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Using data mining to analyse fashion consumers' preferences from a cross-national perspective

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The purpose of this study is twofold: (1) to cluster the respondents into three consumer groups – fashion innovator, fashion follower and laggard and (2) to extract association rules from the data set in order to understand consumers' preferences. A data-mining method was employed to analyse considerable amount of data collected from four cities as well as to understand the complexity of the diffusion process of multiple apparel products. According to the results of the present study, style was not an important factor for the fashion leaders to purchase socks in Toronto, Hangzhou and Johor Bahru. In terms of t-shirts and evening dresses/suits, 53% and 51% of fashion laggards in China had shown their strong preferences for fit and comfort, respectively. Additionally, 60% of the fashion leaders in Canada had shown a strong preference for fit and style of t-shirts. Although this study is exploratory in nature, we believe that data mining has great potential for investigating fashion diffusion of innovativeness, and more replication of this type of research will be worthwhile and meaningful.

Keywords: data mining; diffusion of fashion innovation; cross-national study; product attributes; consumer preferences

1. Introduction

In order to enhance our understanding of adopters' behaviour, scholars have developed different measuring instruments to identify and categorise consumers into different behavioural groups. For example, Rogers' diffusion of innovation (DOI) model categorised the target population into five 'adopter' groups including innovators, early adopters, early majority, late majority and laggards. In the early 1960s, DOI Theory was developed by Rogers (1967, 1976) to further illuminate and understand the social process of how innovative ideas, practices and objects were introduced, communicated and adopted in the marketplace. As Rogers (1995) states 'diffusion is the process by which an innovation is communicated through certain channels (e.g. media and interpersonal contacts) over time among the members of a social system' and 'communication is a process in which participants create and share information with one another to reach a mutual understanding'.

Research on diffusion innovation can be traced back to the early twentieth century – French sociologist Tarde (1903) proposed the S-shaped diffusion curve and the process of 'imitation'. Four decades later, two other sociologists, Ryan and Gross (1943), revolutionised the diffusion research through their seminal study of hybrid seed corn in two Iowa communities.

It is worthwhile to note that research on the DOI has increased tremendously not only in North America but also in many developing countries of Latin America, Asia and Africa since the early 1960s (Rogers, 1995). However, Rogers's model has been criticised by numerous researchers regarding its reliability and validity, time-of-adoption methods and arbitrary categorisation scheme (Goldsmith & Hofacker, 1991, pp. 209–210) despite its acceptance and popularity. With these shortcomings, six items of the domain-specific innovativeness (DSI) scale were developed and validated by Goldsmith and Hofacker (1991). It is a balanced scale with both positive and negative worded items using a five-point response format. The DSI scale demonstrates high internal consistency, reliability and validity (Bearden, Netemeyer, & Mobley, 1993). In addition, the scale items can be adapted and applied to a variety of product domains including fashion clothing.

However, many DSI studies have dealt with relatively limited information and specific product types, with many of these studies focusing solely on just one country. This is due to the burdensome process and difficulty in obtaining trustworthy data in multiple locations, and even more so in understanding adopters' responses towards multiple apparel products in a simultaneous manner. Therefore, in order to handle a considerable amount of data from multiple countries and to understand the complexity of the diffusion process of multiple apparel products, the data-mining method was employed for this study.

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Although very few apparel studies (e.g. Rickman & Cosenza, 2007) have employed data mining to investigate consumers' perceptions and adoption behaviours, this approach has been extensively applied to many different fields as well as different products and services. Data-mining algorithms are often designed to handle a large amount of data with multiple parameters. Indeed, the larger the data set, the higher the likelihood to obtain interesting and meaningful information. Therefore, our current study employs a data-mining approach to investigate a multi-feature data set extracted from a questionnaire survey consisting of product attributes and colour-specific questions, and was conducted in multiple locations including Toronto (Canada), Hangzhou and Hong Kong (China), and Johor Bahru (Malaysia).

2. Review of literature

2.1. Fashion and fashion agents

As many fashion scholars (e.g. Kawamura, 2005; McJimsey, 1973) point out, a form of dress or a way of wearing is not 'fashion'. Fashion is defined as 'until it has been adopted and used by a large proportion of people in a society' (Kawamura, 2005, p. 1). The definition of innate consumer innovativeness is a (Roehrich, 2004) '... predisposition to buy new and different products and brands rather than remain with previous choices and consumer patterns'. Four different explanations have been proposed to further define this predisposition. These are stimulation need, novelty seeking, independence towards others' communicated experience and need for uniqueness. Stimulation need means an 'antecedent of new product adoption, either directly or indirectly, through innovativeness'. Novelty seeking refers to 'interest in new products and any kind of new information, ideas or behaviour'. Finally, independence towards others and need for uniqueness is defined as an independence of judgment towards newness and credible antecedent of innovativeness, respectively. Although the meaning of innovativeness could be varied in different contexts, some measuring scales of innovativeness were proposed. For example, the two most remarkable scales are life innovativeness and adoptive innovativeness – the definition of these two scales is the ability to introduce newness in one's life and innovativeness as a tendency to buy new products, respectively.

It is important to point out that it has been a challenge to distinguish and define each fashion adoption group. For example, as mentioned previously, some studies, such as the ones conducted by Goldsmith, Moore, and Beaudoin (1999) and Schrank and Gilmore (1973), reported that several aspects of fashion innovators and early adopters overlap, and the group is loosely termed as 'innovators'. The late majority are those who adopt new products after they have been widely accepted by the majority of the population. In general, they are sceptical and cautious about new ideas and products. Finally, the laggards are those who prefer 'the old ways' and often prolong the adoption process.

According to a study of adolescents, Beaudoin, Lachance, and Robitaille (2003) found that more female respondents belonged to the category of fashion innovators and early adopters than males. They are more sensitive to brand and play a relatively more significant role in communicating and influencing later fashion adopters. One possible explanation is that female consumers are generally more involved and engaged in fashion consumption and adoption. On the other side of the spectrum, the number of males was significantly higher than females in the last two categories of the DOI model – late majority and laggard.

In another study of fashion leaders and followers conducted by Belleau and Nowlin (2001), the authors found that full-time professionals have higher fashion leadership than part-time professionals. Moreover, the result of a *t*-test has also indicated that most of the respondents who were fashion leaders scored higher in cognitive motivation – meaning that their self-confidence and self-consciousness levels were significantly higher.

According to our literature review, the results of previous studies clearly indicate that fashion leaders have a more favourable attitude towards apparel products than fashion followers. However, no research study has examined fashion innovativeness with multiple products from a cross-national perspective. In addition, data-mining techniques have never been employed for this type of study.

2.2. Objectives and research approach

Fashion adoption has been extensively studied to better understand how fashion leaders influence fashion followers and, in return, to provide valuable information to the decision-makers on product launch and marketing strategies. Previous studies (e.g. Rogers, 1995) listed five categories of fashion adopters: innovators, early adopters, early majority, late majority and laggards. Others argue that the characteristics and behaviours of these fashion consumer groups overlap (Beaudoin, Moore & Goldsmith, 2000; Gorden, Infante, & Braun, 1986), and there is no universal definition or a clear distinction among the fashion change agents. In some studies (Goldsmith et al., 1999; Schrank & Gilmore, 1973), innovators and early adopters were used interchangeably or loosely termed innovators collectively.

For this particular study, our primary objective was to cluster the respondents into three groups of fashion adopters: (1) fashion leaders, who are innovators and early adopters; (2) fashion followers, who are the early majority; and (3) fashion laggards, who are the late majority and laggards.

The second objective of our study is to extract association rules from the data set. Fashion leaders always have a powerful and compelling influence upon fashion followers. Therefore, it is important to discover the hidden relationships between the characteristics of the consumers and the properties of their preferred products in order to help fashion designers in product development and the marketers in launching their marketing strategies/campaigns.

A data-mining tool called RapidMiner was employed to pre-process and analyse the data set. RapidMiner is a Java-based open-source system for data mining, featuring a user-friendly graphical user interface (GUI) (Rapid-I, 2008). It provides all steps of the data-mining processes (made up of various operators) that are described in extensible markup language files and presented in the GUI. Through data-mining analysis, we believe that the results of this study would reflect a higher accuracy in depicting current consumer response.

3. Research analysis and findings

3.1. *RapidMiner and analytical procedures*

In this exploratory study, we employed the open-source tool RapidMiner to analyse our data set. We chose to utilise RapidMiner because it supports every step of data-mining and operation procedures such as data loading, transformation, data pre-processing, visualisation, modelling, evaluation and deployment. In addition, it supports multi-layered data view concepts that ensure efficient and transparent data handling. The first task of proceeding in a linear order was to pre-process our data set, and then cluster similar data into groups, followed by generating class labels for each group of data. After clustering and labelling, we compared gender differences within each category of adopter – fashion innovators, fashion followers and laggards. Furthermore, interesting associations and correlations among the data set were identified.

3.2. *Data used in the study*

The data set in this exploratory study contains a total of 985 samples collected from four locations, with some locations revealing a higher proportion of female respondents (as shown in Table 1). Respondents were recruited from university campuses and the majority were approximately 20 years old. Information was collected through self-administered questionnaire surveys, and in total the data set contained 73 attributes including one special attribute (survey ID); some attributes are listed in Tables 2 and 3.

Table 1. Summary of the data set statistics.

	Locations			
	Toronto (Canada)	Hangzhou (China)	Hong Kong (China)	Johor Bahru (Malaysia)
Male	15	112	22	80
Female	145	188	264	158
Total number	160	300	286	238
Average age	20	22	21	22

Table 2. Item sample of statement about fashion.

- In general, I am the last in my circle of friends to know the names of the latest designers and fashion trends
- Compared to my friends, I do little shopping for new fashions
- In general, I am the last among my circle of friends to purchase a new outfit or fashion
- I know more about new fashions before other people do
- If I heard that a new outfit or look was available through a local clothing or department store I would be interested enough to buy it
- I will consider buying a new fashion even if I have not heard of it yet
- Fashion clothing is a significant part of my life
- I am interested in and think about fashion clothing a lot
- Some individuals are completely involved with fashion clothing, attached to it, absorbed by it, for others fashion clothing is simply not that involving. How involved are you with fashion clothing? (1 = very involved, 5 = not at all involved)
- I find fashion clothing a very relevant product within my life

Table 3. Evaluation of significance for products.

T-shirt	Fit, price, fabric, brand name, colour, comfort, style, country of origin, wardrobe coordination, durability
Evening dress or suit	
Socks	

3.3. *Pre-processing*

In order to ensure reliability, the data set was pre-processed. We also used a data-cleaning technique to fill in missing values and a data-transformation technique to obtain a satisfactory data format to conduct association and correlation analysis. The original data set underwent some pre-processing of merging data sets, removal of invalid data rows and filling in missing values within attributes. However, there are still some missing values, especially for the attributes of colour and race.

In regard to the first section of our questionnaire survey (Table 2), six balanced response levels are used. To compensate for any careless and random answers, some questions in this section were designed to have choices listed in the reversed order. Prior to the data-mining analysis, the scores of all reversed questions were adjusted in order to align with the remaining questions – 'strongly agree' = 6 and 'strongly disagree' = 1.

Although the 'impute missing values' operator in RapidMiner predicted missing values in a carefully designed and sophisticated way, it did not meet our expectations. Therefore, we chose the 'replace missing values' operator to predict missing values instead of filtering them out, and as a result more data could be analysed. For further analysis, cleaned data were directly stored in the RapidMiner repository, and using the RapidMiner Data View, the results of this study could be stored in different ways.

3.4. Clustering

After reversing scores and filling in missing values, RapidMiner was used to perform clustering analysis. Traditional clustering methods were used for subspace clustering rather than conducting experiments on the whole data space (Han, Kamber & Pei, 2011). There are 73 attributes in our data set, but only the first 10 attributes express results of self-evaluation on fashion, while the others are primarily related to specific garments.

Although previous studies (Rogers, 1967, 1976) claim that innovators and early adopters are distinctive groups, these groups inevitably overlap. In this study, we decided to cluster product adopters only into three groups in order to make each group more distinctive:

(1) *fashion leaders* include innovators and early adopters – those who are adventurous and interested in new fashion
(2) *fashion followers* include the early majority – those who follow new fashion trends
(3) *fashion laggards* include the late majority and laggards – those who do not adopt or are the last to adopt new fashions.

Different clustering methods can be used on various types of data sets, such as partitioning methods, hierarchical methods, density-based methods and grid-based methods. In section one of our survey, all attributes are numerical and are scored from 1 to 6 points; therefore, we chose the centric-based technique of k-mean as our partitioning method. This method partitions respondents into k clusters – meaning that respondents in the same cluster are similar to each other but dissimilar to those in a different cluster. It is one of the simplest clustering methods among all partitioning methods.

Although parameter k is specified, the number of clusters is a disadvantage for the k-means method. According to previous research studies, we can easily define the value of k to be equal to a value of three. After the process of data retrieval, the k-means operator was added in the RapidMiner, and the average value of each attribute for each cluster was displayed. Those respondents who received the highest scores were more likely to be categorised as fashion leaders. Conversely, those who had the lowest scores were likely to be fashion laggards and those who received intermediate scores were considered fashion followers (as shown in Table 4).

We integrated the cleaned data from four locations and conducted the clustering analysis. However, the results are not consistent among locations. For example, there were tendencies for remarkably higher proportions of fashion leaders in three locations – Hangzhou, Hong Kong and Johor Bahru – than for Toronto. This is due to a less-distinct distribution of scores received by Canadian participants. Figure 1 is a dot plot of the sum of points from the survey questions. Participants from Hangzhou, Hong Kong and Johor Bahru tended to vary in their fashion adoption patterns, making it easier to define these three groups of adopters. However, there was a smaller difference among Canadian participants.

As such, it becomes difficult to distinguish Canadian fashion leaders from the sample. Therefore, the data sets were analysed separately for each location (as shown in Table 5). Centroid plot views of four locations are shown in Figure 2. In short, our results suggest that the difference in location could have an impact on the clustering results.

Table 4. Results of clustering run together.

	Fashion leader	Fashion follower	Fashion laggard
Canada (Toronto)	19	130	11
China (Hangzhou)	127	36	137
China (Hong Kong)	139	100	47
Malaysia (Johor Bahru)	126	32	80

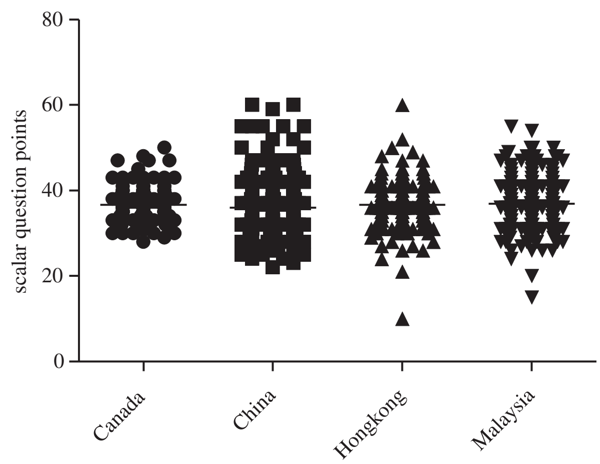

Figure 1. Distribution of scalar question points. (a) Toronto, Canada, (b) Hangzhou, China, (c) Hong Kong, China, (d) Johor Bahru, Malaysia.

Table 5. Results of clustering run individually.

	Fashion leader	Fashion follower	Fashion laggard
Canada (Toronto)	52	89	19
China (Hangzhou)	86	78	136
China (Hong Kong)	87	128	71
Malaysia (Johor Bahru)	101	49	88

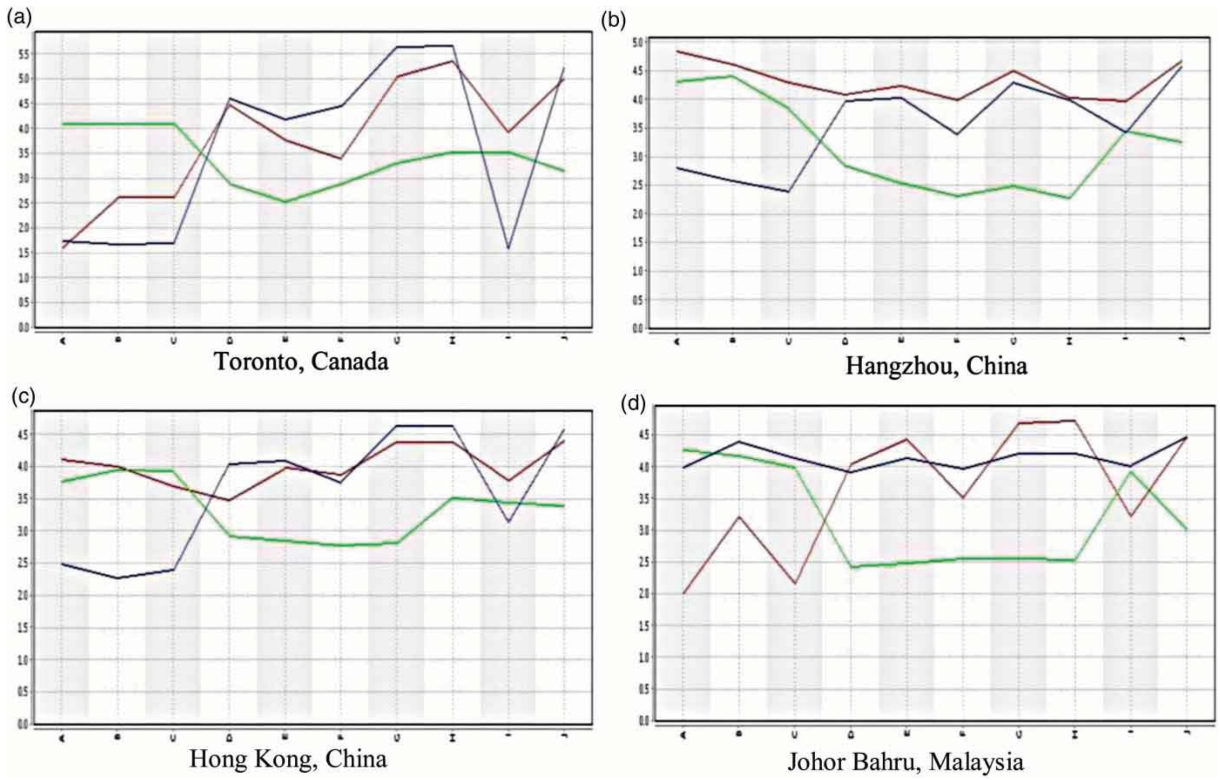

Figure 2. Centroid plot view (red = leader, blue = follower and green = laggard).

3.5. *Association analysis*

In this phase, our objective was to discover the association and correlation patterns existing among these three clustered groups (fashion leaders, followers and laggards) in regard to apparel selection from the four different cities. In order to uncover meaningful and insightful relationships among all these variables, association rule mining was used in our data sets. The two most important steps in the association rule mining process are (Han, Kamber, & Pei, 2011):

- Finding frequent item sets
- Generating a strong association rule from the frequent item sets.

3.6. *Frequent item sets*

We selected the algorithm frequent pattern (FP)-growth in order to find the frequent item sets. The advantages of FP-growth can be summarised into three areas. First, it compresses the database of frequent items into a FP tree (Han et al., 2011). As a result, the process of repeatedly scanning the entire database can be reduced. Second, the 'pattern fragment' approach in the FP tree can be used to avoid the costly generation of large numbers of candidate sets. Third, the partitioning method of 'divide and conquer' significantly reduces the search spaces. Overall, FP-growth is an efficient and scalable mining tool for both long and short FPs.

3.7. *Generate strong association rule*

The association rule that satisfies both the minimum support threshold and minimum confidence threshold would be considered as a strong association rule (Han et al., 2011). In a rule $A \rightarrow B$ with support S and confidence C in a data set D means S is the percentage of transactions in D which contain $A \cup B$ where the probability considered is $P(A \cup B)$ and C is the percentage of transactions in D containing A that also contain B, considered as conditional probability, $P(B|A)$. In this experiment, we generally set the threshold value of the minimum support and minimum confidence at 50%. However, the total population of each cluster group from each country was also considered to determine the confidence threshold. For example, in Canada 89 participants fell into the group of fashion followers among 160 participants in total. Therefore, by dividing the total number of population by the total number of fashion followers, we concluded that about 56% of the total participants are fashion followers. Therefore, we considered only the association rules that have a confidence level of more than 56%. In addition to the confidence level we also considered the positive lift value. Lift is a correlation measure where it presents the occurrence of item set A as independent of occurrence of item set B where $P(A \cup B) = P(A)P(B)$. If the Lift value is negative then it is negatively correlated and if the value is greater than 1 then it is positively correlated. If the value is equal to 1 then there is no correlation between the two item sets.

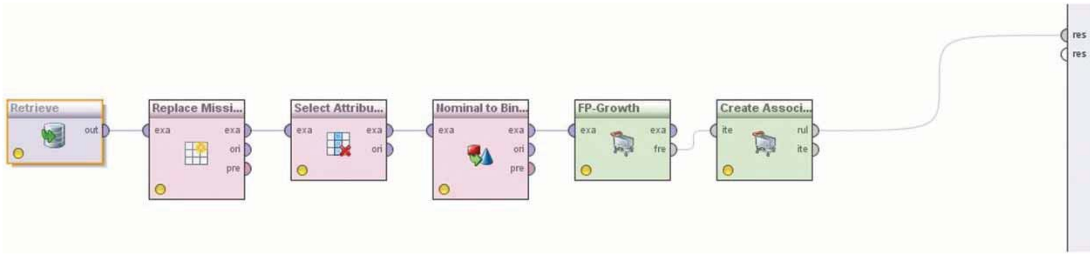

Figure 3. Association rule mining process.

Table 6. Association between three groups and their clothing preferences.

City	Rules	Support	Confidence	Lift
Toronto	[Fashion Leader] → [TshirtFit = 5, TshirtStyle = 5]	.25	.596	1.62
	[TshirtFit = 5, TshirtComfort = 4] → [Fashion Follower]	.175	.750	1.29
	[EveningDressStyle = 5, EveningDressPrice = 4]→ [Fashion Follower]	.28	.685	1.61
	[Fashion Leader] → [EveningDressColour = 5]	.195	.596	1.19
	[Fashion Leader] → [SocksDurability = 5]	.22	.538	1.99
Hangzhou	[Fashion Laggard] → [TshirtFit = 5, TshirtComfort = 5]	.23	.537	1.46
	[Fashion Laggard] → [EveningDressFit = 5, EveningDressComfort = 5]	.25	.515	1.32
	[Fashion Leader] → [SocksComfort = 5, SocksFit = 5]	.35	.581	1.66
	[Fashion Laggard] → [SocksComfort = 5, SocksFit = 5]	.22	.588	1.23
	[Fashion Follower] → [SocksComfort = 5, SocksFit = 5]	.21	.654	1.69
Hong Kong	[TshirtColour = 4, TshirtComfort = 4] → [Fashion Follower]	.15	.529	1.63
	[EveningDressPrice = 4, EveningDressFabric = 4] → [Fashion Follower]	.23	.556	1.56
Johor Bahru	[TshirtComfort = 5, TshirtStyle = 5] → [Fashion Leader]	.21	.561	1.70
	[Fashion Leader] → [EveningDressComfort = 5]	.27	.594	1.66
	[Fashion Laggard] → [SocksFit = 5]	.21	.568	1.23
	[Fashion Leader] → [SocksComfort = 5]	.23	.604	1.69

We initially imported the data set into the RapidMiner repository. Some pre-processing steps were applied before association rules could be applied to our data sets. In the survey question 'What colour do you prefer for the following clothing items?' many of the values are missing. In order to fill in the missing values we considered the value that the majority selected. Additionally, in the data set from China, the 't-shirt-origin' in part 1, two values were missing, and since so few were not presented we took the average number of the total values. Moreover, all the attributes needed to be transformed to Boolean values where the whole table was considered as Boolean vectors. These Boolean vectors analysed information to find the patterns that reflect frequently associated items. In the RapidMiner the operation nominal to the Binominal performs this transformation step after we applied the FP growth algorithm directly to these transformed values. Figure 3 shows the complete process of association rule mining in RapidMiner.

Association rule mining was divided into two parts. In the first part, we attempted to discover the pattern preferences of each cluster in terms of t-shirts, evening dresses/suits and socks from four different countries. The survey questionnaire was designed to measure on five-point scales where 1 = unimportant and 5 = most important. Table 6 shows the comparison results of the association rules from these distinct locations.

From Table 6, we found some interesting patterns where China produced the results. In terms of t-shirts and evening dresses/suits, 53% and 51% of fashion laggards in China had shown strong preferences for fit and comfort, respectively. Additionally, all three groups have the same preference level regarding socks in this country. According to our finding, the comfort and fit for socks are the most important. In contrast, 60% of the fashion leaders in Canada had shown a strong preference for fit and style of t-shirts. For socks, fashion leaders in Canada prefer durability. This observation is further confirmed by the lift value, where having a lift value between 0 and 1 implies a negative correlation, and having a lift value between 1 and 2 implies a positive correlation. The association rule [Fashion Leader] → [SocksDurability = 5] in Canada has a confidence of 54% with a lift value of 1.99, indicating a strong positive correlation between fashion leaders and durability of socks. According to the results of the present study, style was not an important factor for the fashion leaders to purchase socks in Toronto, Hangzhou and Johor Bahru. Among all the participants in Toronto, 22% were fashion leaders and they chose SocksDurability = 5; 35% of participants in Hangzhou were fashion leaders and they chose SocksComfort = 5 and SocksFit = 5; and 23% of participants in Johor Bahru were fashion leaders and chose SocksComfort = 5. It is evident that style, colour and price

Table 7. Association between three groups and their clothing colour preferences.

City	Rules	Support	Confidence	Lift
Toronto	[Q6DWeddingDress = white, Q6HPants = black] → [Fashion Follower]	.158	.556	1.33
	[Fashion Leader] → [Q6DWeddingDress = white, Q6BSocks = white]	.188	.500	1.56
Hangzhou	[Q6DWeddingDress = white, Q6BSocks = white, Q6GTShirt = white] → [Fashion Laggard]	.172	.556	1.24
Hong Kong	[Fashion Follower] → [Q6DWeddingDress = white, Q6BSocks = black]	.156	.602	1.23
Johor Bahru	[Q6DWeddingDress = white, Q6CHoodieTop = black] → [Fashion Leader]	.21	.500	1.56

played a less significant role in evaluating, purchasing and using socks. The reasonable explanation is that fashion leaders did not pay much attention to style, colour and price because they knew exactly what they wanted to purchase prior to their shopping experience. In addition, visual features (style and colour) often play a more important role on symbolic and publicly consumed products than invisible and privately consumed products such as socks (Rahman, Yan, & Liu, 2009; Rahman, Zhu, & Liu, 2008). In terms of the purchase of evening dresses/suits, 19.5% of fashion leaders in Toronto preferred colour while 27% of fashion leaders in Johor Bahru chose comfort.

In the second part of our survey, colour preferences were examined and analysed based on the specific clothing type within each clustered group. The chosen clothing products include sleepwear, socks, hoodie sweatshirts, wedding dresses, evening dresses, summer dresses, t-shirts, pants, bathing suits and tank tops. Table 7 shows the association results, and the most significant outcome that we have found is that regardless of the different groups and various countries the preference for colour of wedding dresses is consistent for our participants. Clearly, a white wedding dress was widely accepted by the respondents because of its symbolic meaning and values (e.g. purity) (Chu & Rahman, 2012) – which have been consciously and unconsciously embedded in a consumer's mind through associative learning.

In terms of purchasing a pair of socks, black and white were frequently selected by the consumers. It is reasonable to suggest that consumers generally know what kind of socks they want to purchase – e.g. black, mid-calf length socks to coordinate with formal attire or suits. Therefore, they seldom spend an enormous amount of time and effort to contemplate, search and evaluate an ordinary and invisible product. According to some studies (Rahman et al., 2009; Rahman, Yan, & Liu, 2010), consumers tended to spend more time on publicly consumed products than privately consumed products to construct their identity, elevate social status and/or express personal taste and ideologies.

4. Conclusion and limitations

In the current exploratory study, we have demonstrated how to use association rule mining to automatically extract interesting patterns from a large collection of survey data. The extracted association rules provide insightful information for apparel manufacturers to design and promote future products for a specific targeted market or group. Clearly, some product attributes may be perceived differently, but other attributes (e.g. colour of wedding dress) may be perceived to be the same across consumer groups/cities. In addition, according to our study, the evening dress designers should focus on fit and comfort for the fashion laggard market in China. In a similar vein, socks manufacturers should pay more attention to the functional aspects (comfort, durability and fit) of the products than on style and colour. Furthermore, at the retail level, an online apparel store may efficiently classify a new customer as a fashion leader, a follower or a laggard by employing this type of study, and recommendation of relevant products could be made according to the needs and aspirations of each consumer group. The present exploratory study has limitations as most research studies have. The size of the sample located in Toronto and consisting of male participants is relatively small. More replication of this type of study in the future is needed to strengthen data validity and reliability.

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