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Abstract
Purpose – The emergence of the fast fashion trend has exerted a great pressure on fashion designers who are urged to consider customers' preferences in their designs and develop new products in an efficient manner. The purpose of this paper is to develop a fuzzy association rule mining (FARM) approach for improving the efficiency and effectiveness of new product development (NPD) in fast fashion.
Design/methodology/approach – The FARM identifies the hidden relationships between product styles and customer preferences. The knowledge discovered help the fashion industry design new products which are not only fashionable, but are also saleable in the market.
Findings – To evaluate the proposed approach, a case study is conducted in a Hong Kong-based fashion company in which a real-set of data are tested to generate fuzzy association rules. The results reveal that the FARM approach can provide knowledge support to the fashion industry during NPD, shorten the NPD cycle time, and increase customer satisfaction.
Originality/value – Compared with traditional association rule mining, the proposed FARM approach takes the fuzziness of data into consideration and the knowledge represented in the fuzzy rules is in a more human-understandable structure. It captures the voice of the customer into fashion product development and provides a specific solution to deal with the challenges brought by fast fashion. In addition, it helps increase the innovation and technological capability of the fashion industry.
Keywords Data mining, Fast fashion, New product development, Fuzzy association rules
Paper type Research paper

1. Introduction
Because of the fast fashion trend, the fashion industry has been forced to shorten new product development (NPD) cycle time, while the newly developed products have to meet the growing expectations of the end customers. Products in the fashion industry are, however, ephemeral items which may no longer be saleable or attractive to consumers when fashion trends change (Christopher *et al.*, 2004). Therefore, it is essential to take customers' preferences into consideration during NPD, motivating many researchers to apply data mining (DM) techniques in order to understand customers' purchasing behavior. In addition, to deal with the uncertainties in actual industrial environments, researchers have started to hybridize fuzzy set theories into DM. Fuzzy association rule mining (FARM) is one of the hybrid approaches taking the fuzziness of data into consideration. The knowledge discovered in terms of fuzzy association rules is believed to be more meaningful than that in terms of Boolean association rules (Lee *et al.*, 2014).

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Despite the usefulness of FARM, the application of FARM in the fashion industry is still sparse. According to Gunesoglu and Meric (2007), the fashion industry is said to be more complicated in nature than the other industries. It is also posited that the NPD in the fashion industry is a critical but very challenging task. In general, there are two types of NPD projects handled by a manufacturer in the fashion industry. The first type begins with sample-order receipts from retail buyers (Leung and Yeung, 1995). Buyers provide manufacturers with technical packages to develop garment samples. Merchandisers have to ensure that all the required materials such as fabrics and accessories are available for the sample-making process and that the finished sample can be delivered to the buyers on time. The sample-making processes involve different labor-intensive operations such as pattern making, cutting, sewing, and finishing. The second type of NPD is initialized by the fashion designers in the manufacturer company when they are inspired by a new fashion trend from exhibitions, conferences, magazines and market reports. Sourcing is required to decide on the fabrics and accessories to be used in the new designs. Panel evaluation is then conducted to judge how good are the designs. Acceptable designs can be presented to retail buyers, and the sample-making process can be started if buyers are satisfied with the designs. On the other hand, if the manufacturer has its own label, the new products can be later sold in its retailing stores.

This paper focusses on the second type of NPD in which the work of fashion designers takes an important role in affecting the decisions of buyers. When the buyers are satisfied with the designs, there could lead to an order placement. In fast fashion, the main challenge is how to shorten the NPD cycle time, in particular, how can designers capture customers' needs and so integrate into their designs as quickly as possible. Failing to consider the relationships between product styles and customers' preference, buyers may have doubts on the salability of the new products, making them hesitate as to whether to develop and launch the products on the market. In addition, improving the NPD cycle time is a critical aspect in fast fashion so as to allow mainstream customers to take advantage of the current most up-to-date clothing styles. Consequently, the profitability of a company can be improved if the company provides customers with the products they want, at the right time (Ho *et al.*, 2005). In this paper, the FARM approach is used to discover the relationship between the product features and customer purchasing behavior, with the aim of improving the effectiveness and efficiency of NPD in fast fashion.

The remainder of this paper is organized as follows. Section 2 presents an overview of existing work related to this study. Section 3 introduces the proposed FARM approach specifically for the NPD in fast fashion. Section 4 is a case study in which the proposed approach is tested on a real-set of data collected in a fashion company. Section 5 discusses the results and Section 6 presents the conclusions.

2. Literature review

NPD is a sequence of tasks that an organization employs to conceive, design and commercialize a product (Ayağ, 2005). It is widely believed that effective NPD can help an organization maintain substantial business growth, and even survival (Zahay *et al.*, 2004; Jang *et al.*, 2005; Zapata *et al.*, 2008; Chan and Ip, 2011). In particular, shortening the NPD cycle time has become of greater importance in the fashion industry since the emergence of the fast fashion trend (Barnes and Lea-Greenwood, 2006; Zülch *et al.*, 2011). The objective of fast fashion is to bring the most up-to-date fashion styles into stores within the shortest time possible (Bruce and Daly, 2006). In line with this view, any delay in the NPD may prevent customers from accessing the latest products before the fashion trend changes, thus lowering the customer satisfaction.

In addition, to cater to the needs of different customers under fast fashion, there is a need to extend the number of seasons (Christopher *et al.*, 2004). Designers are required to work on hundreds of different new fashion products for each season (Choy *et al.*, 2009). However, their decisions have to consider not only the desired product styles, but also the acceptance of customers. Without DM tools to investigate the relationship between product styles and customer purchasing behavior, it is difficult for the industry to guarantee that newly developed products are both fashionable and saleable in the market.

DM is the extraction of implicit, valid and potentially useful knowledge from a large set of raw data (Han and Kamber, 2001). It has been widely applied in the discovery of hidden patterns from data, with an objective of extracting knowledge for decision making, such as making predictions about buyer behavior (Forcht and Cochran, 1999; Çiflikli and Kahya-Özyirmidokuz, 2012). Boolean association rule mining is one of the popular DM techniques to identify groups of items from data sets that occur together (Agrawal and Srikant, 1994). Chougule *et al.* (2011) used Boolean association rule mining to investigate the relationships between anomalies and root causes in the automotive domain. Lee *et al.* (2013) applied Boolean association rule mining to extract defect patterns in the garment industry. The findings in these works are consistent with the view of Ur-Rahman and Harding (2012) who pointed out that product quality can be improved through the discovery of hidden knowledge. However, a major drawback in using Boolean association rule mining is that the attributes concerned are limited to Boolean attributes (Alatas *et al.*, 2008). Considering that there are many other situations where data are numeric, it is not always practical to use Boolean association rule mining to solve problems. Furthermore, there are many forms of uncertainties in industrial decision environments, such as imprecise process times, unpredictable demands and uncertain capacities (Aliev *et al.*, 2007; Mula *et al.*, 2007). Taking the fuzziness of data into consideration is of great importance for improving the usefulness of DM. Therefore, a FARM algorithm has been proposed as a better tool to discover meaningful knowledge in real-life situations.

Compared with traditional Boolean association rule mining, FARM is able to discover knowledge at a parameter level by describing the quantitative values of the parameters in fuzzy terms (Chen and Wei, 2002). Existing publications have proven that it is able to extract useful knowledge for decision support purposes than many other approaches. For instance, it has been applied for supply chain management, (Jain *et al.*, 2008), quality improvement (Lau *et al.*, 2009), marketing (Chiu *et al.*, 2012) and stock market prediction (Ho *et al.*, 2012). However, its application in the field of fashion product development has not been fully explored. On the other hand, common tools used for fashion product development have been mainly limited to case-based reasoning (Choy *et al.*, 2009; Moon and Ngai, 2010; Lee *et al.*, 2012), fuzzy logic (Zeng and Koehl, 2003; Lau *et al.*, 2006; Chen *et al.*, 2009), and artificial neural network (Fan *et al.*, 2001; Hu *et al.*, 2009; Yu *et al.*, 2012). In order to fill the research gap, this study applies FARM to provide knowledge support to the fashion industry during NPD.

In this paper, an attempt is made to design an FARM approach for improving NPD in fast fashion. The FARM discovers the relationship between product styles and the purchasing pattern of customers, which can help the fashion industry effectively develop new products fulfilling the expectation of customers.

3. A FARM approach for fashion product development

The framework of the proposed FARM approach for supporting NPD in fast fashion is shown in Figure 1. There are four modules: namely:

(1) Data Collection Module.

(2) Knowledge Discovery Module.

(3) Rule Evaluation Module.

(4) Decision Support Module.

The Data Collection Module is used to extract relevant NPD parameters for FARM from historical records. Since fuzzy set concepts are involved in FARM, the fuzzy characteristics of each parameter have to be defined before the execution of the mining algorithm. The Knowledge Discovery Module is then used to find the correlations among the parameters. The knowledge discovered is in terms of fuzzy association rules. To ensure that the rules generated contain useful knowledge, the Rule Evaluation Module compares the confidence value of each rule with the predefined threshold value. Only rules with sufficient confidence values are stored in the knowledge repository in the Decision Support Module. These rules are used as decision rules for providing knowledge support to fashion designers when developing new fashion products. Details of each module are described in the following sections.

3.1 Data Collection Module

The function of the Data Collection Module is to extract relevant parameters for FARM. In fashion product development, product feature parameters include the sleeve length, zipper length, front dart length and waist band width. This type of parameters determines the outlook of a fashion product. On the other hand, to measure the salability of products, sales data and company feedback are considered. All these historical data are stored in a data warehouse. In this Module, parameters are identified for FARM and then extracted from the data warehouse. Before inputting the parameters into the mining algorithm in the Knowledge Discovery Module, the fuzzy characteristics of parameters have to be defined. This includes fuzzy terms, such as "Long" and "Short," used for describing the quantitative values of parameters, and membership functions to consider the fuzziness of parameters.

3.2 Knowledge Discovery Module

The Knowledge Discovery Module is the core part of the FARM approach as the mining algorithm is embedded into it. The two main stages involved in the algorithm are:

(1) finding the frequent itemsets from the data; and

(2) using the frequent itemsets to generate fuzzy association rules.

First, a threshold support count value has to be defined for each parameter. Its definition will determine whether a parameter has frequent correlations within the data. Parameters are treated as items in the mining algorithm and different combinations of items are treated as itemsets. Only the frequent itemsets, fulfilling the minimum threshold values, are used to generate fuzzy association rules. Since the rules state the relationship between the product features and the salability of the products, the fashion industry is able to design good products that improve profitability based on the rules generated. An example of application of the algorithm is presented in Section 4.

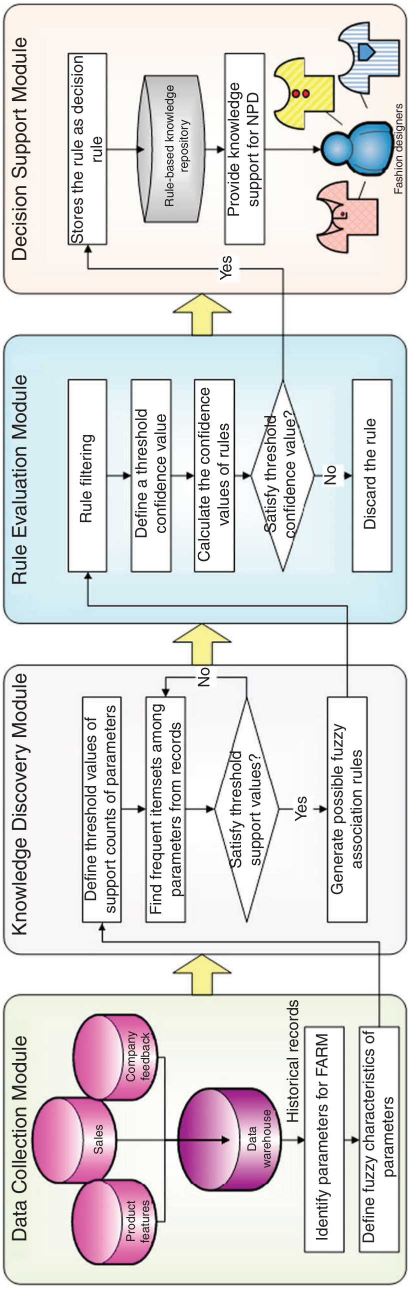

Figure 1.
A fuzzy association rule mining approach for fashion product development

3.3 Rule Evaluation Module

As the threshold values defined are heavily based on a trial-and-error approach, rule evaluation has to be conducted. Depending on the definition of threshold values, there could be a number of rules generated, some of which could be trivial or inexplicable. Therefore, rule filtering is essential to ensure the quality of the rules. Most importantly, the rule structure has to be checked. In this study, the product features will form the antecedent part of the rules while the salability of the products forms the consequent part. Rules violating this structure are eliminated. Furthermore, a confidence value for each rule is calculated. Only rules with confidence values greater than or equal to the predefined threshold values are regarded as useful, and are stored as decision rules in the Decision Support Module. The rule evaluation also provides feedback on the definition of threshold values such as the support counts and confidence. Adjustment of these threshold values can be made, if necessary, so as to improve the mining results.

3.4 Decision Support Module

In the Decision Support Module, there is a rule-based knowledge repository storing the decision rules obtained from FARM. The rules are capable of providing knowledge support for fashion designers for developing new fashion products effectively and efficiently. As both the product features and sales of products are inputted to the algorithm, the hidden relationships between different products and the customers' purchase behavior are discovered. With reference to such kind of knowledge, fashion designers can gain some insights on how to design product features that can increase the salability of products. Since the parameters in the rules are described in fuzzy linguistic terms, the knowledge is represented in a human-understandable structure. Fashion designers, who may lack technical background related to DM or artificial intelligence (AI), can still refer to the knowledge discovered in an effective manner.

4. Case study

The viability of the proposed FARM approach is evaluated by means of a case study, which is developed and implemented in a Hong Kong-based fashion company. The company, founded in 1977, has been a listed company in the Hong Kong stock market since 1988. Its production capacities include the manufacturing facilities in Hong Kong, China, Malaysia, Thailand and Vietnam. It produces over 15 million pieces of fashion products annually, exporting to America, and Europe. For decades, it has been entrusted by a wide range of renowned designer labels and international retail stores in supplying fashionable apparel to its shops. In addition, it operates its own-brand business for retailing in the major cities of China as well as for wholesaling in the USA. It opened its first retail store under its own label in Shanghai in 1989. With a strong team of fashion designers and sourcing personnel, its own-brand business is well received in the market and is set to grow into a core part of the business in the long term. However, faced with the challenges brought by the fast fashion trend, the company has decided to expedite its NPD process. In this case study, FARM is implemented in the company with the aim of providing knowledge support to fashion designers in their attempt to develop new fashion products in an effective and efficient way. The implementation of the FARM approach involves four phases:

(1) identification of parameters;

(2) definition of fuzzy characteristics of parameters;

(3) generation of fuzzy association rules; and

(4) rule evaluation.

Details of each phase are presented in the following sections.

4.1 Identification of parameters

In this phase, parameters which will be inputted for FARM are identified. This is done by conducting interviews with domain experts. Fashion designers are asked to select parameters which are important to their design of product styles. In this pilot run, men's shirts of size M, are selected for illustration and there are six product features identified as shown in Figure 2. To identify the relationships between the product styles and customer preferences in terms of fuzzy association rules, product features such as sleeve length and button spacing form the antecedent part of the rules while the hit rate and the sales of the products form the consequent part of the rules. Both the hit rate and the sales of products are chosen to measure the customer preferences because they are the indicators determining whether a particular product looks attractive to customers. The hit rate of the products is used to describe the success rate of the developed products accepted by the company after evaluation. After the fashion designers finish certain designs, samples are made and evaluated by the management. Based on their experience, the managers interpret whether the customers will be satisfied with the product design. In addition, the overall customer satisfaction with the products can be measured at the point of sale. Thereby, the sales of the products are also chosen for assessing the customer preferences as they reflect the performance of the products in attracting customers for purchasing.

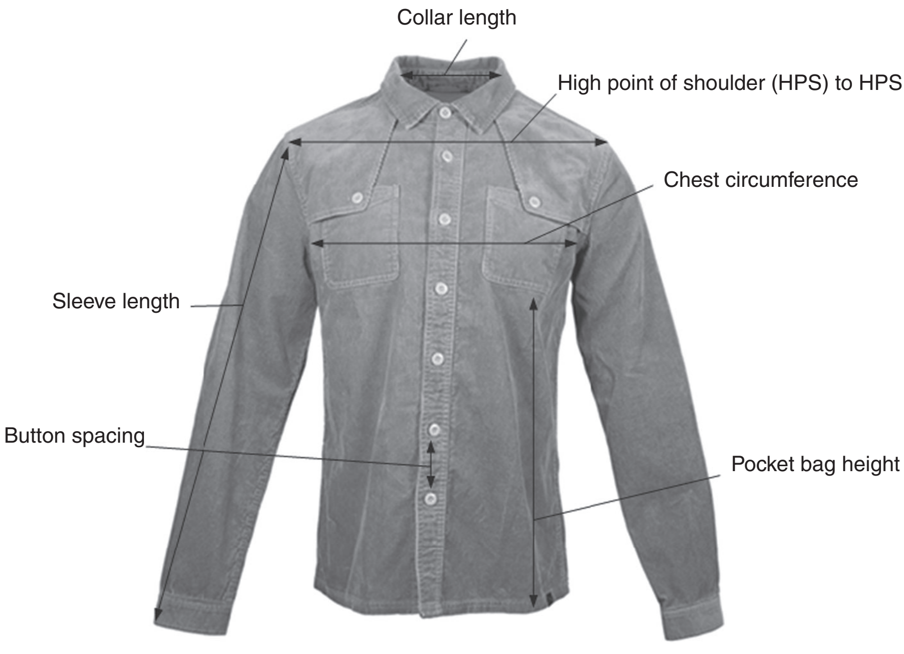

Figure 2.
Product feature parameters identified for the FARM

4.2 Definition of fuzzy characteristics of parameters

Based on the parameters identified in Phase 1, the fuzzy characteristics of each parameter have to be defined. This includes the definitions of fuzzy terms, membership functions and the support counts of parameters. To begin, a range of each parameter is identified, as listed in Table I. It is expected that there are no clear-cut boundaries to associate most values within the range to single fuzzy terms. Therefore, fashion designers are invited to assign fuzzy terms to parameters within the range and associate them with membership functions. Precise membership function positioning is not essential in describing the exact quantitative values of the parameters at this stage, because fine-tuning of the measurement of the product styles will be carried out according to the samples developed before production. Therefore, the choice of membership functions are limited to triangular and trapezoidal membership functions. It is believed that users, such as most fashion designers, who lack AI knowledge, will find it easier to understand triangular and trapezoidal membership functions, compared to other smooth functions such as Gaussian functions. For each triangular and trapezoidal membership function, three points and four points have to be defined for positioning, respectively, by trial and error. The membership functions of the parameter "Pocket bag height" and "Hit rate" are illustrated in Figure 3 as examples.

Table I.
The range of parameters identified for FARM

Parameter		Symbol	Range
Product features	Pocket bag height	A	5-15 cm
	HPS to HPS	B	30-50 cm
	Sleeve length	C	50-70 cm
	Collar length	D	12-28 cm
	Chest circumference	E	30-60 cm
	Button spacing	F	2-10 cm
Salability of the product	Sales	G	0-100 ($,000)
	Hit rate	H	0-100%

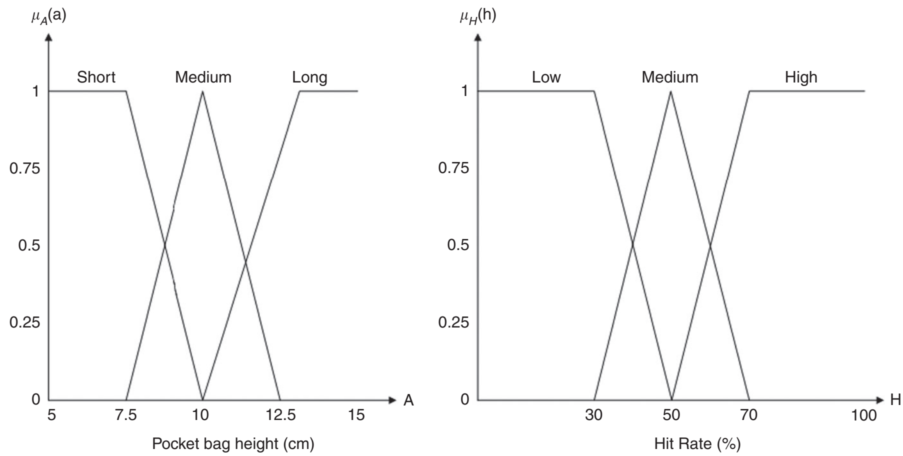

Figure 3.
Examples of membership functions of Parameters "A" and "H"

4.3 Generation of fuzzy association rules

After identification of the fuzzy characteristics, the parameters can be extracted from the historical records and inputted to the mining algorithm for generating fuzzy association rules. In this section, a case scenario is used to illustrate the computational procedures of the FARM algorithm. Six historical records, as listed in Table II, are extracted for illustration.

To begin, threshold values of the support counts of the parameters have to be determined in order to have useful association rules being mined. If the thresholds are set too low, trivial or inexplicable rules could be mined. On the other hand, if the thresholds are set too high, it could be difficult to obtain any rules. Therefore, the final choice of the thresholds is heavily dependent on a trial-and-error approach, until some useful association rules can be mined. The threshold value of the support count of each parameter is shown in Table III. There are ten steps involved in the FARM.

Step 1: convert all quantitative values of the parameters into fuzzy terms based on the membership functions identified. For instance, when parameter A is 9 cm, it lies between "Short" and "Medium." According to the membership functions, it is 0.4 for short and 0.6 for medium. Therefore, the fuzzy set of A is represented as (0.4/A.Short +0.6/A.Medium). All the parameters are converted into fuzzy sets and the results are shown in Table IV.

Step 2: calculate the numbers of occurrences (fuzzy counts) of all the fuzzy classes of parameters appearing in the records. For example, the fuzzy count of "A.Short" from record 1 to 6 is calculated as $(1+0.4+0+0.8+1+0)=3.2$. The fuzzy classes are regarded as items in the algorithm. The fuzzy counts are listed in Table V.

Step 3: only an itemset among each parameter with the maximum fuzzy count is considered in the FARM algorithm. For instance, "A.Short" has a larger fuzzy count compared with "A.Medium" and "A.Long." Therefore, "A.Short" is selected to represent the fuzzy characteristics of parameter A in the later mining process. The itemset of each parameter with the maximum fuzzy count is shown in italics in Table V.

Step 4: compare the fuzzy counts of the selected itemsets with the threshold support count values of the corresponding parameters. Only itemsets with fuzzy counts greater than the threshold values are put in the one-itemset. In this example, all itemsets identified in Step 3 are put in the one-itemset.

NPD record	A	B	C	D	E	F	G	H
1	6	35	55	15	48	5	90	76
2	9	40	70	28	39	7	63	45
3	12	42	60	20	52	9	72	56
4	8	48	64	26	58	4	68	49
5	7	39	58	19	46	8	61	32
6	15	46	52	24	32	6	38	28

Table II. Six samples of historical records used in the case scenario

Parameter	A	B	C	D	E	F	G	H
Threshold support count	2.0	2.2	2.2	2.7	1.5	1.5	1.5	1.8

Table III. Threshold support counts of parameters

Table IV. Converted fuzzy sets of parameters

NPD record	Fuzzy sets of parameters
1	(1/A.Short) (1/B.Short) (1/C.Short) (1/D.Short) (0.2/E.Medium+0.8/E.Long) (1/F.Medium) (1/G.High) (1/H.High)
2	(0.4/A.Short+0.6/A.Medium) (1/B.Medium) (1/C.Long) (1/D.Long) (0.2/E.Short+0.8/E.Medium) (0.33/F.Medium+0.67/F.Long) (0.35/G.Medium+0.65/G.High) (0.25/H.Low+0.75/H.Medium)
3	(0.2/A.Medium+0.8/A.Long) (0.67/B.Medium+0.33/B.Long) (1/C.Medium) (1/D.Medium) (1/E.Long) (1/F.Long) (1/G.High) (0.3/H.Medium+0.7/H.High)
4	(0.8/A.Short+0.2/A.Medium) (1/B.Long) (1/C.Long) (1/D.Long) (1/E.Long) (1/F.Short) (0.1/G.Medium+0.9/G.High) (0.05/H.Low+0.95/H.Medium)
5	(1/A.Short) (0.25/B.Short+0.75/B.Medium) (0.4/C.Short+0.6/C.Medium) (0.33/D.Short+0.67/D.Medium) (0.4/E.Medium+0.6/E.Long) (1/F.Long) (0.45/G.Medium+0.55/G.High) (0.9/H.Low+0.1/H.Medium)
6	(1/A.Long) (1/B.Long) (1/C.Short) (1/D.Long) (1/E.Short) (0.67/F.Medium+0.33/F.Long) (0.6/G.Low+0.4/G.Medium) (1/H.Low)

Table V. Fuzzy counts of parameters in one-itemset

Item	Fuzzy count	Item	Fuzzy count
A.Short	*3.2*	E.Short	1.2
A.Medium	1	E.Medium	1.4
A.Long	1.8	*E.Long*	*3.4*
B.Short	1.25	F.Short	1
B.Medium	*2.42*	F.Medium	2
B.Long	2.33	*F.Long*	*3*
C.Short	*2.4*	G.Low	0.6
C.Medium	1.6	G.Medium	1.3
C.Long	2	*G.High*	*4.1*
D.Short	1.33	H.Low	2.2
D.Medium	1.67	*H.Medium*	*2.5*
D.Long	*3*	H.High	1.3

Step 5: generate each combination of any two items in the one-itemset to form potential two-itemset. The selection of two-itemset is that both fuzzy counts of the two items in the two-itemsets have to be larger than or equal to the maximum of their predefined threshold support count values. Take {A.Short, B.Medium} as an example. The predefined threshold support counts of these two items are 2 and 2.2, and the maximum value is 2.2. Both the fuzzy counts of "A.Short" and "B.Medium," which are 3.2 and 2.42, are larger than or equal to 2.2. Therefore, {A.Short, B. Medium} can be put in the two-itemset. Table VI lists all the combination of parameters in the two-itemset.

Step 6: since the two-itemset is not null, the algorithm can be continued.

Step 7: the fuzzy count of a two-itemset is calculated by summing up the minimum values of their fuzzy counts in each record. For instance, the fuzzy counts of "A.Short" and "B.Medium" in Record 1 are 1 and 0, respectively, so the minimum value is 0. In Record 2, their fuzzy counts are 0.4 and 1, so the minimum value in 0.4. The calculation of the remaining records is the same. By summing up the minimum values of the fuzzy count in each record, the fuzzy count of {A.Short, B.Medium} is $(0+0.4+0+0+0.75+0)=1.15$. The fuzzy counts of the two-itemsets are listed in Table VII.

2-itemset	
{A.Short, B.Medium}	{C.Short, F.Long}
{A.Short, C.Short}	{C.Short, G.High}
{A.Short, D.Long}	{C.Short, H.Medium}
{A.Short, E.Long}	{D.Long, E.Long}
{A.Short, F.Long}	{D.Long, F.Long}
{A.Short, G.High}	{D.Long, G.High}
{A.Short, H.Medium}	{E.Long, F.Long}
{B.Medium, C.Short}	{E.Long, G.High}
{B.Medium, E.Long}	{E.Long, H.Medium}
{B.Medium, F.Long}	{F.Long, G.High}
{B.Medium, G.High}	{F.Long, H.Medium}
{B.Medium, H.Medium}	{G.High, H.Medium}
{C.Short, E.Long}	

Table VI. Combination of parameters as two-itemsets

2-itemset	Fuzzy count	2-itemset	Fuzzy count
{A.Short, B.Medium}	1.15	{C.Short, F.Long}	0.73
{A.Short, C.Short}	1.4	{C.Short, G.High}	1.4
{A.Short, D.Long}	1.2	{C.Short, H.Medium}	0.1
{A.Short, E.Long}	*2.2*	{D.Long, E.Long}	1
{A.Short, F.Long}	1.4	{D.Long, F.Long}	1
{A.Short, G.High}	*2.75*	{D.Long, G.High}	1.55
{A.Short, H.Medium}	1.3	*{E.Long, F.Long}*	*1.6*
{B.Medium, C.Short}	0.4	*{E.Long, G.High}*	*3.25*
{B.Medium, E.Long}	1.27	{E.Long, H.Medium}	1.75
{B.Medium, F.Long}	2.08	*{F.Long, G.High}*	*2.2*
{B.Medium, G.High}	1.87	{F.Long, H.Medium}	1.47
{B.Medium, H.Medium}	1.52	*{G.High, H.Medium}*	*2.35*
{C.Short, E.Long}	1.2		

Table VII. Fuzzy counts of two-itemsets

Step 8: similar to Step 4, compare the fuzzy counts of two-itemsets with the maximum value of threshold support count values of the corresponding parameters. Only the two-itemsets with fuzzy count larger than or greater than the maximum values of thresholds can be kept in the two-itemsets. After comparison, there are only six, two-itemsets remaining, as in italics in Table VII.

Step 9: since two-itemset is not null after comparison, Steps 5-9 is repeated except that the itemset level is increased by one level. The algorithm is complete only when there are no available combinations of itemsets to be formed. In this example, the two-itemset is combined to form three-itemsets as shown in Table VIII. No four-itemsets can be generated.

3-itemset	Fuzzy count
{A.Short, E.Long ,G.High}	2.15
{E.Long, F.Long, G.High}	1.55

Table VIII. Combination of parameters as three-itemsets

Step 10: parameters in the k-itemset with $k \geqslant 2$ are extracted to construct possible fuzzy association rules. For example, {A.Short, G.High} leads to constructing the following two rules:

Rule A: if the pocket bag height is short, then the sales are high.

Rule B: If the sales are high, then the pocket bag height is short.

4.4 Rule evaluation

In this phase, rule filtering is performed to ensure that the rule structure is consistent. As defined in Phase 1, Parameters A-F form the antecedent part of rules while Parameters G-H form the consequent part of rules. As a result, only the abovementioned Rule A generated from {A.Short, G.High} is valid, i.e. having the parameter "Sales" appeared in the consequent part of the rule. On the other hand, if Parameter G or Parameter H is absent in the itemsets, there are no rules generated as the consequent part of the rules cannot be formed.

After rule filtering, a confidence value of each rule is calculated. For instance, the confidence value of the Rule A can be calculated as:

$$\frac{(\text{A.Short} \cap \text{G.High})}{(\text{A.Short})} = \frac{2.75}{3.2} = 0.859$$

Table IX lists the rules obtained after rule filtering with their confidence values. If the confidence value of a rule is larger than or equal to the predefined threshold confidence value, the rule is regarded as useful. In this case scenario, the threshold confidence value is 0.95. There are three rules, as in bold in Table IX, with confidence values > 0.95. Thus, they are used as decision rules for supporting fashion product development.

5. Results and discussion

The FARM approach has been adopted in the company for six months so as to evaluate its performance. The list below shows three samples of the fuzzy association rules mined in the company for supporting its NPD based on its historical data. Rules are obtained after executing the abovementioned ten steps with the threshold confidence value = 0.80. They could not be mined by Boolean association rule mining because simple association rules without integrating fuzzy set concepts could mainly show the relationship between the existences of items. For instance, a Boolean association rule could only suggest the designers to design a zipper when there is a hip pocket on the product. However, clues are not provided for the placement of the zipper or that of the hip pocket. As a consequence, the knowledge discovered by Boolean association rule mining are not sophisticated enough to provide support for NPD. On the other hand, the fuzzy association rules mined can act as useful references for designers to develop

Table IX. Fuzzy association rules with confidence values

Fuzzy association rule	Confidence value
If {A.Short}, then {G.High}	2.75/3.2 = 0.859
If {E.Long}, then {G.High}	*3.25/3.4 = 0.956*
If {F.Long}, then {G.High}	2.2/3 = 0.733
If {A.Short, E.Long}, then {G.High}	*2.15/2.2 = 0.977*
If {E.Long, F.Long}, then {G.High}	*1.55/1.6 = 0.969*

new fashion products at a parameter level. For example, the quantitative values of the parameters such as the zipper length and the hip pocket placement from the waist are described in fuzzy terms in the rules, allowing the designers to make informed decisions during NPD. In this section, the results and benefits offered by the FARM approach are presented, followed by the contributions of this study.

Samples of the mined fuzzy association rules in the case company:

- Rule 1: if the back neck drop from HPS is medium, and the collar length is long, and the waist band width is short, then the sales are high, and the hit rate is medium.
- Rule 2: if the zipper length at the hip is long, and the zipper placement from the waist is medium, and the hip pocket placement from the waist is short, then the sales are medium, and the hit rate is low.
- Rule 3: if the sleeve band width is medium, and the zipper length from the center back is short, and the chest circumference is medium, and the collar band height at the center back is long, then the sales are high, and hit rate is high.

5.1 Benefits of using farm for fashion product development

Table X shows the improvement achieved by the use of the FARM approach over a six-month period of time. It is found that the approach can offer significant benefits to the fashion industry which include as follows.

(i) Improved customer satisfaction. Without the use of FARM approach, fashion designers develop new products mainly based on their own intuition and fashion sense. Therefore, it is difficult to determine whether their decisions are made in response to customer expectations, resulting in adverse effects to customer satisfaction. After the company adopted the FARM approach for NPD, the average sales per season have been improved by 7 percent. The increased sales of the products indicate that customers are satisfied with the product developed. Customer expectations can be met because the relationships with product features are discovered and used as valuable knowledge to support NPD.

(ii) Increased the efficiency of NPD. The traditional experience-based decision making process in fashion product development without the use of FARM takes a lot of time in developing concepts and analyzing different design solutions. Such a long NPD cycle time is unfavorable in fast fashion. On the other hand, the use of FARM has shortened the NPD cycle time per 30 styles by 12 percent. The improvement is due to a faster identification of customer needs and preferences for designers to develop different product features. Though the knowledge discovered by FARM is not the only source for generating new product ideas, having a set of fuzzy association rules as a reference allows designers to make better informed decisions, increasing the efficiency of NPD.

Indicator	Before the use of the FARM	After the use of the FARM	Improvement (%)
NPD cycle time/30 styles	1.7 weeks	1.5 weeks	+12
Sales/season	$980,460	$1,049,100	+7
Hit rate	68%	72%	+4

Table X. Improvement achieved after the use of FARM *(iii) Provided knowledge support in NPD*. The hit rate refers to the success rate of having the company accept the new fashion designs for retailing after evaluation. It has been increased by 4 percent after the use of FARM. This confirms the effectiveness of the FARM approach and reveals that the company is satisfied with the performance of FARM. One may argue that extra constraints are introduced to NPD if fashion designers follow the decision rules in their designs. Nevertheless, since the quantitative values of the parameters in the decision rules are represented in fuzzy terms, designers are still provided with the flexibility to determine the values of parameters to be used. Furthermore, in NPD, it is not necessary for designers to determine the quantitative values of parameters precisely. For instance, it is suggested that designers have short button spacing to suit customers' need. However, they can judge how short the button spacing should be, and how other product features can be incorporated with the design. Thus, the knowledge discovered serves as a useful reference to allow designers to consider customers' preference during NPD, without affecting their fashion ideas.

5.2 Contributions of this study

In addition to narrowing the research gap by applying FARM for supporting NPD in the fashion industry, this study has made the following contributions:

(i) Capturing the voice of the customer into fashion product development. The FARM considers both the product features and customer purchasing behavior for knowledge discovery. The aim is to help designers develop new products which can meet the expectations of customers. In this sense, the voice of customers is captured during NPD and the knowledge discovered provides a better understanding of customer preference on fashion products. In fact, the importance of the voice of the customer is commonly recognized during the development of highly technical products such as electronic devices, so as to design with product functionality. However, the direct relationship between fashion product designs and the voice of the customer in the fashion industry is almost always ignored.

(ii) Providing a specific solution to deal with the challenges brought by fast fashion. The application of this study is specifically designed to tackle the industrial problems arising from the fast fashion trend. There are other research studies investigating different approaches to increase the effectiveness and efficiency of NPD, for example, by improving the processes involved in resource allocation, fabric selection and information sharing. Nevertheless, the main challenge faced by industrial practitioners under fast fashion is how to design products which look attractive to customers and make them available in the market in the shortest time possible. As a result, it is believed that the proposed FARM approach, capturing the voice of the customer, is a powerful specific solution to deal with the challenges brought by the current fast fashion trend.

(iii) Increasing the innovation and technological capability of the fashion industry. It is widely recognized that fashion products are designed based on the intuition and fashion sense of designers. There are few technical applications used in NPD in the fashion industry. Thus, the technological capability of the industry is relatively low. However, without considering the customer preference, fashion products cannot be developed successfully. This study applied DM and fuzzy set theories to help the fashion industry develop successful products by considering the relationship between product features and customer preference. The use of the FARM approach can increase

the innovation and technological capability of the fashion industry. It is hoped that this study can also encourage more researchers to apply DM or AI techniques to improve NPD in the fashion industry.

6. Conclusions

This paper proposes a FARM approach to discover hidden relationships between product features and customer purchasing behavior. It helps the fashion industry improve the NPD process, and even survive, under the fast fashion trend. With the knowledge discovered by FARM, the voice of the customer is captured during NPD to recognize its direct relationship with different product features. As a result, newly developed products are not only fashionable, but are also able to meet customer expectation. In addition, having knowledge supporting the NPD helps shorten the NPD cycle time, allowing mainstream customers to take advantage of the current clothing styles. This is recognized as a critical improvement, as the fashion industry is a very time-sensitive industry. On the other hand, one could argue that the use of FARM will limit the innovation of new products. However, since the rules generated do not strictly make suggestions on the exact sizes or placements of different product features, like sleeves, pockets and zippers, designers are able to apply their fashion sense and integrate different concepts to their designs. The case study results also illustrate that the new products developed after the use of FARM are successful for retailing. Furthermore, the rules are presented in a human-understandable structure with the use of fuzzy concepts. Designers, who lack DM or AI knowledge, find the FARM approach easy to use. It is thus believed that the FARM approach is a practical and effective solution to deal with the challenges brought by fast fashion.

References

Agrawal, R. and Srikant, R. (1994), "Fast algorithms for mining association rules in large databases", *Proceedings of 20th International Conference on Very Large Databases, Santiago de Chile*, pp. 487-489.

Alatas, B., Akin, E. and Karci, A. (2008), "MODENAR: multi-objective differential evolution algorithm for mining numeric association rules", *Applied Soft Computing*, Vol. 8 No. 2, pp. 646-656.

Aliev, R.A., Fazlollahi, B., Guirimov, B.G. and Aliev, R.R. (2007), "Fuzzy-genetic approach to aggregate production-distribution planning in supply chain management", *Information Sciences*, Vol. 177 No. 20, pp. 4241-4255.

Ayağ, Z. (2005), "A fuzzy AHP-based simulation approach to concept evaluation in a NPD environment", *IIE Transactions*, Vol. 37 No. 9, pp. 827-842.

Barnes, L. and Lea-Greenwood, G. (2006), "Fast fashioning the supply chain: shaping the research agenda", *Journal of Fashion Marketing and Management*, Vol. 10 No. 3, pp. 259-271.

Bruce, M. and Daly, L. (2006), "Buyer behavior for fast fashion", *Journal of Fashion Marketing and Management*, Vol. 10 No. 3, pp. 329-344.

Chan, S.L. and Ip, W.H. (2011), "A dynamic decision support system to predict the value of customer for new product development", *Decision Support Systems*, Vol. 52 No. 1, pp. 178-188.

Chen, G. and Wei, Q. (2002), "Fuzzy association rules and the extended mining algorithms", *Information Sciences*, Vol. 147 Nos 1-4, pp. 201-228.

Chen, Y., Zeng, X., Happiette, M., Bruniaux, P., Ng, R. and Yu, W. (2009), "Optimisation of garment design using fuzzy logic and sensory evaluation techniques", *Engineering Application of Artificial Intelligence*, Vol. 22 No. 2, pp. 272-282.

Chiu, H.P., Tang, Y.T. and Hsieh, K.L. (2012), "Applying cluster-based fuzzy association rules mining framework into EC environment", *Applied Soft Computing*, Vol. 12 No. 8, pp. 2114-2122.

Chougule, R., Rajpathak, D. and Bandyopadhyay, P. (2011), "An integrated framework for effective service and repair in the automotive domain: an application of association mining and case-based reasoning", *Computers in Industry*, Vol. 62 No. 7, pp. 742-754.

Choy, K.L., Chow, K.H., Moon, K.L., Zeng, X., Lau, H.C.W., Chan, F.T.S. and Ho, G.T.S. (2009), "A RFID-case-based sample management system for fashion product development", *Engineering Application of Artificial Intelligence*, Vol. 22 No. 6, pp. 882-896.

Christopher, M., Lowson, R. and Peck, H. (2004), "Creating agile supply chains in the fashion industry", *International Journal of Retail and Distribution Management*, Vol. 32 No. 8, pp. 367-376.

Çiflikli, C. and Kahya-Özyirmidokuz, E. (2012), "Enhancing product quality of a process", *Industrial Management & Data Systems*, Vol. 112 No. 8, pp. 1181-1200.

Fan, J., Newton, E., AU, R. and Chan, S.C.F. (2001), "Predicting garment drape with a fuzzy-neural network", *Textile Research Journal*, Vol. 71 No. 7, pp. 605-608.

Forcht, K.A. and Cochran, K. (1999), "Using data mining and data warehousing techniques", *Industrial Management & Data Systems*, Vol. 99 No. 5, pp. 189-196.

Gunesoglu, S. and Meric, B. (2007), "The analysis of personal and delay allowances using work sampling technique in the sewing room of a clothing manufacturer", *International Journal of Clothing Science and Technology*, Vol. 19 No. 2, pp. 145-150.

Han, J. and Kamber, M. (2001), *Data Mining: Concepts and Techniques*, Morgan Kaufmann Publishers Academic Press, San Francisco.

Ho, G.T.S., Ip, W.H., Wu, C.H. and Tse, Y.K. (2012), "Using a fuzzy association rule mining approach to identify the financial data association", *Expert Systems with Applications*, Vol. 39 No. 10, pp. 9054-9063.

Ho, G.T.S., Lau, H.C.W., Lee, C.K.M. and Ip, A.W.H. (2005), "An intelligent forward quality enhancement system to achieve product customization", *Industrial Management & Data Systems*, Vol. 105 No. 3, pp. 384-406.

Hu, Z.H., Ding, Y.S., Yu, X.K., Zhang, W.B. and Yan, Q. (2009), "A hybrid neural network and immune algorithm approach for fit garment design", *Textile Research Journal*, Vol. 79 No. 14, pp. 1319-1330.

Jain, V., Benyoucef, L. and Deshmukh, S.G. (2008), "A new approach for evaluating agility in supply chains using fuzzy association rules mining", *Engineering Applications of Artificial Intelligence*, Vol. 21 No. 3, pp. 368-385.

Jang, N., Dickerson, K.G. and Hawley, J.M. (2005), "Apparel product development: measures of apparel product success and failure", *Journal of Fashion Marketing and Management*, Vol. 9 No. 2, pp. 195-206.

Lau, H.C.W., Ho, G.T.S., Chu, K.F., Ho, W. and Lee, C.K.M. (2009), "Development of an intelligent quality management system using fuzzy association rules", *Expert Systems with Applications*, Vol. 36 No. 2, pp. 1801-1815.

Lau, T.W., Hui, P.C.L., Ng, F.S.F. and Chan, K.C.C. (2006), "A new fuzzy approach to improve fashion product development", *Computers in Industry*, Vol. 57 No. 1, pp. 82-92.

Lee, C.K.H., Choy, K.L., Law, K.M.Y. and Ho, G.T.S. (2012), "Decision support system for sample development in the Hong Kong garment industry", *Proceedings of Portland International*

Center for Management Engineering and Technology: Technology Management for Emerging Technologies, pp. 754-761.

Lee, C.K.H., Ho, G.T.S., Choy, K.L. and Pang, G.K.H. (2014), "A RFID-based recursive process mining system for quality assurance in the garment industry", *International Journal of Production Research*, Vol. 52 No. 14, pp. 4216-4238.

Lee, C.K.H., Choy, K.L., Ho, G.T.S., Chin, K.S., Law, K.M.Y. and Tse, Y.K. (2013), "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry", *Expert Systems with Applications*, Vol. 40 No. 7, pp. 2435-2446.

Leung, C.S. and Yeung, M. (1995), "Communications: quick response in clothing merchandising – a study of the buying office using network analyses", *International Journal of Clothing Science and Technology*, Vol. 7 No. 4, pp. 44-55.

Moon, K.L. and Ngai, E.W.T. (2010), "R&D framework for an intelligent fabric sample management system: a design science approach", *International Journal of Operations & Production Management*, Vol. 30 No. 7, pp. 721-743.

Mula, J., Poler, R. and Garcia-Sabater, J.P. (2007), "Material requirement planning with fuzzy constraints and fuzzy coefficients", *Fuzzy Sets and Systems*, Vol. 158 No. 7, pp. 783-793.

Ur-Rahman, N. and Harding, J.A. (2012), "Textual data mining for industrial knowledge management and text classification: a business oriented approach", *Expert Systems with Applications*, Vol. 39 No. 5, pp. 4729-4739.

Yu, Y., Hui, C.L. and Choi, T.M. (2012), "An empirical study of intelligent expert systems on forecasting of fashion color trend", *Expert Systems with Applications*, Vol. 39 No. 4, pp. 4383-4389.

Zahay, D., Griffin, A. and Fredericks, E. (2004), "Sources, uses, and forms of data in the new product development process", *Industrial Marketing Management*, Vol. 33 No. 7, pp. 657-666.

Zapata, J.C., Varma, V.A. and Reklaitis, G.V. (2008), "Impact of tactical and operational policies in the selection of a new product portfolio", *Computers and Chemical Engineering*, Vol. 32 Nos 1-2, pp. 307-319.

Zeng, X. and Koehl, L. (2003), "Representation of the subjective evaluation of the fabric hand using fuzzy techniques", *International Journal of Intelligent Systems*, Vol. 18 No. 3, pp. 355-366.

Zülch, G., Koruca, H.I. and Börkircher, M. (2011), "Simulation-supported change process for product customization – a case study in a garment company", *Computers in Industry*, Vol. 62 No. 6, pp. 568-577.

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