Personalised Fuzzy Recommendation for High Involvement Products

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***Abstract*—In this paper we introduce a content-based recommendation approach for assisting buyers of high involvement products with their purchasing choice. The approach incorporates a group-based, fuzzy multi-criteria method and provides personalized recommendation to end-users of e-Furniture. E-Furniture is an agent-based system that offers decision making and process networking solutions to furniture manufacturing SMEs. Two are the main characteristics of the proposed approach: (i) it handles vagueness in customer preferences and seller evaluations on furniture products by utilizing the 2-tuple fuzzy linguistic information processing model and ii) it follows a similarity degree-based aggregation technique to derive an objective assessment for furniture bundles and individual furniture products that can match the customer preferences. A numerical example is given as a proof of concept, to demonstrate the applicability of the approach for providing recommendations to customers.**

Keywords—Personalised recommendation; content-based recommendation; product bundling; 2-tuple fuzzy linguistic model; similarity-degree based aggregation; high involvement products; furniture shopping

I. INTRODUCTION

The Internet has brought exponential growth of information about all kinds of products and services. However, rather than supporting users with their choices, the abundance of information has caused the "information overload" problem [1], where customers cannot find what they want in sufficiently short time and are often lost whilst searching. Recommender Systems [2] are shown to be an effective solution to the information overload with "the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options" [3].

This paper presents a content-based personalized recommendation approach that has been implemented in e-Furniture [4], an agent-based system that supports 'smart' networking of furniture manufacturing SMEs. The system facilitates decision making, process networking and collaboration activities among collaborating companies. Its main functionalities include support for purchasing raw materials, intermediate products and products for resale, as well as outsourcing construction work. The e-Furniture system involves an agent-based infrastructure capable of bundling products and services taking into account individual requirements of both manufacturers and customers. The e-Furniture infrastructure is an open system viewed as a grid of distributed interconnecting partner nodes. We have adopted an agent-oriented view in designing the e-Furniture software architecture and all main operations and interfaces are driven by software agents that act autonomously. Upon registration and joining the network, participating companies provide product catalogue descriptions which are uploaded automatically to the main e-Furniture node server. Both business and retail customers connect to the server storing their profile and preferences and navigate searching for products of their interest. In response, a number of e-Furniture agents interact dynamically and the system finally returns a number of product bundle recommendations targeting the particular user characteristics.

In order to provide appropriate recommendations to e-furniture end-users (i.e., furniture buyers), the e-Furniture system utilizes a library of methods that can dynamically formulate and recommend product bundles, having considered an initial set of furniture features and types available from partners on the network, as well as historical data. For example, a customer interested in buying a sofa through the e-Furniture network will get a recommendation for a bundle of a sofa, an armchair and a small table that suit his/her preferences, in a competitive price. In this paper, we present one of the recommendation approaches included in the system's toolset with the aim to support E-furniture customers with their purchasing choice. The approach provides recommendation for furniture products consistent with customer preferences. Given that the content-based paradigm [5,6] has been mainly applied to recommendations of high-involvement products (such as furniture, cars etc.) [7], the proposed approach adheres to content-based recommendation by requiring from an e-Furniture customer to express linguistically his/her preferences for a set of furniture product bundles already registered in the system's knowledge base. By considering the customer's preferences in combination with evaluations derived from e-Furniture seller agents, the approach results in customer profiling. Customer profiles are then used to obtain an ordered list of recommended furniture products, consistent with the customer needs/preferences and matching the product bundle that the customer has selected. To perform the above, the proposed approach integrates two methods: (i) a content-based fuzzy recommendation method [8] that utilizes customer preferences and seller evaluations both expressed in the form of 2-tuple fuzzy linguistic terms, and (ii) a group-based fuzzy multi-criteria method [9] that applies similarity degree-based aggregation to derive an objective assessment of product bundles and individual products which match customer preferences. The main contribution of this work is that it focuses on deriving objective assessments of items matching customer preferences and it adopts a group and similarity degree-based aggregation algorithm to obtain a less subjective aggregation of item ratings.

The outline of the paper is as follows. Section 2 presents related work on recommender systems and recommendation requirements for high involvement products, as well as a brief introduction to the fuzzy linguistic 2-tuple representation / computation model. Section 3 presents the proposed approach along with a working example. Finally, Section 4 briefly compares the approach with recent similar work and presents conclusions and future work.

II. Related Work

A. Recommender Systems

Recommender systems are mainly classified into three categories: (i) Collaborative Filtering (CF) approaches - recommendation is based on products liked before by other people with similar tastes and preferences; (ii) content-based approaches - recommendation is based on products that are similar to those the user liked before; and (iii) hybrid approaches - combinations of collaborative filtering and content-based approaches [1,5,10,11].

The content-based approach is very effective in recommending textual items, such as documents, web sites, news etc. It is built on the analysis of products previously rated by users, and it makes recommendations through matching item characteristics to user profiles [12,13]. The content representation (also called item profile) mainly refers to the description of the item characteristics. It is often represented by a list of attributes for an item, which are also the keywords that characterize an item [5]. At the same time, user preferences (also called user profile) can be represented by keywords. The composition of a user profile can be particularly useful in case there is a need to support a customer decision to purchase a high involvement product that fulfils his/her preferences.

Knowledge-based approaches and data mining are also very popular for recommendations. Knowledge-based approaches attempt to recommend based on reasoning about what the current user's needs and preferences are [3,13]. Case-based reasoning [14] is commonly applied to the reasoning process. It collects user preferences, and the experts or the system further infer user profiles. The best match of products to a user profile represents the potential recommendation [15]. However, the knowledge-based approach requires significant efforts to identify the factors affecting user preferences in choosing products [3,16]. In contrast, data mining approaches are automatic, inferring rules or building models from large data sets. A widely used data mining technique is association rules mining [17]. This technique identifies relationships between products (or product attributes) by analysing possible correlations between joint purchases of independent product items [18,19].

Understanding user preferences is an important step for generating recommendations in all approaches. There are two main methods for recommendation reasoning: (i) direct/explicit, and (ii) indirect/implicit [20]. The explicit method relies on users to inform a recommender system of their preferences, such as user ratings of products, user profiles (e.g. personal demographics), or user explicit requirements. The implicit method gathers information by observing user behaviour, instead of asking users to provide their preferences. Examples of implicit preferences include visit frequency, visit duration, and bookmarks [18]. The proposed approach adopts a direct or, more precisely, a semi-direct method [21]. The method is characterized as semi-direct since a customer is not required to express his/her preferences on item (furniture) attributes, but merely to rate items (furniture bundles) offered by the system. Subsequently, the approach recommends furniture products which are in compliance with customer preferences and can be complementary with the furniture bundle that the customer has selected.

B. High Involvement Products

In most recommendation problems, single criterion preference consideration only does not meet users' personalized needs. For example, when purchasing a furniture product, a customer evaluates the product through multiple criteria, such as price, comfort, construction quality, style, colour and material. It is often the case that there are conflicts among different criteria. To facilitate a product recommendation procedure, particularly for high involvement products, such as furniture, cars, appliances, video and photo cameras, one can apply a multi-criteria decision making method [22,23]. Compared to low involvement products (e.g. books, CDs, DVDs, films etc.), high involvement products are more distinctive over time [24]. For instance, one does not need to purchase many furniture products of the same type in a short period of time. Furthermore, the product's price/cost is higher, and its quality is supposed to be superior to that of low involvement products. In addition, the sensory appeal, such as the product visual attractiveness or quality related to the way it smells or feels, is quite influential in high involvement products. As a result, customers tend to spend more time and effort when selecting high involvement products [24]. However, there are situations where users cannot express their preferences precisely. In these cases, a fuzzy linguistic method can be useful to derive and analyze vague user evaluations expressed in qualitative form.

C. Fuzzy Linguistic Methods

A fuzzy linguistic description approach performs well when cases are described based on qualitative aspects instead of quantitative aspects, or when the information is vague or imprecisely described. Herrera and Martinez [25] proposed a 2-tuple fuzzy linguistic approach which is a continuous model that carries out "computing with words", namely it processes descriptions without losing information. Their model has been applied to several application areas [26]. For example, in [8] that model was used to recommend relevant human experts in a knowledge management system, while in [27] the model was applied to assist researchers in obtaining information from various research sources. In this paper, we use the fuzzy linguistic 2-tuple representation/computation model to build a recommendation approach for high involvement products, like furniture. The basic concepts of the 2-tuple fuzzy linguistic model are introduced in the following section, where the proposed approach is described along with a working example.

III. Personalised Product Bundle Recommendation Approach

The proposed approach includes six main steps. This section describes these steps in detail accompanied with short intuitive examples where appropriate.

Step 1. The proposed approach follows a content-based recommendation paradigm by requiring from an e-Furniture customer to express preferences for a set of m furniture product bundles, already registered in the e-Furniture knowledge base. For example, if a customer is interested in buying furnishing bundles for a living room, the system will ask the customer to rate available living room furniture bundles, already registered in e-Furniture, each one consisting of a sofa, chairs and a table. Customer preferences are expressed in a qualitative form by utilizing 2-tuple fuzzy linguistic terms [25]. The 2-tuple linguistic representation/computation model was adopted as it can effectively avoid loss/distortion of information, an issue typical with other linguistic methods [25,28]. A 2-tuple linguistic variable is denoted as (s_i, a_i), where s_i corresponds to the central value of the ith linguistic term and $a_i \in [-0.5,0.5)$ is the distance from s_i.

Example. Let us assume that a customer has rated four (m = 4) product bundles, PB_1, PB_2, PB_3 and PB_4, for a living room. The corresponding preferences for these bundles are presented in the second column of Table I. We further assume that in order to express preferences, the customer has used a Label Set $S = \{s_0, s_1, \ldots, s_g\}$ selected from the label sets offered by the e-Furniture system, which includes the following linguistic terms: s_0 = VVL(Very Very Low) = (0,0,0,17), s_1 = VL(Very Low) = (0,0.17,0.34), s_2 = L(Low) = (0.17,0.34,0.5), s_3 = M(Medium) = (0.34,0.5,0.67), s_4 = H(High) = (0.5,0.67,0.84), s_5 = VH(Very High) = (0.67,0.84,1), and s_6 = VVH(Very Very High=(0.84,1,1). By using the transformation function θ, defined for 2-tuple fuzzy terms [25] to obtain the corresponding 2-tuple linguistic fuzzy information (1), the linguistic preferences of the customer are transformed into 2-tuples of the form (s_i, 0) which are also shown in the second column of Table I. From these 2-tuples, we conclude that the customer prefers the product bundle PB_4 (i.e., the customer rated PB_4 by the 2-tuple (VVH,0)).

$$\theta : S \rightarrow S \times [-0.5,0.5),\ \theta(s_i) = (s_i,0),\ s_i \in S \qquad (1)$$

Step 2. In the knowledge base of e-Furniture, all furnishing product bundles as well as all individual furnishing products (when they are initially registered in e-Furniture) are evaluated by K expert sellers associated with *e-Furniture*. Evaluation of furniture product bundles or individual furnishing items is performed by following a group-based decision making technique. Each of the involved seller agents e_κ (k =1,2…, K) subjectively expresses a corresponding score for each of the m product bundles (or individual products) on n attributes. The list of attributes includes criteria such as construction quality, price, ease of maintenance, longevity, comfort, and style (traditional, modern, casual) of available furniture bundles/products. All subjective evaluations (provided by the seller agents) are expressed linguistically by using 2-tuple linguistic term sets. Seller agents may use different linguistic term sets (i.e., sets having different granularities or semantics) to express assessment of product bundles (or individual products). In addition, seller agents may use different linguistic terms by the one used by the customer to express preferences on product bundles. Thus, the linguistic assessment information should be transformed into a uniform linguistic term set. To achieve this, e-Furniture utilizes the technique suggested in [29,30]. In addition, each seller agent can be assigned to a different relative importance level ε_κ, by considering, for example, the volume-variety of products that the agent offers in the knowledge base.

Example. Let us assume that three seller agents are involved in e-Furniture, all having equal relative importance levels, i.e., $\varepsilon_1 = \varepsilon_2 = \varepsilon_3 = 1/3$. Due to space limits of the paper, we assume that all sellers have agreed to use the same linguistic term set S, which is also used by customers to express their preferences. Therefore, there is no need to transform any linguistic evaluation into a homogeneous linguistic term set. Let us further assume that four product bundles (m = 4) for a living room (the ones rated by the customer in Table I) are registered and evaluated by the three seller agents according to four attributes (n =4), namely c_1 = Price, c_2 = Traditional, c_3 = Modern, and c_4 = Casual. Table II presents the evaluations of product bundles PB_1, PB_2, PB_3 and PB_4 in a linguistic 2-tuple form through applying the transformation function θ (1). Similarly, the three seller agents have evaluated four products available in e-Furniture (products P_1, P_2, P_3 and P_4), which are complementary with furniture for a living room. Evaluations of these products are also shown in Table II. The e-Furniture customer should receive a proper recommendation for each one of these products. The approach will result in a final ordered list of products that is consistent with the customer needs and can match the product bundle that the customer has rated higher (i.e. the product bundle PB_4).

Step 3. By performing the previous step, all registered product bundles and individual products in the knowledge base are characterized by the subjective judgments of the seller agents. However, some sellers may provide biased judgements towards their own furnishing product bundles (or products). In addition, some sellers, due to unawareness of the characteristics of product bundles (or products) offered by other sellers, may not rate these products fairly. To derive a more objective assessment, the proposed approach adopts the similarity degree-based aggregation technique proposed in [9]. The final aggregated assessment considers not only the relative importance levels ε_k of sellers but also the similarities in seller evaluations. The steps of this aggregation technique are briefly presented in the following paragraphs. The reader should note that the discussion refers to the aggregation of product bundle ratings. The same technique is applied for deriving an objective aggregation of the ratings of individual products.

a) The similarity degree value $sim(x_{ij}^k, x_{ij}^l) \in (0,1]$ is calculated between the evaluations provided by any two seller agents e_k and e_l ($k \neq l$, $k = 1,2\ldots, K$, $l = 1,2\ldots, K$) for each product bundle x_i ($i = 1,2,\ldots,m$) with respect to the attribute c_j ($j = 1,2,\ldots,n$). To calculate each similarity degree value, the distance between x_{ij}^k and x_{ij}^l is computed, a value that is equal to $\left|\Delta^{-1}(x_{ij}^k) - \Delta^{-1}(x_{ij}^l)\right|$. The similarity degree $sim(x_{ij}^k, x_{ij}^l)$ is derived by computing (2), where g is the granularity of the used linguistic term set (e.g., in the presented example g is equal to 6). The closer the similarity degree to 1, the more similar are the evaluations of any two seller agents for the same product bundle with respect to the same attribute.

$$sim(x_{ij}^k, x_{ij}^l) = 1 - \left|\frac{\Delta^{-1}(x_{ij}^k) - \Delta^{-1}(x_{ij}^l)}{g}\right| \tag{2}$$

Δ^{-1} is the reverse function that transforms a 2-tuple linguistic variable into its equivalent numerical value, in (2). Given a linguistic term set $S=\{s_0, s_1,\ldots,s_g\}$, $\beta \in [0,g]$ is a number representing the aggregation result of a symbolic aggregation operation. Let $i = round(\beta)$ and $\alpha = \beta - i$ be two values such that $i \in [0,g]$ and $a \in [-0.5,0.5)$, respectively. The number a is called a symbolic translation. The 2-tuple that expresses the equivalent information with β results from the translation function Δ as follows (3):

$$\begin{aligned} &\Delta : [0,g] \rightarrow S \times [-0.5,0.5) \\ &\Delta(\beta) = (s_i, a) = \begin{cases} s_i, i = round(\beta) \\ \alpha = \beta - i, a \in [-0.5.05) \end{cases} \end{aligned} \tag{3}$$

A 2-tuple linguistic variable can be transformed into an equivalent number $\beta \in [0,g]$ by the reverse function Δ^{-1} (4):

$$\begin{aligned} &\Delta : S \times [-0.5,0.5) \rightarrow [0,g] \\ &\Delta^{-1}(s_i, a) = i + \alpha = \beta \end{aligned} \tag{4}$$

Example. Equation (2) can take as input two evaluations respectively from two seller agents e_1 and e_2 for the product bundle PB_2 with respect to the attribute c_1 (Table II). The result will be the similarity degree between these two evaluations:

$$sim(PB_{21}^1, PB_{21}^2) = 1 - \left|\frac{\Delta^{-1}(PB_{21}^1) - \Delta^{-1}(PB_{21}^2)}{g}\right| =$$

$$= 1 - \left|\frac{1-0}{6}\right| = 0.83$$

The values of $sim(PB_{21}^1, PB_{21}^3)$ and $sim(PB_{21}^2, PB_{21}^3)$ are computed in the same manner and they are 1 and 0.83, respectively.

b) The average similarity degree $SM_{ij}(e_k)$ and the relative similarity degree $RSM_{ij}(e_k)$ are calculated for each seller agent e_k, regarding the evaluation of the product bundle x_i with respect to the attribute c_j. These are respectively given by two equations (5):

$$SM_{ij}(e_k) = \frac{\sum_{l=1, l \neq k}^{K} sim(x_{ij}^k, x_{ij}^l)}{K-1}, RSM_{ij}(e_k) = \frac{SM_{ij}(e_k)}{\sum_{l=1}^{K} SM_{ij}(e_l)} \tag{5}$$

Example. The first formula of (5) calculates $SM_{21}(e_1)$ $SM_{21}(e_2)$ $SM_{21}(e_3)$ as follows:

$$SM_{21}(e_1) = \frac{sim(x_{21}^1, x_{21}^2) + sim(x_{21}^1, x_{21}^3)}{K-1} = \frac{0.83+1}{3-1} = 0.92$$

$$SM_{21}(e_2) = \frac{sim(x_{21}^1, x_{21}^2) + sim(x_{21}^2, x_{21}^3)}{K-1} = \frac{0.83+0.83}{3-1} = 0.83$$

$$SM_{21}(e_3) = \frac{sim(x_{21}^1, x_{21}^3) + sim(x_{21}^2, x_{21}^3)}{K-1} = \frac{1+0.83}{3-1} = 0.92$$

The second formula of (5) calculates $RSM_{21}(e_1)$ as follows:

$$RSM_{21}(e_1) = \frac{SM_{21}(e_1)}{SM_{21}(e_1) + SM_{21}(e_2) + SM_{21}(e_3)} =$$

$$\frac{0.92}{0.92+0.83+0.92} = 0.34$$

c) The importance weight w_{ij}^k of the assessment of the seller agent e_k is calculated by considering the relative importance level ε_k of the seller agent and the relative similarity degree of the agent evaluations (6):

$$w_{ij}^k = \frac{\varepsilon_k \times RSM_{ij}(e_k)}{\sum_{l=1}^{K} (\varepsilon_l \times RSM_{ij}(e_k)} \tag{6}$$

Example. Since we have assumed equal importance levels for the three seller agents (i.e., each ε_k is equal to 1/3), applying (6) to compute the weight w_{21}^1 of the assessment of the seller agent e_1 for the product bundle PB_2 with respect to the attribute c_1 will result in a value equal to $RSM_{21}(e_1)$, that is equal to 0.34.

Step 4. The objective aggregation for all product bundles' ratings is computed by utilizing the weighted average operator, as it is defined for fuzzy linguistic 2-tuples [25]. In particular, for a set of linguistic 2-tuples $\{(s_1, a_1), (s_2, a_2),\ldots, (s_n, a_n)\}$ and their corresponding weights $(w_1, w_2,\ldots, w_n)$, the 2-tuple weighted average operator is computed as follows (7):

$$\Delta\left(\frac{\sum_{l=1}^{n}\Delta^{-1}(s_i,a_i)\times w_i}{\sum_{l=1}^{n} w_i}\right) = \Delta\left(\frac{\sum_{l=1}^{n}\beta_i\times w_i}{\sum_{l=1}^{n} w_i}\right) \qquad (7)$$

In (7), the value β_i is calculated by the reverse function Δ^{-1} presented in (4). Thus, the final (aggregated) rating FPD_{ij} of each product bundle PD_i with respect to each attribute c_j is computed by applying the weighted average operator on the linguistic evaluations of the product bundles and using as weights the previously calculated importance weights for these assessments. Thus, (7) can be written as follows (8):

$$FPD_{ij} = \Delta\left(\frac{\sum_{l=1}^{K}\Delta^{-1}(s_{ij}^{l},a_{ij}^{l})\times w_{ij}^{l}}{\sum_{l=1}^{K} w_{ij}^{k}}\right) (8) \quad \Delta\left(\frac{\sum_{l=1}^{n}[\Delta^{-1}(s_i,a_i)\times\Delta^{-1}(w_i,a_i^{w})]}{\sum_{l=1}^{n}\Delta^{-1}(w_i,a_i^{w})}\right) (9)$$

It should be noted again that Steps 3 and 4 are applied to calculate the final aggregated rating FP_{ij} of each available product P_i with respect to each attribute c_j.

Example. Based on the evaluations of the four product bundles (Table II) and the importance weights of the assessments of the seller agents (step 3.c of the approach), eq. (8) can be used to derive the final (aggregated) ratings of the product bundles, which are depicted in Table I. In addition, the similarity degree-based aggregation technique can be used to compute, from the evaluations of the four individual products (Table II), the final (aggregated) ratings of the four individual products. The results are shown in Table III.

Step 5. The customer profile is constructed as a vector of linguistic 2-tuples which represents the customer preferences for the attributes of furniture product bundles (or products). These preferences should be consistent with the customer preferences for the product bundles. The customer profile is obtained by applying the linguistic weighted average operator, as it is defined for fuzzy linguistic 2-tuples [25]. In particular, let a set of linguistic 2-tuples $\{(s_1, a_1), (s_2, a_2),\ldots, (s_n, a_n)\}$ and $\{(w_1, a_1^w), (w_2, a_2^w),\ldots, (w_n, a_n^w)\}$ be their associated linguistic 2-tuple weights. The linguistic weighted average operator can be computed as it is shown in equation (9) and it is applied to the final (aggregated) ratings of the product bundles (i.e., the tuples presented in columns 3-6 of Table I) by using as associated weights the customer preferences (i.e., the tuples presented in the 2nd column of Table I). The result is the customer profile, i.e. a vector of linguistic 2-tuples presented in the last row of Table I. From this profile, we can conclude that the specific customer is highly interested in furniture of traditional style (i.e., the corresponding 2-tuple is equal (H,0.14)) and not so in modern or casual furniture (i.e., the corresponding 2-tuples are equal to (L,0.24) and (VL,0.34), respectively). Furthermore, according to the customer profile, the customer can afford buying furniture having a high price (i.e., the corresponding 2-tuple is equal to (H,-0.13)).

Step 6. In this final step, the customer is provided with recommendation for each one of the available products that are complementary with the customer's choice of the product bundle. A final list of products is computed that is ordered in compliance with the customer profile. To obtain the final recommendation list, the approach computes a score for each product by applying the linguistic weighted average operator (9) to the final (aggregated) product ratings (i.e., the tuples presented in Table III). The tuples which comprise the customer profile vector are used as linguistic 2-tuple weights (i.e., the tuples presented in the last row of Table I). The final resulted scores for the available products are presented in the form linguistic 2-tuples in the last column of Table III. Since the comparison of 2-tuple fuzzy linguistic terms can be performed on the basis of an ordinary lexicographic order [25], the final recommendation list of products is derived by ordering the available products according to their scores, i.e., P4:(H,-0.05) > P3:(H,-0.36) > P1:(L,0.07) > P2:(L,-0.27). We have performed sensitivity analysis to check if this ranking is stable to changes in the weights of the assessments of the seller agents. In most cases we have noticed that P4 and P3 were the most recommended products.

IV. CONCLUSION & FUTURE WORK

This paper presented a personalised, content-based recommendation approach for high-involvement furniture products which adopts fuzzy linguistic information to express customer preferences and product evaluations. The use of the fuzzy linguistic 2-tuple model enables considering the vagueness of customer preferences and seller assessments of furniture products. In comparison with other similar work [31], the presented approach focuses on deriving an objective assessment of the items stored in the e-Furniture knowledge base which matches customer preferences. Further to other recommendation approaches also based on calculating similarity of product descriptions, our approach adopts a group and similarity degree-based aggregation algorithm to obtain a more objective aggregation of the ratings of the items registered in the system's knoweledge base. As future work we plan to: (i) validate experimentaly the efficiency and performance of the approach, and (ii) consider the history of customer transactions with the e-Furiniture system. For the second research goal we have plans to consider collaborative filtering for the recommendation of furniture products based on neural networks and clustering techniques [32]. In addition, we intend to utilize association rules for deriving possible relationships between the purchase of one item and the purchase of another, as well as identification of possible causal relationships between the evaluation attributes. Finally, we have plans to handle incomplete characterization of furniture products by exploiting existing techniques from the domain of 2-tuple fuzzy linguistic sets [33].

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TABLE I. CUSTOMER PREFERENCES FOR PRODUCT BUNDLES, FINAL AGRREGATED RATINGS OF PRODUCT BUNDLES & CUSTOMER PROFILE

Product Bundle	**Customer Preferences for Product Bundles**	**Final Aggregated Ratings of Product Bundles**			
		***Price** (c_1)*	***Traditional** (c_2)*	***Modern** (c_3)*	***Casual** (c_4)*
PB_1	VL(VL,0)=(1,0)	(5,0.43)=(VH,0.43)	(1,0)=(VL,0)	(2,0.43)=(L,0.43)	(5,-0.25)=(VH,-0.25)
PB_2	L(L,0)=(2,0)	(1,-0.31)=(VL,-0.31)	(1,0.31)=(VL,0.31)	(5,0.31=(VH,0.31)	(2,-0.31)=(L,-0.31)
PB_3	M(M,0)=(3,0)	(6,-0.31)=(VVH,-0.31)	(5,-0.25)=(VH,-0.25)	(2,0)=(L,0)	(1,0.31)=(VL,0.31)
PB_4	VVH(VVH,0)=(6,0)	(4,-0.25)=(H,-0.25)	(5,0.31)=(VH,0.31)	(1,0.31)=(VL,0.31)	(1,-0.31)=(VL,-0.31)
Customer Profile		(4,-0.13)=(H,-0.13)	(4,0.14)=(H,0.14)	(2,0.24)=(L,0.24)	(1,0.34)=(VL,0.34)

TABLE II. SELLER EVALUATIONS FOR PRODUCT BUNDLES & INDIVIDUAL PRODUCTS

Seller Agent	**Ratings of Product Bundles *PD* / Ratings of Products *P***				
	Product Bundle / Product	***Price** (c_1)*	***Traditional** (c_2)*	***Modern** (c_3)*	***Casual** (c_4)*
e_1 (ε_1 =0,33)	PB_1 / P_1	(4,0) / (1,0)	(2,0) / (2,0)	(1,0) / (4,0)	(6,0) / (5,0)
	PB_2 / P_2	(1,0) / (1,0)	(1,0) / (1,0)	(5,0) / (5,0)	(1,0) / (2,0)
	PB_3 / P_3	(5,0) / (3,0)	(5,0) / (5,0)	(2,0) / (4,0)	(2,0) / (2,0)
	PB_4 / P_4	(2,0) / (5,0)	(6,0) / (6,0)	(1,0) / (1,0)	(1,0) / (1,0)
e_2 (ε_2 =0,33)	PB_1 / P_1	(6,0) / (2,0)	(1,0) / (1,0)	(3,0) / (5,0)	(5,0) / (3,0)
	PB_2 / P_2	(0,0) / (1,0)	(1,0) / (1,0)	(6,0) / (4,0)	(2,0) / (2,0)
	PB_3 / P_3	(6,0) / (4,0)	(3,0) / (5,0)	(2,0) / (2,0)	(1,0) / (1,0)
	PB_4 / P_4	(4,0) / (6,0)	(5,0) / (5,0)	(1,0) / (1,0)	(1,0) / (1,0)
e_3 (ε_3 =0,33)	PB_1 / P_1	(6,0) / (1,0)	(0,0) / (0,0)	(3,0) / (5,0)	(3,0) / (2,0)
	PB_2 / P_2	(1,0) / (0,0)	(2,0) / (1,0)	(5,0) / (5,0)	(2,0) / (2,0)
	PB_3 / P_3	(6,0) / (2,0)	(6,0) / (6,0)	(2,0) / (3,0)	(1,0) / (1,0)
	PB_4 / P_4	(5,0) / (5,0)	(5,0) / (5,0)	(2,0) / (1,0)	(0,0) / (0,0)

TABLE III. FINAL AGRREGATED RATINGS OF PRODUCTS & FINAL PRODUCT SCORES

Product	**Final Aggregated Ratings of Products**				**Scores of Products with respect to the Customer Profile**
	***Price** (c_1)*	***Traditional** (c_2)*	***Modern** (c_3)*	***Casual** (c_4)*	
P_1	(1,0.31)=(VL,0.31)	(1,0)=(VL,0)	(5,-0.31)=(VH,-0.31)	(3,0.25)=(M,0.25)	(2,0.07)=(L,0.07)
P_2	(1,-0.31)=(VL,-0.31)	(1,0)=(VL,0)	(5,-0.31=(VH,-0.31)	(2,0)=(L,0)	(2,-0.27)=(L,-0.27)
P_3	(3,0)=(M,0)	(5,0.31)=(VH,0.31)	(3,0)=(M,0)	(1,0.31)=(VL,0.31)	(4,-0.36)=(H,-0.36)
P_4	(5,0.31)=(VH,0.31)	(5,0.31)=(VH,0.31)	(1,0)=(VL,0)	(1,-0.31)=(VL,-0.31)	(4,-0.05)=(H,-0.05)