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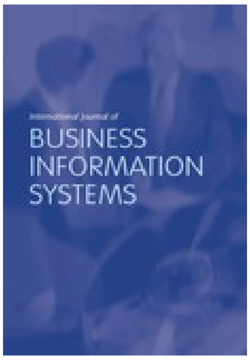

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Chi On Chan, Henry Lau, Youqing Fan

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Modelling intended product demand in fashion retail using IoT and AI

Chi On Chan*

Department of Business Administration,
Hong Kong Shue Yan University,
Hong Kong, China
and
School of Business,
Western Sydney University,
Sydney, Australia
Email: cochan@hksyu.edu
*Corresponding author

Henry Lau and Youqing Fan

School of Business,
Western Sydney University,
Sydney, Australia
Email: h.lau@westernsydney.edu.au
Email: y.fan@westernsydney.edu.au

Abstract: The fashion industry operates in a fast moving and dynamic environment which requires fashion designers to respond to market trends quickly and continuously. This study investigates potential for application of internet of things (IoT) and artificial intelligence (AI) in fashion retail. The customer product interaction that takes place in retail stores reflects hidden preferences. As information now spreads faster than ever before, sharing product information or product evaluation by different groups can be reported in no time, which can help estimate real demand of products. But detecting these changes in real time has been difficult in the past. However, this paper analyses data collected by using IoT through the application of adaptive neuro-fuzzy inference system to learn demand changes, so as to know the intended product demand in real time.

Keywords: internet of things; IoT; fashion retail; customer product interaction; CPI; adaptive neuro-fuzzy inference system; ANFIS; artificial intelligence; AI.

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Biographical notes: Chi On Chan has over 30 years of industrial, training and consultancy experience in the field of operations management and business process improvement. His research interests are business process management and improvement, Six Sigma and LEAN, business statistics, operations management, supply chain management, and quality management. He holds a BSc (Engineering) degree in Engineering from University of Hong Kong, MSc, MEng and postgraduate study from Imperial College London, Oxford

University, UK and Sydney University in Australia respectively in technology field. He received his Doctorate degree from City University of Hong Kong in Engineering Management.

Henry Lau is currently a Senior Lecturer of the School of Business at The University of Western Sydney, involved in research and teaching activities. He received his Master's degree at Aston University in Birmingham in 1981 and Doctorate at the University of Adelaide in 1995. His current research areas cover logistics and supply chain management, operations research, engineering management and artificial intelligence systems. He has published about 230 refereed journal papers, 11 book chapters, one textbook and attracted a total of HKD 20 million in research grants during his time in HK PolyU.

Youqing Fan was an Assistant Professor of Chinese business and economy at Nottingham University's China campus from 2013–2015, prior to joining UWS. He also used to serving as a teaching and research associate at University of Melbourne and Monash University from 2010–2013. Over the past ten years, He has won awards or scholarships from Australian and Chinese governments to fund his PhD, master, and undergraduate studies. Of particular importance is the highly competitive merit-based award scheme, the Endeavour Postgraduate Award, which provided him an approximately AUD$200,000 funding in total for his PhD study in Australia.

1 Introduction

The fashion industry operates in an increasingly fast moving and dynamic environment which requires fashion companies to be highly responsive to market trends in order to capture potential customers. Market acceptance of products is crucial for both supply chain and product designers (Hilletofth and Eriksson, 2011; Schoenherr and Swink, 2015; Hall and Schneider, 2011; Primus and Stavrulaki, 2017). But obtaining real-time and extensive information of the ever-changing consumer preferences at the retail level has historically been difficult (Camargo et al., 2020; McNeill and Moore, 2015). The online to offline (O2O) concept has become increasingly popular in recent years, as this approach to marketing offers a new way for fashion retailers to expand business and boost sales (Wang et al., 2021; He et al., 2021). While browsing behaviours on-line are being traced (Williams and Waller, 2011; Nilashi et al., 2015; Hwangbo et al., 2018), in-store behaviours in brick-and-mortar stores have seldom been traced and responded to appropriately. Under these conditions, ability to detect and understand customer product interaction (CPI) may constitute a competitive advantage. The retailer is keen to know everything about the customer the moment he or she enters the store, in order to tailor a marketing message that meets specific needs of the customer (Landmark and Sjobakk, 2017; Karpischek et al., 2012).

The model proposed in this paper collects information of how the customers are behaving toward specific products in brick-and-mortar stores through internet of things (IoT) in real time. CPI includes the time taken by the customer to hold a specific product, the number of times it is taken out and put back on the shelf, and number of times it is tried per day in the fitting room. These indicators contain ambiguity. How long is too long and how quick is quick enough is always debatable (Dogan and Öztaysi, 2018; Wu et al., 2015); due to subjective uncertainty and the imprecise meaning of preferences, fuzzy logic provides an excellent framework for describing uncertainty, vagueness and imprecise data (Yan and Ma, 2015; Sadikoglu, 2017). Especially, after a new product is launched in the market, its demand changes according to the different stages of the product life cycle. Therefore, detection of any change in the frontline demand in real time and taking decisions on the basis of data collected has become crucial for marketers and designers. Subjective determination of membership function is very common in fuzzy logic (Khokhar et al., 2020). The proposed model for the proper use of adaptive neuro-fuzzy inference system (ANFIS) can help adjust its membership function by learning from the data collected, so that the fuzzy inference system (FIS) can more accurately reflect its results (Esfahanipour and Aghamiri, 2010; Gharghan et al., 2018).

Figure 1 The concept of IoT in fashion retail (see online version for colours)

Now sensing devices such as radio frequency identification (RFID), Beacon, closed-circuit television (CCTV) and near field communication (NFC) (Figure 1) can be used to track CPI in a manner similar to the general clickstream behaviours online (Chan et al., 2018). Therefore, this research proposes a model for use of IoT to study CPI in-store and application of artificial intelligence (AI) to detect the trend of consumer behaviours toward the product. The proposed research is expected to assist fashion retail in capturing and analysing data from the front-line market situation by using sensing devices and wireless technology. The results from such analysis can provide intended product demand (IPD) instantly for reference. Fashion retailers can plan their marketing and supply chain strategies and respond more quickly to the fast-moving, dynamic trends as they seek to attract potential customers and keep existing customers (Choi, 2018; Ovezmyradov and Kurata, 2019).

POS can record only the customer's buying decision, i.e., what has been purchased. It cannot tell us whether the customer has made the purchase intentionally or emotionally (Narayanan et al., 2019; Hartzel and Wood, 2017). Scenario 1 of Table 1 indicates that some customers have clear intention to buy as they pick up and look through the product and finally make the buying decision. On the other hand, some customers pick up or look around the products for varying durations, but they eventually do not buy and there is no record of that in POS (see scenario 2). Scenario 3 represents that some customers pick up without detailed looking through the products and then pay the bill in cash. Scenario 4 is easily understood. The customers just wander around the display shelves/racks without picking up and buying any product until they leave the store. However, the purpose of this study is to collect data indicative of CPI in brick-and-mortar stores through IoT and to deduce IPD using ANFIS.

Table 1 Different shopping and buying behaviours

Scenario	*1*	*2*	*3*	*4*
Show interest on specific products	Yes	Yes	No	No
Make buying decision	Yes	No	Yes	No

The CPI data collected in the store through IoT are ambiguous. For example, how long should a customer have held a product for treating it as long? The definition of membership function by experts alone cannot avoid subjectiveness. This paper uses ANFIS to redefine the membership function from the collected data and make the results more objective. The research objectives of this paper can be summarised as follows:

1 How to collect CPI data in fashion retail stores through IoT platform?

2 How to apply ANFIS to ensure the collected data more objectively reflect the IPD?

The rest of the paper is structured as follows. Section 2 provides a review of literature related to CPI in fashion retail, IoT and ANFIS; Section 3 explains the methodology; Section 4 illustrates the model development and case example; in Sections 5 and 6, the results and conclusions of the study are presented.

2 Background

2.1 CPI in fashion retail

In online shopping, the main task of the recommender system is to recommend the right product to the customer. Analysis of human-website interaction pattern can be used to observe user preferences. Researchers have studied customers' online behaviours (Table 1) such as monitoring mouse usage, scrolling activities and time spent on website, total distance of vertical page scrolling, total distance of mouse pointer movement, clickstream compactness, clickstream stratum, revisited page ratio, etc. (Sulikowski et al., 2017; Senecal et al., 2005), and contextual factors such as website characteristics also affect online shopper purchase intention (Mallapragada and Chandukala, 2016; Aslam et al., 2019; Pujadas-Hostench et al., 2019). Recent studies show quality of personalisation leads to high product demand in e-commerce (Pappas et al., 2015). Unfortunately, few similar studies have been conducted for examining offline consumers' behaviours; a more accurate description is that the real-time customer preferences for the product obtained through analysis of behaviour between customer and products at the physical store are missing (Nurhayati and Hendar, 2017). This paper is targeted to fill this gap. Comparison of customer interaction online and offline in retail is shown in Table 2.

The CPI must be considered as a part of the decision-making process and of purchasing behaviours which can be viewed from both attitudinal and behavioural perspectives (Chan et al., 2018). Zuo and Yada (2015) use statistical learning theory to analyse purchase behaviour in-store (Zuo and Yada, 2015). However, it is not in real time. Pantano and Timmermans (2014) discuss the features of IoT technology in the retail context but fail to discuss customer interaction with products and environment. For instance, if a consumer spends more time in a store or holds the product for a longer time, she/he may become more purposeful. Therefore, the study of CPI helps better understand the factors that drive the dynamics of a consumer's shopping trip and incentives (Hui et al., 2009).

Table 2 Comparison of CPI in online and offline retail

	Online	*Offline*
Name	Customer-website interaction	Customer product interaction
Place	Website	Brick-and-mortar
Implicit interaction	Mouse move/clicks/scrolls, keyboard input, text selection, copy event (Sulikowski et al., 2018)	Product picked up, product hold time, product tried in fitting room (Liaghat et al., 2013; Landmark and Sjobakk, 2017)
Application	Design, ergonomics and usability of a website design layout	Product selected to display in-store design and layout guidance for salespeople recommendation
Data analytics (recommender system)	Collaborative filtering content-based filtering hybrid (Adomavicius and Tuzhilin, 2005; Walter et al., 2012)	Fuzzy logic adaptive neuro-fuzzy inference system

Many retailers still do not provide POS data to their suppliers. Some high-profile retailers, such as Walmart, readily share POS with suppliers. In most cases, forecasts based on POS data exhibit lower forecast errors than those based on order data (Williams and Waller, 2011). Demand or showing interest is always greater than the sales data recorded in POS. However, some information is still missing in the process of forecasting besides POS data, which is not shared with the supplier. In this research, CPI data are considered. This hitherto ignored data can be used as complementary information for supply chain planning. It is especially important for gauging instant popularity or acceptance of a newly launched product. Any fast response in a dynamic market such as fashion is crucial. Application of IoT to capture CPI is still rare. It is crucial for fashion retailers to respond to changes in styles. However, overlooking customers' first impression of the product expressed by touching and picking it in-store may provide some indication of preferences. These behaviours are seldom captured or considered as demand for the product, unlike browsing on the Internet where browser tracking is common. In the most recent works on in-store customer behaviours, for example, some researchers have used RFID to track customer behaviours in the usage of fitting room and the relationship between treatments of different products. However, their research was limited to single behaviour instead of multi-behaviours in-store (Landmark and Sjobakk, 2017; Liaghat et al., 2013).

2.2 IoT

The IoT is recognised as one of the most important areas of technology in the future and is gaining vast attention from a wide range of industries (Abbass and Mehmood, 2020; Sabry, 2021; Asghari et al., 2019). The IoT system can capture real-time data through the use of digital objects or devices, facilitate integration of the data and help analysts make better operational decisions such as monitoring, control, optimisation and autonomy in terms of higher efficiency, privacy, convenience, security and high quality decision making in retail environment (Porter and Heppelmann, 2014; Balaji and Roy, 2017; Weinberg et al., 2015). Recently, researchers have studied use of sensor technologies to monitor elderly persons suffering dementia (Newcombe et al., 2017). Another application in medical field, for example, is monitoring all parameters such as heart rate, respiration, blood oxygen and skin temperature of patient at home. These can be linked to the health care unit. In case of another potential application researchers used IoT in hotel environment to collect guest reviews without indicating each guest. However, the data provided is not real-time (Shoukry and Aldeek, 2020). There are also some sensing technologies being applied in retail environment. For example, Grewal et al. (2018) used eye-tracking technology to study the effect of mobile phone use in-store having positive significant effect on some in-store customer behaviours (Grewal et al., 2018). Generosi et al. (2018) proposed an emotional tracking system to monitor the customer's shopping experience in retail store using biometric data and facial expressions (Generosi et al., 2018). Most applications in retail are using a single sensing device and without further data analytics. In this study, we propose to use multi-sensing devices to capture in-store behaviours. For example, RFID, NFC, Beacon and CCTV camera which can help understand the interest of the customer in a given product completely.

2.3 ANFIS

Retailers can use AI to analyse customer shopping behaviours by identifying the pain points. Researchers predict that the future of physical stores will eventually be dominated by AI (Shankar, 2018; Pillai et al., 2020), with smart sensors and robots replacing humans in applications from demand forecasting to segmentation, to recommender systems, to inventory management. Some researchers use similarity and neighbourhood based collaborative filtering model for predicting user preferences as the effect is better than traditional collaborative filtering model, but these are only used in online retailing (Shamshoddin et al., 2020).

In this research, we propose to use fuzzy logic and ANFIS to address the problem. Human decisions can use fuzzy logic approach. Using IoT can obtain a set of experiential data. These data can generate some knowledge in neural networks. Integration of the fuzzy system and neural networks is very suitable since systems without a priori information such as interaction between customers and retail contexts and associated uncertainties in fashion trends can learn from experiential data (Paul et al., 2015; Tadesse et al., 2019).

ANFIS can replace humans in the knowledge acquisition process by using a training process with a set of input-output training dataset (Mehrbakhsh et al., 2014). Thus, instead of depending on human experts the neuro-fuzzy system can determine the parameters associated with the neuro-fuzzy system through a training process, by minimising an error criterion.

ANFIS are a class of adaptive neural networks that are functionally equivalent to FIS. They offer a combination of learning, adaptability and nonlinear, time variant problem-solving characteristics of artificial neural networks plus the important concepts of approximate reasoning and treatment of information provided by the fuzzy set theory (Mavi et al., 2017; Jang, 1993; Al-Hmouz et al., 2012). In fashion retail, data sets are large. It does not cover only one retail; for example, for Zara, it can cover up to 2,200 stores around the world. If the input/output data set is large, fine tuning of MFs is necessary as the MFs determined by an expert may not be optimal. However, it can be considered as an initial setting. In this study, three in-store behaviours are selected as a crisp signal collected by sensing devices under IoT platform. All these behaviours are then used to formulate the product of interest.

3 Methodology

The model established in this research obtains data on the interaction between customers and products in brick-and-mortar stores through the IoT platform (Figure 2). IoT are used in retail businesses because of their ability to uniquely identify products, ease of communication and their ability to provide real time information (Sarac et al., 2010; Fu et al., 2020). The model is constructed using a three stage architecture (Figure 3) which has

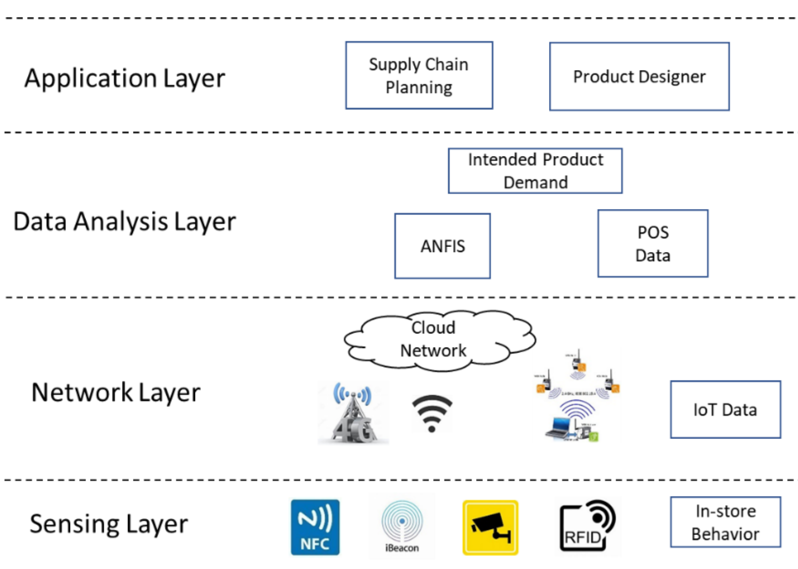
1 CPI data collection

2 data inference system

3 data analysis using ANFIS.

The CPI data such as product holding time, product pick up frequency and product tried in fitting room are used for generating the expected product demand. In this stage, instead of using physical sensors and IoT systems to collect data, the data developed in the research are based on a case company, with the input from the field expert, and data are slightly adjusted for illustration purpose. Therefore, this research is more focused on the data analysis layer. Simulation was conducted by using MATLAB 2018a (fuzzy logic tool box and neural network).

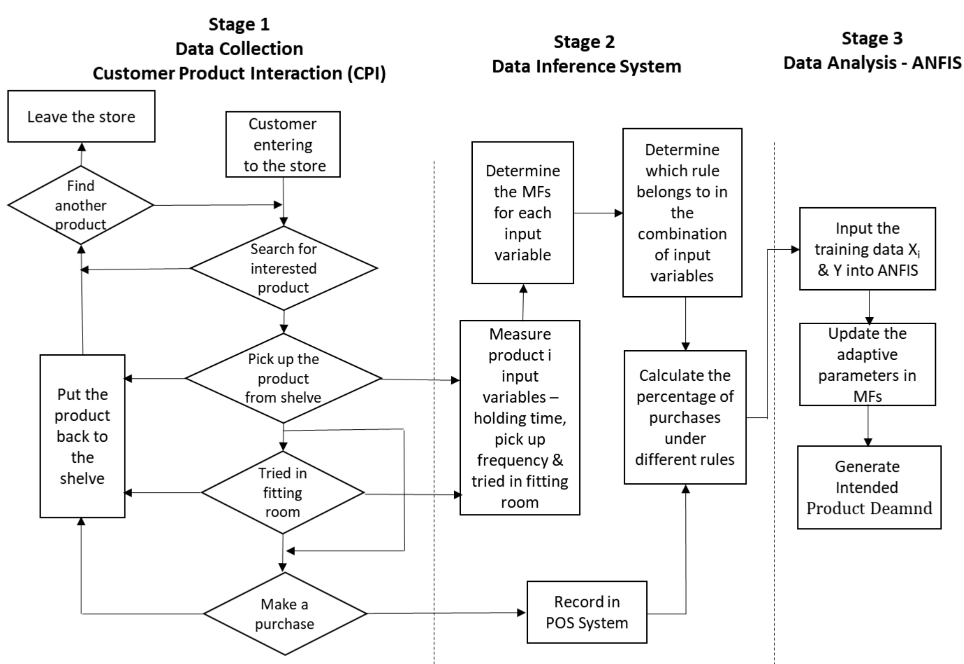
Figure 2 IoT data collection framework (see online version for colours)



4 Modelling and case illustration

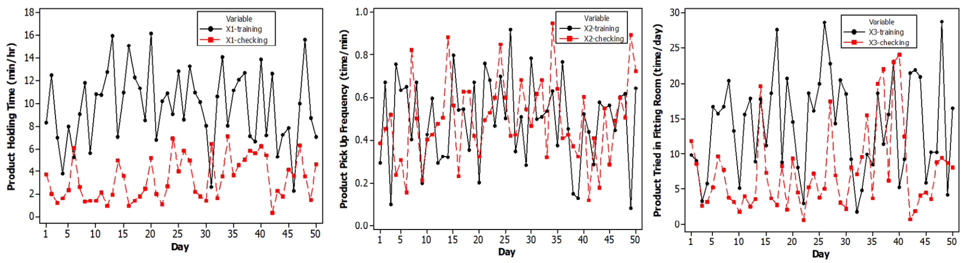
The case company in this study is a women's fashion retail store located at an area with high people flow in Hong Kong. The store is about 1,100 square feet with two fitting rooms and has about 100 kinds of products on shelves and racks. The business hours are from 10 am to 10 pm daily. The data collected is based on the observation of CPI (Figure 3) and is considered as an input variable, covering a period of 100 days in total. Therefore, 50 days is used for training dataset and another 50 days is used for checking dataset. The data was collected in different periods of time. $A = \{(x, \mu_A(x)) | x \in X\}$ where $\mu_A(x)$ is called the membership function for the fuzzy set A. X is referred to as the universe of discourse. The membership function associates each element $x \in X$ with a value in the interval [0, 1]. Here, we use the three CPIs X_1, X_2 and X_3, to represent three different fuzzy sets and their purchasing decisions as observed and recorded. To simplify the problem, the fuzzy set of each behaviour is the same, i.e., low, medium and high. Purchasing decisions of customers with the same combination were recorded and calculated as percentages of purchase. This is then used as a dataset for training and checking.

Figure 3 Model of CPI using IoT-AI in fashion retail



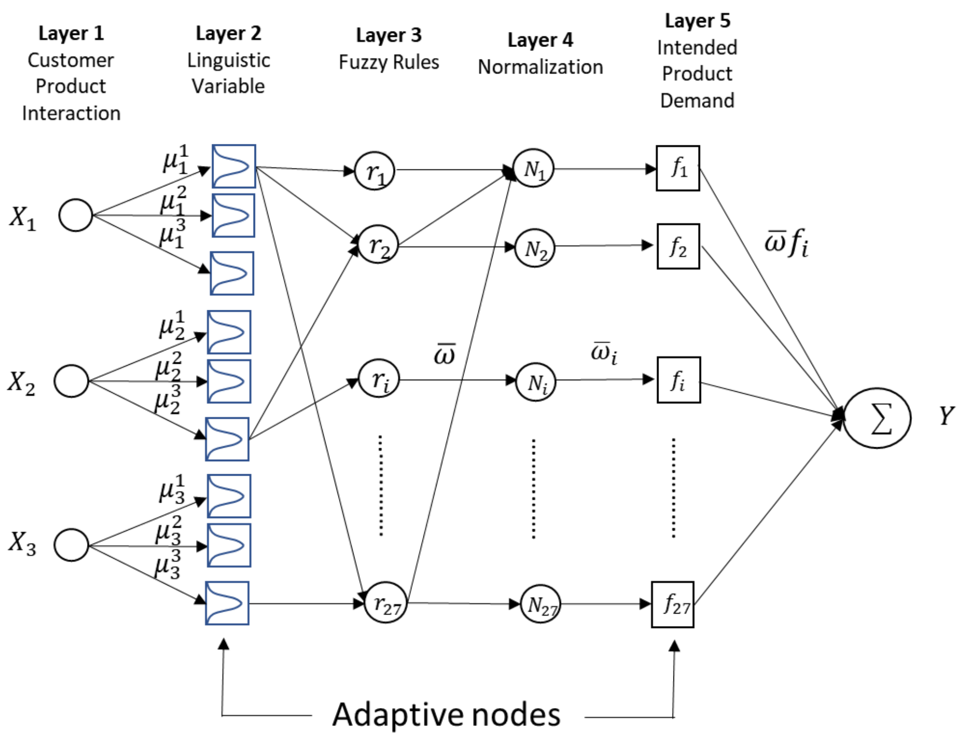
In order to easily show the operation of the entire model, three highly common CPIs, namely a specific product's holding time, number of times it is picked up and number of times it is tried in fitting room are selected. The customer's appearance is recorded anonymously through the CCTV pointing to shop entrance. After the customer is identified, the customer's interaction with the specific product (A) in the store is linked. For example, if the customer picks up and puts back the product A in the shelf it is immediately sensed, and the time and frequency are recorded as average time per hour for which that customer held product A, i.e., X_1 (min per hour) and the average number of times product A is picked up by customers per minute, i.e., X_2 (time per min). RFID is used to detect the movement of the product in and out of the fitting room as the average number of times product A enters and exits the fitting room per day, i.e., X_3 (time per day). These variables are inputs in layer 1. These input variables of training and checking dataset are plotted in Figure 4.

Figure 4 Input variables of training and checking dataset (a) product holding time, (b) product pick up frequency and (c) product tried in fitting room (see online version for colours)



(a) (b) (c)

Figure 5 ANFIS architecture for IPD driven by CPI (see online version for colours)



In this research, the three types of CPIs in a fashion store are captured by IoT technologies and the collected data is analysed by ANFIS algorithm based on the approach of Figure 5. The ANFIS algorithm is a combination of neutral network and FIS. The rules generated in layers 2 and 5 below that are adaptively learning to approximate nonlinear function through steepest descent nonlinear optimisation techniques. CPI data are highly nonlinear in nature and ANFIS approach is a better choice for seeking high predictability rates (Krishankumar and Ravichandran, 2018).

Layer 2 Input variable MF definition

Next to the Layer 1 of buying behaviours X_1, X_2 and X_3, every node in this layer is an adaptive node with bell-shaped MF. Among them, the mean, standard deviation and slope are adapted and changed according to the collected data. These nodes calculate the membership grade of the inputs according to (1) where n_j^k is MF of input variable X_k with k = 1, 2, 3 in this case.

$$\mu_{n_j^1}(X_1) = \frac{1}{1+\left|\frac{X_1 - m_{n_j^1}}{\sigma_{n_j^1}}\right|^{2b_{n_j^1}}}, \mu_{n_j^2}(X_2) = \frac{1}{1+\left|\frac{X_2 - m_{n_j^2}}{\sigma_{n_j^2}}\right|^{2b_{n_j^2}}}, \quad \mu_{n_j^3}(X_3) = \frac{1}{1+\left|\frac{X_3 - m_{n_j^3}}{\sigma_{n_j^3}}\right|^{2b_{n_j^3}}}. \tag{1}$$

n_j^1, n_j^2 and n_j^3 represent the number of MFs in input variables such as $x_1 = \{n_j^1, n_j^1, n_j^1\}$ or {L, M, H} in this case. $\{m_{n_j^1}, \sigma_{n_j^1}, b_{n_j^1}\}, \{m_{n_j^2}, \sigma_{n_j^2}, b_{n_j^2}\}$ and $\{m_{n_j^3}, \sigma_{n_j^3}, b_{n_j^3}\}$ with j = 1, 2, 3 are the parameters of the input MFs, where $m_{n_j^1}$ is mean, $\sigma_{n_j^1}$ is standard deviation and $b_{n_j^1}$ is slope of MF. The MF narrows with increasing value of $b_{n_j^1}$, representing that the distinction between MFs is relatively obvious.

Learning of the antecedent MFs

Layer 3 Rule

This research studies three input variables (X_1, X_2 and X_3) each of which has three MFs. A total of 27 rules are generated, labelled r_i, i = 1, ……, 27. Each node in this layer is a fixed node and determines the firing strength of a rule defined in equation (2).

$$w_i = \mu_{n_j^1}(X_1) \cdot \mu_{n_j^2}(X_2) \cdot \mu_{n_j^3}(X_3), \ j = 1, 2, 3 \tag{2}$$

Layer 4 Normalisation

Every node in this layer is a fixed node labelled N_i, i = 1, 2 …… 27. Each node calculates the normalised firing strength of the i^{th} rule according to equation (3).

$$\overline{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i}, \ n = 27 \tag{3}$$

Layer 5 Consequent parameters

Each input variable X_i and output Y (IPD) are assumed to have a linear relationship. Each node in this layer is an adaptive node with a linear function as defined by equation (4).

$$f_i = a_i X_1 + b_i X_2 + C_i X_3 + d_i \tag{4}$$

where a_i, b_i, c_i and d_i are the parameters of the consequent part of rule r_i. Each node calculates the weighted value of the consequent part of each rule in equation (5).

$$\overline{w}_i f_i = \overline{w}_i \left(a_i X_1 + b_i X_2 + C_i X_3 + d_i \right) \tag{5}$$

The single node in this layer produces the overall output Y, IPD by aggregating all the fired rule values in equation (6).

$$Y = \sum\nolimits_{i=1}^{n} \overline{w}_i f_i \tag{6}$$

where n is the number of rules generated based on product operator of input variables. In this case, n is 27.

In the ANFIS learning algorithm, the training dataset is offered to the ANFIS cyclically. Each training cycle is composed of a forward and a backward pass (Negnevitsky, 2002; Jang and Sun, 1997). By using adaptive nodes in layer two (m_n, σ_n and b_n) and layer five (a_i, b_i, c_i and d_i these parameters can be adjusted after learning, which can be explained through the results obtained.

Examples of dataset to illustrate the measurement of each input variable X_i and calculation of output variable Y.

Example 1 On day one, product A was held by customers for 8.29 minutes per hour on average. The average number of times it was picked up by a customer was 17.4 times per hour or 0.29 times per min, and the average number of times it was picked up and taken out to the fitting room is 9.8 times per hour. And it is observed whether the customer finally bought product A. According to this combination and calculation of percentage of purchase of product A with this same combination, the chance of buying this product works out to 0.3234.

Example 2 Product A was held by customers for 12.45 minutes per hour on average on day two. The average number of times it was picked up is 40.2 times per hour or 0.67 times per min, and the average number of times it was taken out to the fitting room is 8.9 times per hour. It is observed whether the customer eventually bought product A. According to this combination and calculation of percentage of purchase of product A with this same combination, the chance of buying this product is 0.5937.

A similar dataset was taken for 50-days in total to train the model. Another 50-days to check the model.

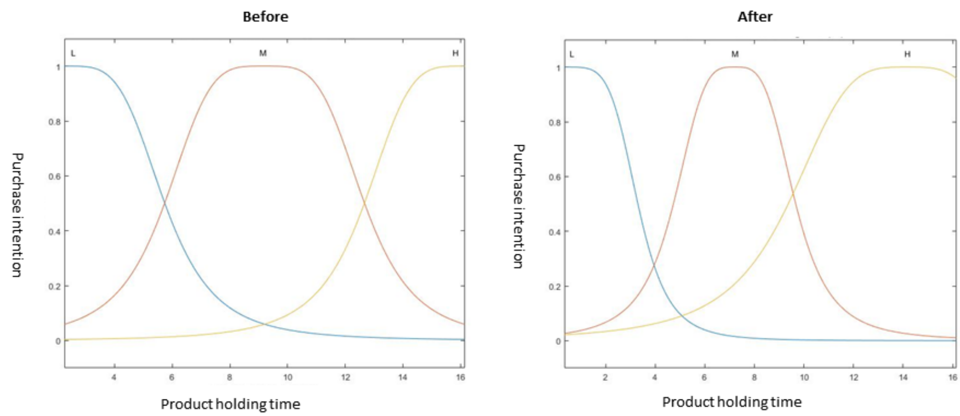
There are arguments that learning mechanisms should not be applied in MFs since they represent a subjective description of the problem. MFs should be kept fixed if the available input/output data set is small. However, if the input/output data set is large, fine-tuning of MFs is necessary as MFs determined by experts may not be optimal (Siddique and Adeli, 2013). After collecting certain data application of ANFIS can redefine the membership function of each input variable. For fast fashion brands, such as Zara, H&M and UNIQLO, have thousands of brick-and-mortar stores worldwide. Buying behaviours and product popularities relationships are subjectively judged by salespersons in the stores. By applying ANFIS learning algorithm, the relationships can be objectively established based on the collected big data.

5 Results

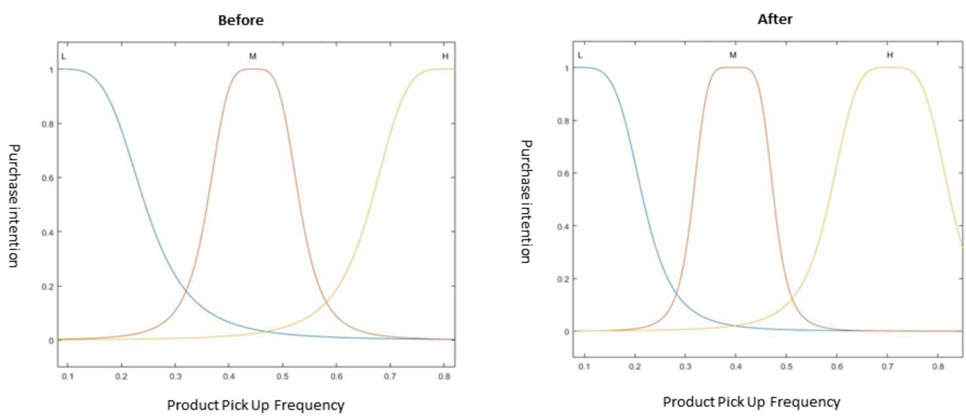
The results reported in this section are after applying training and checking dataset covering three inputs and one output. Section 4, Table 3 show the parameters value of each membership function before and after applying ANFIS. In Figure 6, the mean (m) value of membership function of the three input variables has a decreasing trend while only the low level of X_3 has a slight increase. The value is more clearly shown in Table 4, where the low and medium level changes of X_1 are 95.581% and 21.765% respectively, while the membership function of X_3 changes 26.212%. In table, the medium and low-level MFs of X_1 and X_3 have decreased significantly, i.e., 28.864% and 49.372%% respectively, while high level membership functions of X_1 have increased 37.45%. This shows that the standard deviation (σ) of the membership function of the CPI in product holding time and product tried in fitting room changes significantly after application of ANFIS, showing that the actual behaviour of customers in this group is quite different from the original group. This result shows that this adaptive parameter set of the input membership functions such as mean and standard deviation was learnt from the updated data. It is especially important for retail environment since the set of input data is large. It is necessary to fine-tune MFs instead of using an expert input only. This also means that behaviours of customers of these groups are different. The low-level membership function of X_1 and X_3 have a more obvious change in slope (b) (Table 4); the fuzzy range is reduced, and the slope increases 30.435% and 49.025% respectively after applying ANFIS. Besides, medium level of membership function of X_2 also has obvious change, i.e., 31.458%.

The overall average change in membership function can also reflect whether there are major changes in the market. Of course, each input variable and its parameters have different meanings, but these changes enable the designers and marketers to keep an eye on fashion and product trends on an ongoing basis. If this result can be matched with POS data, the saleability of the product can be fully understood. For example, the product holding time decreased by 43.24% on average, which means that regardless of the membership function, there is a downward trend as a whole. When POS increases in sales, it means that the product is very popular, and customers can quickly make a purchase decision.

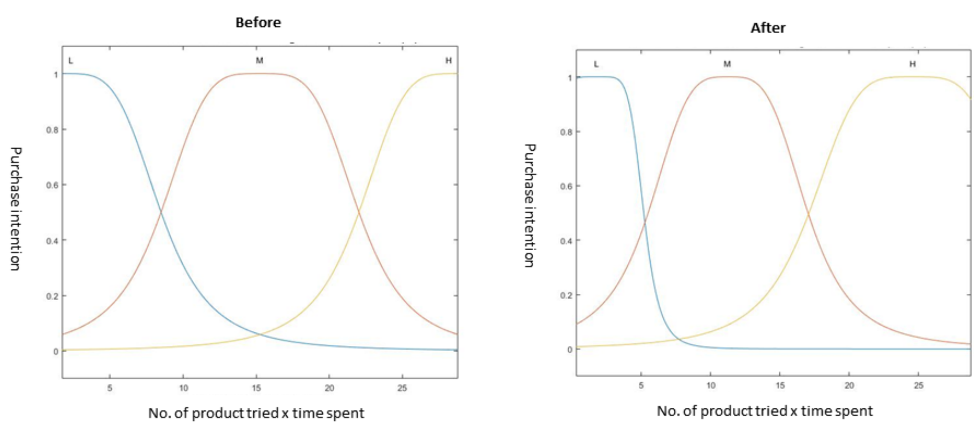
Figure 6 Comparison of parameter of membership function between before and after using ANFIS, (a) product holding time X_1 (b) product pick up frequency X_2 (c) product tried in fitting room, X_3 (see online version for colours)



(a)



(b)



(c)

Table 3 Parameter value of MFs before and after using ANFIS

Input variable	*MF*	*m*		*σ*		*b*	
		Before	*After*	*Before*	*After*	*Before*	*After*
X1	L	2.263	0.100	3.478	3.200	2.001	2.610
	M	9.203	7.200	3.468	2.467	1.997	1.762
	H	16.150	14.150	3.482	4.786	2.000	1.800
X2	L	0.078	0.077	0.166	0.140	2.002	2.320
	M	0.446	0.395	0.086	0.080	2.009	2.641
	H	0.808	0.705	0.144	0.120	2.006	2.042
X3	L	1.719	1.750	6.771	3.428	2.001	2.982
	M	15.260	11.260	6.768	5.767	1.998	1.797
	H	28.790	24.620	6.773	7.523	2.002	2.030

In addition to the above applications, we can use the state of different input variables to derive the level of IPD (0–1). For example, when $X_1 = 6.21$, $X_2 = 0.341$ and $X_3 = 17$, the result of IPD is 0.237 (Table 5). This result is before applying ANFIS. However, ANFIS can be used to learn from the data collected to redefine the membership function. Therefore, the results obtained are more realistic to reflect the real situation. In this case, the IPD is changed to 0.789, which is obviously much higher than the one derived without ANFIS. This result can better reflect the popularity of the product.

Table 4 Parameters change in percentage of MFs after using ANFIS

Input variable	*MF*	*m*	*σ*	*b*
X1	L	–95.581%	–7.993%	30.435%
	M	–21.765%	–28.864%	–11.768%
	H	–12.384%	37.450%	–10%
X2	L	–1.913%	–15.884%	15.884%
	M	–11.355%	–6.758%	31.458%
	H	–12.758%	–17.175%	1.795%
X3	L	1.803%	–49.372%	49.025%
	M	–26.212%	–14.790%	–10.060%
	H	–14.484%	11.073%	1.399%

Table 5 Product demand in particular case of X_i before and after application of ANFIS

X_1	X_2	X_3	*Y(before)*	*T(after)*
6.21	0.341	17	0.237	0.789

Therefore, after the application of ANFIS, the XS and Y models become more realistic. And the IPD can be inferred by recording CPI in the physical store. Instead of relying on POS reflected product demand it can use CPI in-store to more effectively reflect the intended demand of the product. In addition to reflecting the sales situation in quantity, it can use the behaviour of customers in physical stores to a certain extent. As mentioned above, if the IPD is close to the record in POS, it may implicate that the product is as popular as it can. It can be considered as a trendy product. This information was previously difficult to obtain. It can be now collected through the IoT platform for in-depth analysis to master the market trends quickly and precisely. If these results can be disseminated to the designer or marketer in real time, it will provide a clearer direction about the upcoming product design or better coordination of the supply chain.

6 Conclusions

In the fashion retail industry, product demand keeps changing at a fast pace. Driven by smart devices and multimedia, the current speed of information dissemination is much faster than in the previous eras. The ability to quickly grasp the markets trends on specific product styles is beneficial to supply chain management and product design. The behavior of customers in the store reflects willingness to buy the product to a certain extent. Although such demand is actually greater than the actual purchases, it is sufficient to complement the limitation of POS data. In this paper, the application of ANFIS can make the membership function of each CPI more accurate, such that the error caused by subjective determination by humans is reduced. The contribution of this paper is to demonstrate the parameters of MFs of CPI can be learnt from the data collected. The generated IPD can better reflect the actual situation, so that marketers and designers can instantly grasp the market pulse and respond appropriately. This paper proposes a model to resolve this with simulation illustration. Further research, such as systematic sensory technology should capture different human behaviours in brick-and-mortar stores. Behaviour fusion platform and data analytics can further examine product attributes. Through this an offline recommender system can also be developed.

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