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A belief rule based expert system for predicting consumer preference in new product development

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ABSTRACT

In the decision making process of new product development, companies need to understand consumer preference for newly developed products. A recently developed belief rule based (BRB) inference methodology is used to formulate the relationship between consumer preference and product attributes. However, when the number of product attributes is large, the methodology encounters the challenge of dealing with an oversized rule base. To overcome the challenge, the paper incorporates factor analysis into the BRB methodology and develops a BRB expert system for predicting consumer preference of a new product. Firstly, a small number of factors are extracted from product attributes by conducting both exploratory and confirmatory factor analysis. Secondly, a belief rule base is constructed to model the causal relationships between the characteristic factors and consumer preference for products using experts' knowledge. Furthermore, a BRB expert system is developed for predicting consumer preference in new product development, where the factor values transformed from product attributes are taken as inputs. Relevant rules in the system are activated by the input data, and then the activated rules are aggregated using the evidential reasoning (ER) approach to generate the predicted consumer preference for each product. Finally, the BRB expert system is illustrated using the data collected from 100 consumers of several tea stores through a market survey. The results show that the prototype of the BRB expert system has superior fitting capability on training data and high prediction accuracy on testing data, and it has great potential to be applied to consumer preference prediction in new product development.

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1. Introduction

Consumer preference is a description of consumer needs and expectations for a product. Nowadays it is essential for companies to understand consumer preference for a newly developed product [12]. Since consumers are usaually diverse and heterogeneous, and their preferences are widely scattered, it is becoming much more difficult than ever before to obtain consumer preference in the new product
Q3 development process [24].

Market researchers have been attempting to develop predictive models for understanding consumer preference of newly developed products. Preference mapping techniques are the most popular methods among these prediction models to understand what product attributes are driving preference [19]. They link external information about product attributes, such as appearance, packaging, flavour and aroma, with consumer preference.

Preference mapping methods in the literature generally fall into two categories: linear regressions and artificial intelligence methods. In the context of linear regression methods, multiple linear regression (MLR) is a classic approach and provides some useful models to interpret causal relationships by linear models. Since it ignores strong correlations among product attributes, it is proved unreliable and unstable in predicting consumer preference from multiple product attributes [14,33]. Principle component analysis (PCA) is another Q5
kind of linear regression methods and offers some advantages over MLR by handling highly correlated explanatory variables. It produces least-square approximation in a lower dimensional space based on a covariance matrix [5]. A small number of principle components extracted from attribute data can be used to model the causal relationships between attributes and preferences [13,23]. However the components may complicate the interpretation of the model and increase the risk of over-fitting [11].

Although MLR and PCA can provide a good solution to model linear relationships, they are not adequate to address the non-linearity issue which is quite common between product attributes and consumer preference. Artificial intelligence methods, such as artificial neural networks (ANN) and support vector machines (SVM), are

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attracting attentions for their flexibility and nonlinear learning capability [2,3]. Krishnamurthy et al. [19] established an ANN to predict consumer likings and proved that it was an effective preference modelling tool. Cortez et al. [9] adopted SVM to predict human wine taste preferences and achieved superior results, compared with MLR and ANN methods.

Since the parameters and kernel functional forms in both ANN and SVM play a significant impact on predictive performance, they should be predetermined in modelling causal relationships. However, as the relationships between product attributes and consumer preference are not known, it is difficult to specify the functional forms of the relationships in advance. As a recently developed artificial intelligence method, the belief rule based (BRB) system has been used for prediction without specifying any function beforehand [33]. Numerical and theoretical studies have demonstrated that the BRB methodology can achieve superior prediction accuracy in a range of applications [7,28,34,35]. A cooperative belief rule based decision support system has been proposed for lymph node metastasis diagnosis in gastric cancer [36]. A new BRB based prognosis model has been developed to predict the system failure in real-time [37]. The highly nonlinear relationship between circuit component parameters and the performance of circuits has also been modelled by belief rule bases [27]. Chen et al. [7] introduced the BRB methodology for modelling uncertain nonlinear systems.

The data of product attributes used in those aforementioned applications of the BRB methodology are mainly quantitative and continuous, and they must be collected through technical experiments. However, the consumer preference is often collected by surveys using terms which is easily understood by consumers. Likert sample scale (1–5) is a common expression used by consumers in market surveys. The format of Likert items is uncertain and ordinal. This gives rise to the first research question to be dealt with in the paper: "how to formulate the causal relationships among these qualitative ordinal data". Moreover, a large number of rules should be constructed to build a BRB system when there are many product attributes. The second question is then "how to downsize the belief rule base and improve its learning efficiency". Although some techniques, such as PCA, have been used to reduce the number of attributes [5,6], only key attributes are identified to construct a rule base and some non-critical attributes are neglected. There still exists the difficulty of establishing a rule base to cover all attributes. In this paper, we firstly incorporate both exploratory and confirmatory factor analysis into the BRB methodology to produce a low number of interpretable factors from all attributes, and further to develop a prototype expert system for consumer preference prediction in new product development. The prototype system can model the causal relationships among ordinal data and reduce the size of a belief rule base. Using a learning module, the system can automatically update its knowledge base and improve prediction accuracy.

The rest of the paper is organized as follows: factor analysis for product attributes is discussed in Section 2. Then aggregated factors are used to construct belief rule base and a prototype BRB expert system is developed for predicting consumer preference in Section 3. The prototype system is validated by the sample data on a case study of red teas in Section 4. Conclusions about the research are presented in Section 5.

2. Factor analysis of product attributes

A product is usually characterized by many attributes, such as appearance, aroma and taste for a drink. The attributes can all be used to build a belief rule base in a typical BRB structure. The rules in a BRB system will be normally constructed by taking all possible combinations of the referential values for all of the attributes. Therefore, the number of rules in the rule base will be very large when there are many attributes and each attribute has a number of qualitative

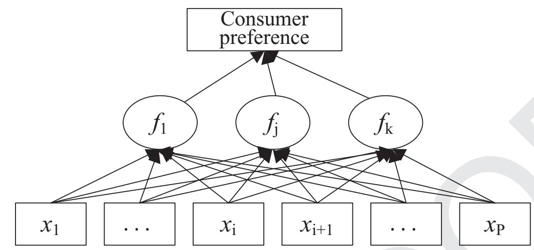

Fig. 1. A BRB model structure with both factors and attributes.

assessment grades. To reduce the size of a rule base, we employ factor analysis methods to process the data collected on product attributes. A small number of factors will be extracted and used to construct a BRB system, as shown in Fig. 1. There are two main procedures to conduct factor analysis: one is exploratory factor analysis (EFA) to obtain the factor models with a simple structure, and the other is confirmatory factor analysis (CFA) to test the fit of factor models. If the factor model is inconsistent with specific theoretical expectations, we will revert to the EFA procedure.

2.1. Exploratory factor analysis

Suppose that there are a set of p observed attributes $x_1, x_2,\ldots, x_p$ for predicting consumer preference. If these attributes are not independent, there will be some unobserved latent variables $f_1, f_2,\ldots, f_k$, namely factors, to represent these p observed variables [8]. Factor analysis methods are used to search for such latent variables. After conducting factor analysis, the unobserved latent variables can be found and modelled as linear combinations of those observed attributes. The factor models are presented as follows.

$$\begin{cases} f_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ f_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \vdots \\ f_k = l_{k1}x_1 + l_{k2}x_2 + \cdots + l_{kp}x_p \end{cases} \tag{1}$$

Here $L = \{l_{ij};\ i=1,\ldots, k;\ j=1,\ldots, p\}$is a loading matrix, with each element representing the correlation coefficient between the factor f_i and the observed attribute x_j. It shows how strongly each attribute is related to a certain factor and how well each attribute measures the factor. There are three steps for conducting exploratory factor analysis, namely correlation analysis, factor extraction and factor rotation.

(1) Correlation analysis
Correlation analysis is to find out the relationships among product attributes. For ordinal variables, the Spearman coefficient method is more appropriate than others to get a correlation matrix [1]. It uses a monotonic function to assess the relationship between two variables. Suppose that there are m levels respectively for two attribute variables, x_i and y_i, in a sample of size n. The Spearman coefficient ρ is presented as:

$$\rho = 1 - 6\sum_{i=1}^{m} d_i^2/n(n^2-1), \quad \rho \in [-1, 1],$$

Here $d_i = x_i - y_i$is the difference between the ranks of the two variables.

(2) Factor extraction
Extracting factors is to determine the initial factors existing in product attributes. The PCA method is often employed to conduct the extraction [5,33]. Suppose that the correlation matrix is $R = (\rho_{ij})_{p\times p}$ $(i = 1, 2, \ldots, p;\ j = 1, 2,\ldots, p)$. There exists a characteristic equation $\det(R - \lambda I) = 0$to be solved to find the matrix's eigenvalues$\lambda_j\,(j = 1, 2, \ldots, p)$, where I is an identity matrix. The corresponding eigenvectors $u_j = (u_{j1}, u_{j2}, \ldots, u_{jp})^T$

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