value represents a more important attribute). Thus, in the experiment, the ranking of the attribute's degree of importance in the other weight calculation methods must be the same as that of the weight value of the experienced preference weight.

(3) Because the linguistic variable of the attribute's degree of importance with a normalized fuzzy weight is divided into five grades, five numerical data attributes are selected at random to conduct the experiment.

Two experiments were conducted in this research. The environment settings of the two experiments regarding the steps of a RS for mobile phone products are presented in Table 1.

Table 1. Condition setting of the two experiments with the conformity ratio.

	First Experiment	Second Experiment
Step 1	Select the categorical data attribute and 382 sets of data in line with the attribute	
	Type of operational system: no limit	The same as with the first experiment
	Mobile phone internal processor Central Processing Unit (CPU) speed: no limit	
	Built-in camera automatic focus ability: no limit	
	Built-in storage capacity: no limit	
Step 2	Select the numerical data attribute	
	Pixel of the main camera: 1200 pixels	Pixel of main the camera: 1200 pixels
	Dimension of the home screen: 5.8 inches	Dimension of the home screen: 5.8 inches
	Read-Only Memory (ROM) storage space: 256 GB	ROM storage space: 128 GB
	Pixel of the front camera: 16 million pixels	Pixel of the front camera: 8 million pixels
	Resolution of the home screen: 2436 × 1125 pixels	Maximum call time: 20 h
	Maximum call time: 36 h	Stand-by time: 360 h
Step 3	Calculation method of attribute weight: three methods are used in the experiment	
Step 4	Individual setting of attribute importance and the recommended threshold value is 85%	
	Attribute ranking of integrating fuzzy OWA and gray relational analysis: pixel of the main camera > ROM storage space > dimension of the home screen > maximum call time > pixel of the front camera > resolution of the home screen Note 1	Attribute ranking of integrating fuzzy OWA and gray relational analysis: pixel of the main camera > dimension of the home screen > ROM storage space > pixel of the front camera > maximum call time > stand-by time
	Semantic quantifier of an attribute's degree of importance with a normalized fuzzy weight:	
	Pixel of the main camera is very important. ROM storage space is very important. Dimension of the home screen is important. Maximum call time is important. Maximum call time is ordinary. Resolution of the home screen is unimportant.	Pixel of the main camera is very important. Dimension of the home screen is very important. ROM storage space is important. Pixel of front camera is important. Maximum call time is ordinary. Stand-by time is unimportant.
Experimental result	Sorted in Table 5	Sorted in Table 6

Note: Condition parameters for integrating fuzzy OWA and gray relational analysis weights of 0.55, 0.65, 0.75, 0.85, 0.95, and 1.0 are used for the experiment.

Tables 2 and 3 summarize the two experimental results. It can be observed from Table 2 that during the first experiment, when the integration of fuzzy OWA and gray relational analysis weight is 1.0 in the three attribute weight calculation methods, at most, 42 sets of data were sent back and recommended to the users. The weight of 1.0 meant that only the attribute first in order (with the highest degree of importance) was used, and this was the most extreme case. When the experienced preference weight and integrating fuzzy OWA and gray relational analysis weight were 0.55, 10 sets of data were sent back. After comparison, it was found that the mobile phone product materials sent back in the experiment where the two kinds of weight calculation methods were used were the same (as shown in Table 4), but the recommendation result of the fuzzy OWA weight contained a higher average conformity ratio (90.1%), showing that the recommendation quality of the fuzzy OWA weight is higher than that of the experienced preference weight. The normalized fuzzy weight could only send back seven sets of data for recommendation, but it had a higher average conformity ratio (94.8%).

Table 2. Comparison of the first experimental result.

	Integrating Fuzzy OWA and Gray Relational Analysis (D_{0i}=0.68)						Normalized Fuzzy Weight	Modified Delphi Method
D_{0i}	**0.55**	**0.65**	**0.75**	**0.85**	**0.95**	**1**		
Number of recommendations (piece)	10	8	7	8	9	42	7	10
Average conformity ratio (%)	90.1	91.9	93.8	92.6	92.8	98.9	94.8	89.6

Table 3. Comparison of the second experimental result.

	Integrating Fuzzy OWA and Gray Relational Analysis (D_{0i}=0.65)						Normalized Fuzzy Weight	Modified Delphi Method
D_{0i}	**0.55**	**0.65**	**0.75**	**0.85**	**0.95**	**1**		
	61	46	31	26	18	21	39	60
	89.2	86.3	87.9	86.8	89.3	96.1	86.3	88.3

Table 4. Mobile phone product data recommended by the first experimental result.

	Integrating Fuzzy OWA and Gray Relational Analysis Weight (D_{0i}=0.55)			Modified Delphi Method		
	ID	**Manufacturer**	**Model**	**ID**	**Manufacturer**	**Model**
1	Ph-8	Samsung	Tab A 10.5	Ph-8	Samsung	Tab A 10.5
2	Ph-26	Apple	8	Ph-26	Apple	8
3	Ph-61	Sony	XZ Premium	Ph-61	Sony	XZ Premium
4	Ph-77	Apple	8 Plus	Ph-77	Apple	8 Plus
5	Ph-89	Apple	7 Plus	Ph-89	Apple	7 Plus
6	Ph-128	Sony	XA1 Ultra	Ph-128	Sony	XA1 Ultra
7	Ph-198	Sony	X Compact	Ph-198	Sony	X Compact
8	Ph-268	Samsung	Tab S3 (WiFi)	Ph-268	Samsung	Tab S3 (WiFi)
9	Ph-365	Sony	XZ Dual SIM	Ph-365	Sony	XZ Dual SIM
10	Ph-379	HTC	U Ultra	Ph-379	HTC	U Ultra

The results shown in Table 3 indicate that when the integrating fuzzy OWA and gray relational analysis weight was 0.55, 61 sets of data could be sent back, which was higher than, and included all of, the 60 sets of data sent back with the experienced preference weight. The average conformity ratio was also higher with the integrating fuzzy OWA and gray relational analysis weight (89.2%) than with the experience preference weight (88.3%). However, the normalized fuzzy weight was slightly worse; only 39 sets of product data could be sent back, and the average conformity ratio could only reach 86.3%. The two experiments showed the following:

(1) The result gained by using the integrating fuzzy OWA and gray relational analysis weight method included the results obtained by using the other two weight calculation methods. Thus, the integrating fuzzy OWA and gray relational analysis weight is recommended as highly efficient.

(2) The experimental result can truly reflect the actual situation. A comparison of the setting conditions and recommendation results of the two experiments shows that the attribute grade set by the first experiment was higher, and the number of digital cameras sent back was smaller; however, they were very high-grade digital camera products sold on the market. In the second experiment,

the attribute grade was set as the middle order, and more results were sent back for recommendation, which reflects the fact that there are more middle-order cameras in the mobile phone market.

(3) The experimental results show that the experienced preference weight also covers the integrating fuzzy OWA and gray relational analysis weight, which indicates that the experienced preference weight collected by this research is very useful in making recommendations.

4.2. System Efficiency Evaluation and Satisfaction

This research used the F1 index to measure the efficiency of three RSs [1], as detailed below.

In practical application, an increase in precision will cause a decrease in the recall, and so recall and precision are integrated into the F1 index, and the formula is defined as Equation (7):

$$\mathrm{F1} = 2[(\mathrm{recall} * \mathrm{precision})] \div (\mathrm{recall} + \mathrm{precision}). \tag{7}$$

This research used the Normalized fuzzy weight [29] and Modified Delphi method [30] to compare the Integrating fuzzy OWA and gray relational analysis, as shown in Table 5.

Table 5. Condition setting of evaluating the efficiency measurement index.

		Integrating Fuzzy OWA and Gray Relational Analysis	Normalized Fuzzy Weight	Modified Delphi Method
Average value of experimenters	Recall	12.36%	9.8%	12.98%
	Precision	60.03%	26.89%	22.38%
	F1 index	20.5%	14.36%	16.43%

In this research, 30 experimenters were selected to carry out the experiment to measure the index of RS efficiency. The scholars had to have purchased mobile phones online on at least two occasions and be in the field of decision-making. Table 5 sets forth the experimenters' environmental setting. After the review, 30 experimenters calculated the F1 indices of the three kinds of weight calculation methods to be 20.5%, 14.36% and 16.43%. According to the operational results of the 30 experimenters, the recommended products obtained by the fuzzy OWA weight method included the recommended products obtained with the other two weight calculation methods and they have a higher recommendation effect.

The objective of this research was limited. Due to limitations in time and manpower, this research used convenient sampling to select the sample that best fit the purpose of this research (based on which experimenters had shopped online to purchase mobile phones). The main contents of the questionnaire included information quality, system quality and service quality for overall satisfaction analysis. The questionnaire was conducted in an academic seminar in 2018. A total of 131 questionnaires were sent, and 100 valid questionnaires were collected.

This research also used a questionnaire to assess the users' satisfaction with the recommendation prototype system of mobile phone products. In an academic seminar, the system's operational method was explained to the audience first to make the audience actually operate the prototype system for recommendation. After the operation, the satisfaction questionnaire was administered. Out of 100 questionnaires recovered, only 6% of users checked "dissatisfaction" with the overall system, and 42 users recommended the integrating fuzzy OWA and gray relational analysis method. Moreover, the average satisfaction for the integrating fuzzy OWA and gray relational analysis method was higher than that of the other two weight calculation methods.

According to the calculations shown in Equation (7), the ratio of recall and precision is high, so that the ratio of F1 can be increased. Due to the large number of functions of the mobile phone and the fact that the expectation of the mobile phone is different, the reported precision and recall are particularly low; however, the integration of fuzzy OWA and gray relational analysis shows that the precision ratio and F1 are better than other methods, so it can be used as a reference for the mobile phone product recommendation prototype system.

5. Conclusions and Suggestions

This research used three kinds of different weight calculation methods: the integrating fuzzy OWA and gray relational analysis method, the normalized fuzzy weight method, and the experienced preference weight method. The integration of fuzzy OWA and gray relational analysis can make the weight distribution proportion better align with the users' demand by adjusting the condition parameters. The experiments in this research verified that integrating fuzzy OWA and gray relational analysis has good efficiency in product recommendations. The normalized fuzzy weight method provides more flexible query conditions to the users, and the normalized attribute weight can reflect their degree of emphasis on an attribute in a more objective way. In the experienced preference weight method (a modified Delphi method), a large number of questionnaires is used to analyze and obtain the degree of emphasis on each attribute by the people purchasing mobile phones so that users can refer to the "group opinion" as the basis for a purchase decision, which is of great help to the recommendation effect.

There are many applications from the results herein that can be investigated in subsequent research. The mobile phone recommendation prototype system aims to verify the framework proposed by this research instead of taking the complete function and overall efficiency as the relevant considerations. Thus, satisfaction with the human–machine interface can be strengthened, and the optimization algorithm can be improved. In terms of establishing an attribute membership function, in consideration of data attributes and calculation convenience, this research focuses on the triangular fuzzy number and applies different types of fuzzy numbers and expert opinions to establish the membership function of mobile phones.

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