Recommendation System for Apparel Online Shopping

TERUJI SEKOZAWA
Department of Information Systems Creation, Kanagawa University,
Yokohama 221-8686, JAPAN
sekozawa@ie.kanagawa-u.ac.jp http://www.is.kanagawa-u.ac.jp/

Abstract: - Clients who visit an apparel marketing website but have little previous knowledge of fashions tend to have difficulties selecting clothes that suit their tastes. Faced with an immense number of products on display, they can become quite confused and even hesitate to make any selections at all.

This study proposes a system that supports online purchases of garments with functions to select and recommend garments on the basis of the customer's tastes. The system has three basic capabilities: (1) It analyzes the customer's tastes using the analytical hierarchy process (AHP) and selects and suggests clothes. (2) It designates a priority for suggesting the garments using correlations found by clustering. (3) It suggests second purchases of items that have been chosen by previous customers with similar tastes who bought a garment that the current online customer has just decided to buy. The second purchases are selected using market basket analysis. Two databases are essential to this process: one for the attributes of garments and one for simultaneous purchases of garments.

Key Words: - Analytical hierarchy process, Online shopping, One-to-one, Recommendation system, Coordination, Market basket analysis

1 Introduction

The apparel trade has undergone a revolution since 1960, when it was characterized by "mass fashion," i.e., mass production and mass sales, and became a segment-oriented fashion market by 2000. This orientation emphasizes small groups of target customers, and has gained acceptance amid the recent flood of economic activity. Service to individual customers is also increasingly emphasized, and "one-to-one marketing" based on a personal relationship is expected by many customers(1)(2)(3)(4). This relationship is an integral part of sales strategies in the apparel market, which is focusing on symbiotic trust relationships between the customers and the businesses (retailers), where each seeks to build relationships that are of mutual benefit.

When looking for apparel on a conventional shopping website (Fig. 1(7)), the only way the customer can judge an item on display is to read the descriptions on the computer monitor (for example: type of apparel; color; price; brand; quality label; size) and look at the image of the item. Customers who do not have full knowledge about fashion often find themselves unable to find any among the great number of possible purchases that match well with their own tastes. Others find it impossible to make up their minds among the choices they like and give up on the purchase. Others make purchases, but are still uncertain whether they have bought something that really suits them.

There is a system called "Virtual Model" that provides a three-dimensional (3D) image of a manikin wearing a selected item of apparel(8), but even with this system, there are so many possible selections that customers can find it difficult to select items that satisfy their preferences.

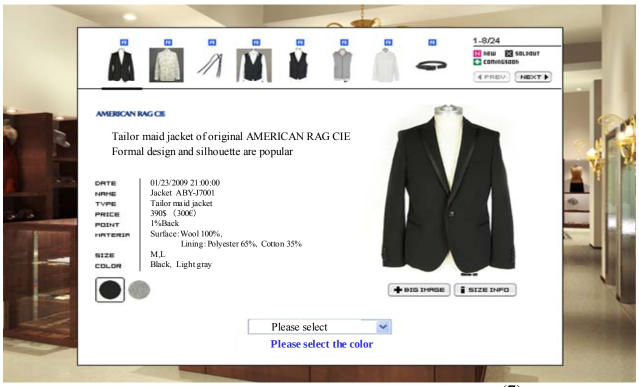

Fig.1: Example of on-line apparel shop(7)

Thus, online shopping sites have several challenges. The ultimate goal of this research is a system to offer customers the same level of assistance that is provided by a human sales representative. This new system or "fashion advisor" will have the ability to select and recommend clothes that fit the individual customer's tastes, thus supporting the purchase of clothes just as a sales clerk does.

The analytical hierarchy process (AHP) is a procedure for digitization of human perceptions and tastes. It is able to assign numerical values to vague aspects of perceptions. Chanhao *et al.* suggested some new additional features of AHP(13)(18)(20). One example of practical application of AHP is in a system for aiding a sponsor of a conference to select convention venues (10). Other systems have used AHP to assess plans for practice by golfers, and to assess the contributions of individual members to teams of students(16)(17). However, perhaps due to the great diversity in clothing and in human tastes found in the online apparel sector, no one has applied this technique in this field, let alone to such complicated tasks as extracting the attributes of clothing.

Even if a system is able to select the apparel out of a broad collection that suits a customer's tastes, it will still be difficult to assign priorities to the items within a cluster of appropriate merchandise. In other words, even when suggesting clothes items to a customer that meet her preferences, it has been difficult to satisfy the sellers' desires to make further suggestions in the proper order after the customer has refused one suggestion. Here, "cluster" means a set of appropriate clothes that have been pre-selected by their attributes and the customer's preferences. Internet sellers also desire the ability to make suggestions for other well-coordinated apparel, once the customer has purchased something. This function would also use data from previous purchases by the customer and provide opportunities for further sales.

The aim of this study is to offer basic functions to resolve the above issues in online shopping. Specifically, the objectives are to (1) analyze a buyer's tastes using AHP, and select and offer pertinent clothes items; (2) create a cluster of apparel based on their correlation with a buyer's tastes, and prioritize the items in the cluster; and (3) suggest garments bought by other buyers with similar tastes, on the basis of market basket analysis(11).

The above functions will enable the system to choose apparel meeting the customer's tastes, make suggestions from a taste cluster in order of priority, and make recommendations with a high degree of confidence (probability of purchase during the same session) for further items for purchases as good combinations with an item already selected for purchase by the customer.

2 Outline of One-to-one Recommendation System

Fig.2 is a diagram of the system. As already described, the essential procedures in the function of this system are: (1) AHP; (2) cluster analysis; and (3) market basket analysis. These were used in combination. Also, databases for (a) apparel attributes and (b) simultaneous purchases were used with the three procedures above. Databases (a) and (b) in Fig. 2 are described in Section 2, and examples of the application of procedures (1), (2) and (3) above are described in Sections 3, 4 and 5, respectively.

2.1 Databases required by the system

(a) Database of apparel (product) attributes

This is shown in (a) of Fig.2. Each apparel **type** was entered with its digitized assessment scores before the experiment. One standard of these criteria, for example, was Design. The score was entered in absolute values as follows: 9, Very Good; 7, Good; 5, Average; 3, Bad; 1, Very Bad. Another example of assessment criteria was System, recorded in another nine-stage hierarchy for each sector of Mode, Casual, and Individuality. In the Sensitivity classification, the criteria were Avant-garde, Contemporary, and Conservative. In the Silhouette classification, the criteria were Heavy build, Average build, and Slim each in nine stages. Thus, the database was constructed with nine-level rankings of all the clothes according to their attributes. Table 1 shows some examples of the apparel attributes. There were 160 articles of clothing that had the potential to be suggested as alternative purchases.

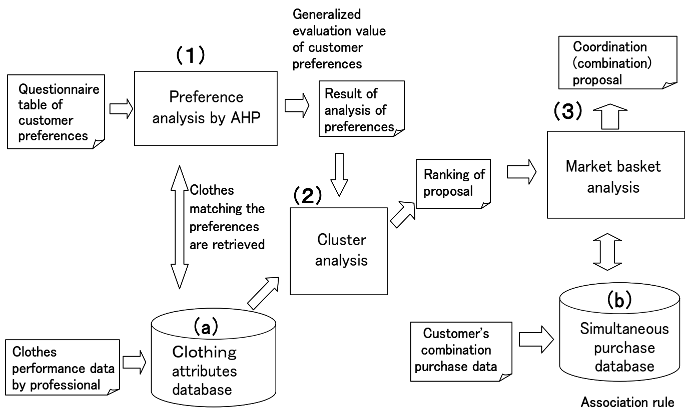

Fig. 2 Overall structure of online system

(b) Simultaneous purchase database

A diagram of this database is presented in Fig.2(b). This database is a tabulated record of all apparel items that were bought together on any date, after analysis of the apparel items. The database can be used to calculate the incidence of purchase of items and the confidence that they will be bought with something else. Association rules can be constructed to anticipate what combinations customers are most likely to select.

Table 1: Digitization of apparel attributes

Sample name	Mode	Casual	Indivi-duality	Plump build	Normal	Slim build
M-1020	1	5	7	1	3	9
M-1030	9	3	1	1	3	9
M-1040	1	9	3	9	3	1
M-1050	5	1	7	3	5	7
M-1060	3	5	7	3	5	7
M-1070	3	7	5	7	5	3
M-1080	1	3	9	9	3	1
M-1090	1	3	9	7	5	3
M-1100	1	3	9	7	5	3

2.2 Outline and procedure of analysis

(1)Grasping the customer's tastes with AHP and selecting apparel

An apparel (product) database is created for digitized characterizations of clothing. The system surveys customers, analyzes their tastes with AHP procedures and searches for clothes popular with them. This allows the system to suggest popular items.

(2) Cluster analysis for customer tastes

K-means clustering is applied in cluster analysis by grouping items in the database that have strong correlations with each other in order to classify popular apparel in clusters.

(3) Recommending apparel combinations

A simultaneous purchase database is created for use by the "fashion advisor." Market basket analysis is used with the clustered apparel items to recommend apparel with a high degree of confidence that the customer will like, while the customer is buying a part of a combination. In other words, when the customer has bought an item that suits one particular kind of taste, the system can recommend the purchase of a different item with a high degree of confidence that the customer will follow through and buy it.

The above three functions (1), (2), and (3) are also shown in Fig.2. The key functions of the system mentioned in the above overview are described below in more detail.

3 Digitization of customer tastes with AHP

One feature of AHP is its capability to quantify the vague elements in human perceptions and assign numerical values for decisions. In this research, AHP was applied for digitization of human tastes and objective judgments.

3.1 Hierarchical structure for searching for popular attire

AHP allows the user to assess apparel from a wealth of different angles, and on this basis, to construct a system capable of searching for the optimal attire. Fig. 3 shows the hierarchical structure that was created. Level 1 is the general "Apparel customers like" objective, and Levels 2 and 3 include assessment standards. The lowest, Level 4, has suggestions for alternative purchases, including Cut and Sewn, Shirts, Pants, and Jackets.

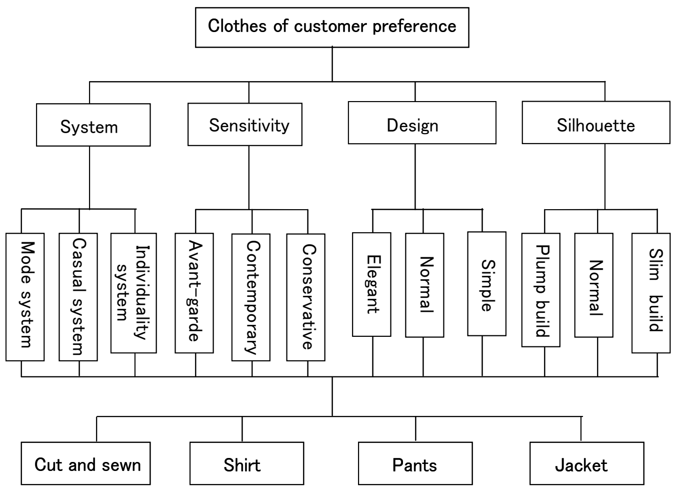

Fig.3: Hierarchical structure in AHP

3.2 Analysis of priority of assessment standards by AHP

The priority of each element in the assessment standards is determined. First, the essential assessment standards on Level 2 of the hierarchical structure are compared with each other and analyzed. Customers are surveyed for their own priorities among the four assessment standards shown in Fig.4 on Level 2, and the results are analyzed.

The paired-comparison matrix in Table 2 shows the results of the survey in Fig.4 after multiplication by weighting vector W. For this customer, the most important factor was Factor 1 System (0.558), followed by Sensitivity (0.263), Design (0.122) and Silhouette (0.057).

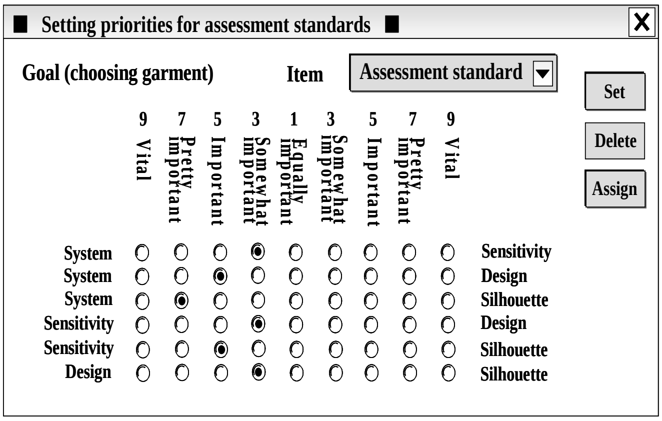

Fig.4: Screen used to survey respondents for assessment standards

Table 2: Paired comparison of assessment standards (prioritization)

	System	Sensitivity	Design	Silhouette	(Weight)
System	1	3	5	7	0.558
Sensitivity	1/3	1	3	5	0.263
Design	1/5	1/3	1	3	0.122
Silhouette	1/7	1/5	1/3	1	0.057
λ max	4.118			C.I	0.039

The highest-valued eigenvalue of the paired comparison matrix for the standards provided by the survey was $\lambda_{max} = 4.118$, and the consistency index (CI) was $0.039 < 0.1$. This value was significant. CI is defined in Eq.(1).

$$C.I. = \frac{\lambda'_{max} - n}{n-1} \qquad (1)$$

Next, customers were surveyed for their own scores of the relative importance of System, Sensitivity, Design and Silhouette in order to learn about customers' tastes.

Fig.5 shows simple explanations and images of clothing so that even customers with little knowledge about clothes can understand the images of garments classified into Casual and Individuality. This makes it easier for the customer to judge which of the two is more important, speeding extraction of the customer's tastes and suggesting a more accurate evaluation.

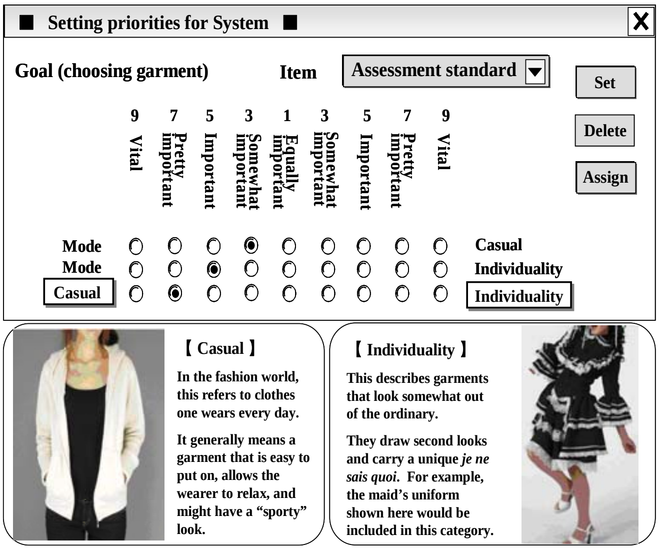

Fig.5: Examples of screens in the customer survey for standards for judging System

Table 3 shows customers' evaluations when there were three assessment standards for System. The reader can see that this customer's rating of the factors was Mode, Casual, Individuality, in diminishing order of importance. This evaluation had a CI under 0.1, so it can be considered valid.

Let us analyze a survey of customers for the importance of the third-level factors in Sensitivity. The factors in Design and Silhouette were also prioritized.

Table 3: Paired analysis of three factors in System (evaluating priority)

System	Mode	Casual	Individuality	(Weight)
Mode	1	3	5	0.633
Casual	1/3	1	3	0.26
Individuality	1/5	1/3	1	0.106
λ max	3.039	C.I	0.019	

3.3 Procedure for absolute evaluations

Let us turn to the set of articles from which alternative purchases could be suggested, the fourth level of hierarchy. When the CI exceeded 0.1, the values in the paired comparison matrix had to be re-confirmed. However, it is difficult to identify which pair violates consistency if the set of clothes (to put it another way, the set of possible recommendations) contains 160 articles. In addition, when another item is added to the database, the paired comparison must be re-run. Thus, there are problems in the conventional method for comparative assessment.

Absolute assessments were employed instead of comparative assessments. This method compares standards, rather than comparing specific clothing articles according to the standards.

・Procedure1: Setting absolute assessment standards

The absolute standards are as follows: Very good; good; average; bad; and very bad. Table 4 shows these standards. The following evaluation vector was normalized to the maximum eigenvalues of the assessment standard comparison matrix:

$$u^T = (0.503, 0.260, 0.134, 0.068, 0.035) \quad (2)$$

Table 4: Absolute assessment standard

	Very good	Good	Normal	Bad	Very bad	(Weight)
Very good	1	3	5	7	9	0.503
Good	1/3	1	3	5	7	0.26
Normal	1/5	1/3	1	3	5	0.134
Bad	1/7	1/5	1/3	1	3	0.068
Very bad	1/9	1/7	1/5	1/3	1	0.035
λmax	5.243		C.I	0.061		

・Procedure 2: Assessment matrix

S_{ij} shows assessed value for alternate garment *i* with respect to standard *j*. S_{ij} is defined as the assessed value a_{ij} for alternate garment *i* with respect to standard *j* is divided by the maximum assessed value a_{imax}. The reason for dividing by the maximum assessed value is, the maximum value for standard *j* is set at 100% and it is found what score attire *i* attains on that scale. In other words, the score is normalized with respect to the maximum.

This S_{ij} is assessed again for alternate garment *i* with respect to standard *j*. S_{ij} is displayed as follows in matrix form:

$$S_{ij} = \frac{a_{ij}(\text{alternate i value by standard j})}{a_{imax}(\text{maximum value under alternate i})} \quad (3)$$

The (9,7,5,3,1) values stored in the attire attributes database were modified to the normalized values in Eq.(2), and these transformed figures were used to calculate the numerators a_{ij} in Eq.(3). Equation (3) was then evaluated to create the assessment matrix S_{ij}.

・Procedure 3: Overall assessed value

The survey results shown in <3.2> were processed with AHP and indicated the following weighting vectors for the assessment standards (four elements), System (three elements), Sensitivity (three elements), Design (three elements) and Silhouette (three elements).

$$\left.\begin{aligned} w_1^T &= (0.558, 0.263, 0.122, 0.057) \\ w_2^T &= (0.633, 0.260, 0.106) \\ w_3^T &= (0.633, 0.260, 0.106) \\ w_4^T &= (0.633, 0.260, 0.106) \\ w_5^T &= (0.057, 0.295, 0.649) \end{aligned}\right\} \quad (4)$$

w_1^T corresponds to the second level of the hierarchical structure, and $w_2^T - w_5^T$ correspond to the third level. The weight vector $\boldsymbol{W}$ in Eq.(5) contains the following 12 elements in combination with Eq.(4):

$$W = \begin{pmatrix} 0.558 & \times & w_2 & = & (0.3532 \quad 0.1451 \quad 0.0591)^T \\ 0.263 & \times & w_3 & = & (0.1665 \quad 0.0684 \quad 0.0279)^T \\ 0.122 & \times & w_4 & = & (0.0772 \quad 0.0317 \quad 0.0129)^T \\ 0.057 & \times & w_5 & = & (0.0032 \quad 0.0168 \quad 0.0370)^T \end{pmatrix} \quad (5)$$

In this example, the customer considered System the most important standard. The reader can see that the customer then emphasized "Mode, Avant-garde, Elegant Design, and Slim".

The above shows how the relative weights were assigned between assessment standards and to the standards themselves. The assessment matrix was found in Procedure 2, so the overall evaluation scores for the clothing articles to be suggested are calculated as follows:

$$E_i = S_{ij} \cdot W \quad (6)$$

In absolute comparisons, the evaluation vector $\mathbf{u}^T$ is identified, the attire attributes database is established, and the assessment matrix is found with Eq.(3) above. This is calculated using the assessment matrix instead of the relative comparison weighting matrix.

Fig.6 provides an example of the results of this kind of analysis. It is graphs of three clothing articles selected by weighting for cut and sewn.

The M-4070 in the graph means that it is item #4070 from "Cut and sewn." The reader can see from this figure that all three samples have high weights in System, a standard important to this customer. These have high weights in Mode, Avant-garde, Elegant Design, and Slim.

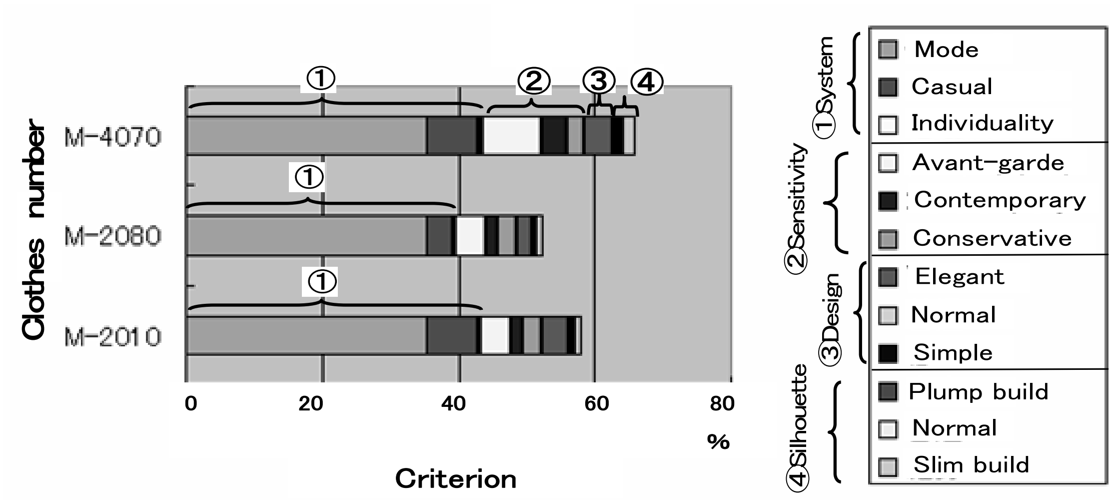

Fig.6: Examples of overall scoring of three clothing articles

4 Classification of tastes and recommending attire on the basis of cluster analysis

Clothes items were grouped into clusters using the clothing attributes database. The intent of this clustering was to assemble groups of clothes that are likely to appeal to a wide variety of people's tastes. Clothes suiting customers' likes (clothes with high overall scores) are classified into clusters on the basis of the items suggested by AHP. Cluster analysis also makes it easier to apply market basket analysis effectively, as described below. This generates suggestions for garments coordinated with other purchases that also meet the customer's tastes.

4.1 Clustering using K-means

This study employed K-means clustering, a partitioned optimization procedure within nonconfigurational classifications. In K-means clustering(9), the cluster centroid c_i is considered the representative point and the set of data is divided into k clusters by minimizing the following evaluation equation:

$$J = \sum_{i=1}^{k} \sum_{x \in c_i} (D(x, c_i))^2 \qquad (7)$$

x: Article of clothing classified into cluster
$D(x,c_i)$: Distance between centroid c_i and attire x

4.2 Clustering results

Clustering analysis is performed with the clothes attributes database in order to group articles of clothing that can correlate with each other in any of many different ways. The examples shown here were obtained using clustering about the System criterion and setting the number of clusters at 12. The cluster numbers are set automatically by the system in the order of increasing sample number, and the system can be set to create clusters of uniform size. This is shown in Table 5.

Table 5: Results of Clustering

Sample name	Cluster No.	Mode	Casual	Indivi-duality	Plump build	Normal	Slim build
M−1040	1	1	9	3	9	3	1
M−4090	1	5	7	3	7	5	3
M−1080	2	1	3	9	9	3	1
M−1100	2	1	3	9	7	5	3
M−3080	2	1	3	9	7	5	3
M−4050	2	1	3	9	7	5	3
M−2020	3	3	5	7	9	3	1
M−2070	3	1	3	9	9	3	1
M−3050	3	3	5	7	7	5	3
M−1030	10	9	3	1	1	3	9
M−2080	10	9	3	1	1	3	9
M−2090	10	9	1	3	3	5	7
M−3020	10	7	3	1	3	5	7
M−4100	10	1	3	5	3	5	7
M−1010	11	1	3	9	1	5	7
M−2030	11	1	3	9	3	5	7
M−4060	11	1	3	9	3	5	7
M−2050	12	3	1	9	1	3	9
M−4080	12	1	3	9	3	5	7

The number in the table shows to which cluster the item belongs. Each cluster is displayed in a simple manner, and it is easy to display what characteristic a cluster has in common.

Clothes items with similar attributes of each type can be combined into a single large display, as shown in Table 6.

The table presents items clustered for similarities in Individuality, Avant-garde, Simple design and Slim build. The M-1420 cut and sewn, S-2030 Pants, G-2110 Shirt and V-3230 Jacket are grouped here because of their similarity.

Table 6: Combinations of similar clothing items

Cluster No.	Number of samples	Mode	Casual	Individuality	Avant garde	Contemporary	Conservative	Elegant	Normal	Simple	Plump build	Normal	Slim build
C-M-4	3	2.33	5	7	8.33	3	2.33	1	3	9	1	3	9
C-S-2	4	3	5	7	8	3	3	1	3	9	1	3	9
C-G-2	3	1	3.66	8.33	8.33	3.66	1	2.33	4.33	7.66	1.66	4.33	7.66
C-V-3	7	1	3.57	8.42	8.42	3.57	1	2.42	4.42	7.57	1.85	4.42	7.57

4.3 Prioritizing merchandise for recommendation to the customer

Clothes items bearing certain similarities were grouped into clusters, as described in the previous section, as a way of organizing them in accordance with a wide variety of customers' tastes. The items in each cluster were then prioritized to plan the appropriate order to present them to the customer. Ordinarily, however, the first natural groups for selecting clothes are Cut and Sewn, Shirts, Pants and Jackets. Here, in order to avoid the bother of selecting names to apply to new clusters and keep things easy for the customers to understand, the clothes are displayed using the above classifications. The system can recommend articles selected to meet the customer's tastes in order of priority, as shown in Table 7.

The priority is assigned, beginning with the item having the highest weighting. In the above example, the recommended items were the M-3070 cut and sewn, the S-1050 Pants, the V-3100 Jacket and the G-2020 Shirt.

Table 7: Priorities set for clothes items

Customer's priority	1st place	2nd place	3rd place
Cut and sewn	M-3070	M-2020	M-1040
Pants	S-1050	S-3010	S-4100
Jacket	V-3100	V-3040	V-2020
Shirt	G-2020	G-3040	G-3100

5 Coordination of attire with market basket analysis

In market basket analysis, the "fashion advisor" recommends items to the current customer that other customers with similar tastes have bought. This form of recommendation is an essential role of the human sales staff in a brick-and-mortar store. A virtual sales girl on an online shopping site can perform the same task, using market basket analysis.

Here, to attain the goal of coordinating attire, the clothes are previously sorted into the above four clusters of Cut and Sewn, Shirts, Pants, and Jackets. It is investigated how to suggest clothes in combinations that will suit the client. Once the client has bought an item, she needs and expects the seller to suggest something from one of the other categories that goes well with it.

5.1 Issues and Policies in the creation of purchase databases

An attire attributes database is used to create a database that allows calculation of the probability that two items will be bought at the same time, and this is essential when applying market basket analysis. Performing market basket analysis with the simultaneous purchase database allows the seller to suggest attire besides the item that was just purchased that has a high potential of sale.

Association rules are constructed to calculate the rate of appearance of an item in the purchase database and the confidence that it will be bought along with something else.

The issue in this process is how to deal with the expansion of inventory. The number of fashion garments in inventory can reach several hundred. The incidence of sales of the preceding garment is used to generate association rules, so the system must count the incidence of simultaneous purchases of any one with any other of the items. The number of these combinations increases exponentially. For example, let us suppose that a certain three-piece combination of pants, a cut and sewn and a jacket appears often in the database. If there are 100 items, then the number of combinations of any three of these is 161,700. If the seller is a large mass merchandise outlet, it will actually stock from several thousand to several tens of thousands of items. The number of association rules to be created rises sharply with the number of items to be included in combinations, and can easily rise to a number quite impossible to handle. Therefore, the K-means method was used in this study to establish clusters and reduce the scale of combinations to be handled.

5.2 Construction of association rules

Association rules are constructed using clothes items that have been clustered by many applicable characteristics and gathered into a simultaneous purchase table in order to calculate the probability of simultaneous purchases. An intermediate product such as a simultaneous purchase table can provide information about which combinations of garments appear most often in transactions.

The following shows how a simultaneous purchase table and association rules are created.

"Confidence" in Table 8 describes how high the probability is that the customer will buy any of the pants (S-1010 – 1030) after buying V-1010 and G-1010.

Table 8: Simultaneous purchase table (partial) and confidence levels

Combination			Incidence of preceding garment and following garment	Incidence of preceding garment	Confidence
Preceding garment sold		Following garment sold			
V-1010	G-1010	S-1010	0.00666667	0.0366667	0.181818
V-1010	G-1010	S-1020	0.00666667	0.0366667	0.181818
V-1010	G-1010	S-1030	0.01	0.0366667	0.272727

"Incidence" is the quantity obtained by dividing the total number of purchases of the given item simultaneously with some other item by the total number of items purchased at the same time as any other garment. "Incidence of sales of the preceding garment" means the incidence of sales of the combination of V-1010 and G-1010. "Incidence of simultaneous sales of the preceding and following garment" means the incidence of sales of all three items, V-1010, G-1010 and S-1010−1030.

The confidence is found in the following calculation:

$$\text{Confidence} = \frac{\text{Incidence of simultaneous sales of the preceding and following garment}}{\text{Incidence of sales of the preceding garment}} \quad (8)$$

This allows the advisor to select combinations of clothes items with high confidence levels for recommendation. Here, once the V-1010 jacket and G-1010 shirt have been selected for purchase, the probability of purchase of the S-1030 pants reaches its highest value of 0.27.

The calculated confidences for all combinations of preceding garment purchases were used to establish the following example of the association rules:

(i)「V-1010」&「G-1010」→「S-1030」「S-1010」
(ii)「V-1010」&「S-1010」→「M-1010」「G-1020」
(iii)「V-1020」&「S-1020」→「M-1010」「G-1030」

It is possible to put the confidence values in numerical order as well, so a rule was written to recommend the most likely (highest confidence value) and, if necessary, the second most likely item for additional sale.

These rules are used in the creation of the simultaneous purchase database. For example, if (iii) of the above association rules is changed to「V-1020」&「G-1020」→「M-1010」「G-1030」, the M-1010 cut and sew and the G-1030 shirt can be recommended to a client who buys a V-1020 jacket and S-1020 pants.

Using these association rules allows the advisor to recommend combinations of clothes purchases by a previous client whose tastes resemble those of a client who is shopping now. The ability to recommend items coordinated with a new purchase is essential for a human sales clerk in a brick-and-mortar store, and all the more so for an advisor on an online shopping site.

6 Assessment of proposed system

Thirty-two subjects used a conventional online system and the proposed system, and subsequently surveyed whether the conventional or the new system was better in the following respects:

(i) After which system did you feel more satisfied, the conventional system or the new system?
(ii) Which system made relevant suggestions, finding clothes that suited your preferences?
(iii) Do you think there is a need for the functionality to suggest coordinated clothing (coordinated outfits)?
(iv) In which system were you able to select clothes meeting your tastes more efficiently and in a shorter time?

The subjects were also interviewed after they had used the systems. Fig.7 shows how they rated them.

(1) The conventional system was rated satisfactory by 6% of the subjects, while the proposed system was rated satisfactory by 70%, an overwhelming majority for this system.

(2) Asked whether the offered clothes had suited their tastes, 3% said yes about the conventional system and 75% said yes about the proposed system, again, an overwhelming majority for this system. Those who felt this way were asked if the system had provided

suggestions relevant to their personal tastes, and a majority of them said yes.
(3) Nine percent of the subjects did not consider it necessary for a system to recommend coordinated clothing items, but 72% replied in the affirmative. Of those who thought it necessary, however, some thought it was good to have, as long as it was there and did not become a distraction, and others replied that they were not necessarily ready to buy recommended items, but found the suggestions useful. In sum, this function is not viewed as essential.
(4) Asked whether they had been able to select attire efficiently and in a short time, 13% replied affirmatively for the conventional system in comparison with 43% for the proposed new system. The subjects showed some annoyingness over how to respond to the survey questions about the proposed system's functionality with regard to the client's tastes. However, when the subjects were using the conventional system, they tended to look through large numbers of garments, one by one, as caught their attention, and thus spent large amounts of time and often found themselves unable to make up their minds. Shoppers often compromise when they cannot make up their minds on which item they want. The proposed system was considered more efficient than the process of choosing from the large selection offered by a conventional system.

The above results indicate that many of the subjects complimented the proposed system as superior to the conventional system from the viewpoints of customer satisfaction, relevance, coordination of outfits, and efficiency.

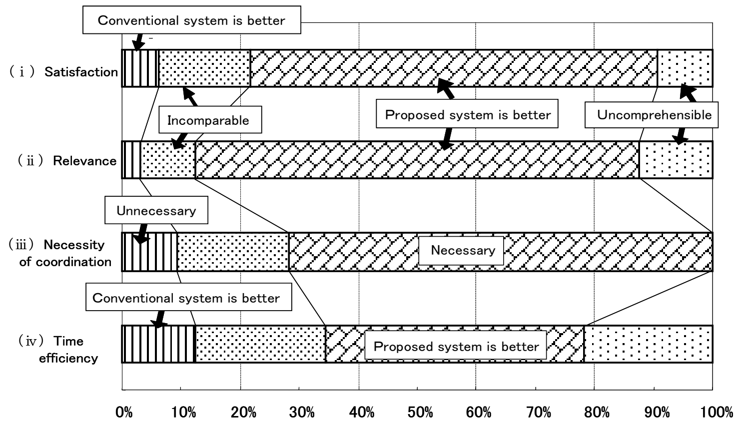

Figure 7: Quantitative assessment of proposed system

7 Conclusions

The authors wrote system to select and recommend garments on the basis of the customer's tastes, and proposed a solution to the problems on the conventional online system. Currently, a customer wishing to purchase a garment online must read the descriptions and look at the images of clothes and rely completely on her own subjective judgment to find and select the garment. This system aids the customer in selecting garments and also makes recommendations.

In this study, a system was constructed using three analytical processes: AHP, cluster analysis and market basket analysis, that operate with a clothes attributes database and a simultaneous purchase database, with the ultimate goal of serving a customer at the same level as provided by a human sales representative. The proposed system has the following effective functions:

1) Digitization of tastes using AHP

People's tastes and perceptions of clothes must be expressed in the form of numbers. AHP was used to accomplish this. An AHP-based data search system was used to create a database of the attributes of garments, and this was used to perceive individual customers' tastes and to suggest garments they were inclined to like.

2) Classification of tastes and recommendations of clothes on the basis of cluster analysis

Clustering of the data in the clothes attributes database allows the system to respond appropriately to customers of many different preferences. Clothes fitting customers' tastes can also be classified into clusters consisting of the items recommended by AHP. By using K-means clustering, the number of items to be examined can be reduced to a manageable level. Alternative garments can be suggested in order of priority, within the cluster of garments meeting the customer's preferences.

3) Coordination of garments by market basket analysis

Market basket analysis allows the system to suggest clothes to a customer on the basis of what has been bought by other customers who have similar tastes. A complete database must be prepared of garments clustered on the basis of their characteristics. This is used to calculate the probability of simultaneous purchase of pairs of garments, and this calculation is applied to suggest potential second sales to customers.

4) Comparison with the conventional online system

Several subjects were asked to use both a conventional online shopping site and the system proposed here, and were then surveyed for their reactions to the two systems on the basis of satisfaction and correctness of the suggested purchases to their own tastes. The proposed system was preferred by an overwhelming majority of the subjects. A relative majority of the subjects thought that the functionality of suggesting coordinated outfits was useful, but did not go so far as to call it "essential." When asked to compare the efficiency of the two systems, the subjects felt that the proposed system was more time-efficient than the conventional system, which displays a large variety of clothes to choose from. Overall, the proposed system was considered superior to the conventional website.

It is necessary to design and develop GUIs that are easy to understand and use (eliminating the explanations of the mathematical techniques provided in this paper) in order to provide the same level of service when a customer buys apparel online as when she buys apparel from a human sales representative in a brick-and-mortar store. This will require creation of a recommendation system that is capable of suggesting attire that suits the tastes of the customer. Such a system is anticipated to strengthen the seller's relationship with the customer.

References:

[1] P. Seybold, Costomers.com, *Random House*, 1998

[2] A. Cliff, K. Deborah, Y. Beth, Internet World Guide to One-to-one Web Marketing, *ISBN :4822241491*, 1999

[3] Pat House, Siebel Systems Successfully Completes Merger with Scopus Technology, *Siebel Magazine*, Vol.2, pp.9

[4] Jeff Hess, John Story, Relationship Investment Model -Linking Relationship Strength to Profitable Customer Behaviors, *http://www.trgisky.com/*

[5] Anthony E. Marsh, Jay Blumenfield, Robert Moritz, Sponging: A Guide to Living Off Those You Love, *Harpercollins*,1996

[6] Florence Muller, Fashion Game Book, A World History of 20th Century Fashion, *Editions Assouline*, 2008

[7] ZOZOTOWN, *http://zozo.jp/*

[8] My Virtual Model, *http://www.mvm.com/cs/*

[9] Tien-Chin Wang, Ying-Hsiu Chen, Selection of the MAS by applying fuzzy preference relation, *WSEAS Transactions on Business and Economics*, Vol.3,2006, pp.667-222

[10]Ching-Fu Chen, Applying the Analytical Hierarchy Process (AHP) Approach to Convention Site Selection, *Journal of Travel Research* Vol. 45 Issue 2, 2006, pp.167-174

[11]Balan S, Vrat Prem, Kumar Pradeep, A strategic decision model for the justification of supply chain as a means to improve national development index, *International Journal of Technology Management* Vol.40 Issue1-3, 2007, pp.69-86

[12]Michael J.A. Berry, Gordon S. Linoff, Data Mining Techniques, 2 Sub Edition, *John Wiley & Sons Inc*

[13]Chunhao Li, Yonghe Sun, Yanhui Jia, Hui Li, An improved ranking approach to AHP alternatives based on variable weights , *IEEE Proceeding on Intelligent Control and Automation*, 2008, pp.8255-8260

[14]Hou Junming, Su Chong, Zhu Lida, Wang Wanshan, Partner Selection System for Collaborative Design, *IEEE International Symposium on Computational Intelligence and Design*, 2008, pp.317-321

[15]Hou Junming, Su Chong, Wang Wanshan, AHP Methodology for Partner Selection in Collaborative Design, *IEEE International Symposium on Computer Science and Computational Technology,* 2008, pp.674-677

[16]Wei-Hsin Chou, Using AHP to Assess a Plan of Training the Adolescent Golf Player, *IEEE Fifth International Conference on Fuzzy Systems and Knowledge Discovery,* 2008, pp.575-579

[17]Frair, L, Student peer evaluations using the analytic hierarchy process method, *IEEE Frontiers in Education Conference*, 1995, pp.4c3.1-4c3.5

[18]Jao-Hong Cheng, Shiuann-Shuoh Chen, Yu-Wei Chuang: An Application of Fuzzy Delphi and Fuzzy AHP for Multi-criteria Evaluation Model of Fourth Party Logistics, *WSEAS Transactions on Systems*, Issue 5, Vol.7, 2008, pp.466-478

[19]Tien-Chin Wang, Ying-Hsiu Chen, Yu-Chen Chiang, Incomplete Linguistic Preference Relations to Evaluate Multimedia Authoring System, *WSEAS Transactions on Mathematics*, Issue 5, Vol.7, 2008, pp.214-222

[20]Subramanian N., Ramakrishnan R., Robust decision making using Data Envelopment Analytic Hierarchy Process, *7th WSEAS International Conference on Artificial Intelligence Knowledge Engineering and Data Bases*, 2008, pp.269-275