The following publication V. Tang, S. W. Y. Cheng, K. L. Choy, P. K. Y. Siu, G. T. S. Ho and H. Y. Lam, "An intelligent medical Replenishment System for managing the medical resources in the healthcare industry," 2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Vancouver, BC, Canada, 2016, pp. 154-161 is available at https://doi.org/10.1109/FUZZ-IEEE.2016.7737682.

An intelligent medical replenishment system for managing the medical resources in the healthcare industry

Valerie Tang, Stephen W.Y. Cheng, K.L. Choy, Paul K.Y. Siu, G.T.S. Ho, H.Y. Lam
Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong

***Abstract*—Due to rapidly ageing population, the need for care and attention homes for the elderly and patient with chronic illnesses has increased significantly in recent years. However, the continuous increase in operation and medical costs and the problem of drugs shortages bring increasing pressure to care and attention homes in regard to medical resource allocation. In such situations, patients may not receive appropriate treatment and hence dissatisfaction with the quality of service may result. Therefore, it is essential to have a decision support system to ensure that an optimal amount of medical resources are stored so as to maintain a sustainable healthcare service. In this paper, an intelligent medical replenishment system (IMRS) is proposed to assist healthcare workers in arranging the appropriate type and quantity of drugs, based on the needs of patients. In IMRS, artificial intelligent techniques, i.e. fuzzy association rules mining and fuzzy logic, are applied to evaluate the historical diagnosis records of patients and determine the amount and frequency of medical resources for replenishment. To validate the feasibility of the proposed system, a pilot study is conducted in a care and attention home located in Hong Kong. The result shows that the IMRS is effective in improving the healthcare service quality for the elderly in terms of the elderly satisfaction and medical resources fulfillment.**

***Keywords*—Medical resource replenishment, care and attention home service, healthcare industry, fuzzy association rule mining, fuzzy logic**

I. INTRODUCTION

The increasing ageing population is a tremendous challenge for the healthcare industry all over the world. The number of people aged 65 or above is expected to increase from under 800 million in 2011 to over 2 billion in 2050 which occupied around 22% of world population [1]. Low fertility and increased longevity are two factors that lead to the population aging trend [2]. In addition, total expenditure on healthcare is around 10% of gross domestic product (GDP) in 2013 [3]. This phenomenon was caused a great impact on both society and the economy. With increasing numbers of the elderly, the need for long term care services is rapidly increasing. Hence, high operational and medical costs, and drugs shortage problems brings great pressure to the healthcare industry which may lead to low patient satisfaction. In order to provide a high quality of services to the elderly, a comprehensive medical resources replenishment system is essential for healthcare workers to maintain an optimal level of medical resources, especially for consumable products, and to meet the patient needs.

Care and attention homes provide residential care, personal care and nursing care for the elderly with poor health or physical mental disabilities. Figure 1 shows the existing problems in medical resource replenishment in care and attention homes. Generally, healthcare equipment and consumable products are common resources that healthcare workers have to order from different medical suppliers. For healthcare equipment, regular maintenance is provided from the suppliers to ensure durability. Therefore, healthcare workers mainly focus on ordering consumable medical resources, such as masks, diapers and drugs in the replenishment processes [4]. Currently, healthcare workers rely on past experience and personal judgment, based on current needs, to place orders for medical resource replenishment. However, there are two major problems in existing replenishment decision making system. Firstly, workers prefer to refill with large quantities of medical resources in order to prevent the out of stock problem. It causes unnecessary resources being stored in the inventory and results in high operating and medical costs. Secondly, the demands for drugs is based on the health status of patients. It is difficult for workers to forecast and order drugs immediately if there is an unpredictable change in the demand, hence causing drugs shortages. Without appropriate tools and techniques for data storage and analysis, it is challenging for healthcare workers to replenish an adequate amount of medical resources to fulfill the demand. This may result in low satisfaction from the elderly due to delays in treatment and high costs. In order to tackle these problems, an intelligent medical replenishment system (IMRS) is presented to determine the order frequency and the amount of medical resource replenishment using the fuzzy association rules mining and fuzzy logic technique.

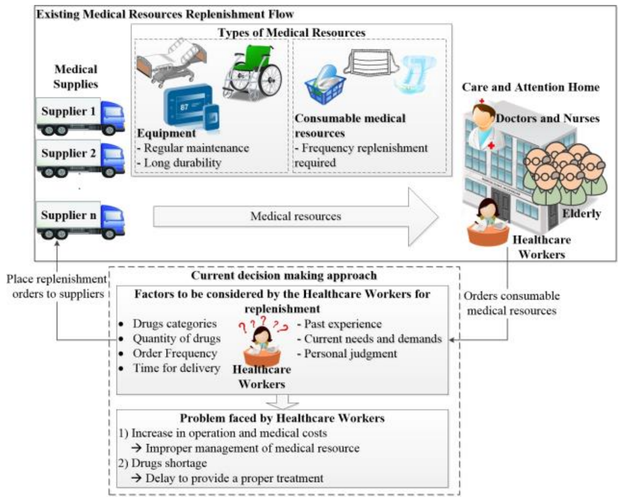

Fig. 1. Existing problems of medical resource replenishment in the care and attention home

This paper is divided as follows: Section 2 contains a literature review on medical resource replenishment. In section 3, the architecture of IMRS is described while in section 4, a pilot study is implemented in a local care and attention home. In section 5, the results and discussion of the system is presented. Section 6 is the conclusion.

II. LITERATURE REVIEW

In this section, the background of healthcare industry and existing replenishment approaches in the industry are investigated to highlight the current problems. After that, decision support tools, including data mining and AI techniques, are studied for providing the basic understanding in designing a replenishment model in order to tackle the problems.

A. Healthcare Industry and existing replenishment approaches

Due to the improving quality of life, the life expectancy of people is increasing and leads to an aging population all over the world [5]. Rising demands in healthcare services significantly increase the pressure and workload of healthcare workers in public hospitals. According to Lee et al [6], other than providing medical care to patients, hospitals are expected to focus on the problem of improving customer satisfaction. Maccellan et al [7] proposed that the hospital should provide healthcare services which are more patient oriented, more reliable, comfort and safe. However, because of the limited resources in hospitals, excessive demands in healthcare services result in long waiting times for patients to receive treatment, and result in low patient satisfaction levels [8]. Therefore, nursing homes, elderly homes and care and attention homes are an emerging trend for providing long term care services to the elderly. Long term care is defined as care for patients who have long term or chronic illness, such as heart diseases, hypertension and hyperglycemia [9]. The continuous monitoring of health status data, such as heart rate, blood pressure, blood glucose level and weight, is essential to effective manage the elderly with these chronic diseases [10-11]. However, these homes for the elderly are facing problems in placing orders for medical resource replenishment. Rosales et al. [12] proposed a Two Bin Replenishment System for inventory control under continuous and periodic review by considering the stock out costs, replenishment cost and the number of medical supplies used. Through the continuous-review of reorder points, based on demands and lot sizes in replenishment, Grewal, Enns & Rogers [13] proposed a framework to minimize the inventory level under various seasonal patterns. Although the above studies based on the demands and costs evaluation are adopted to tackle the replenishment problem, no relationships between historical records of patients and symptoms of diseases, or symptoms of diseases and the frequency and quantity adjustment in replenishment, were considered. Healthcare workers still rely on traditional approaches to deal with the replenishment problems. Thus, it is essential to develop a system aggregating various data from patients and supplies for knowledge discovery in a database in order to optimize the medical resources in a dynamic demand situation.

B. Knowledge Discovery in Database

In the process of knowledge discovery in database (KDD), data mining is a critical step which aims at extracting potentially useful knowledge and patterns from a large database [14]. Data mining techniques have been implemented in different areas such as machine learning, statistics, databases and pattern recognition [15-17]. Association rule (AR) mining is one of popular data mining methods which discovers the hidden relationships among data from all the possible items in database [18]. "X→Y" is a common format for representing the association rule in which X and Y are the "If' part and the "Then" part [19]. Agrawal & Srikant [20] proposed the Apriori algorithm to effectivel mine the association rules between items in large itemsets y [21-22]. In addition, defining the appropriate support and confidence values is important in generating the rules with high quality [23]. Chaves et al. [24] integrated the AR mining and discretization to classify the emission computed tomography images for diagnosing Alzheimer's disease. A hybrid system combined AR and Neural Network (NN) was proposed by Karabatak and Ince [25] for diagnosing the issue of erythemato-squamous diseases. Unfortunately, association rule mining only can handle the binary transaction data. It is hard to discover medical data with fuzzy and quantitative values [26]. Therefore, fuzzy association rule (FAR) mining has been proposed to extend the interpretation of the rules in order to deal with medical diagnosis problems [27]. Rajendran and Madheswaran [28] applied novel FAR mining to assist the physicians in a medical decision support system. Muyeba et al. [29] adopted FAR mining to understand low back pain through the identification of hidden relationships between psychosocial and physical factors. Although FAR is able to discover the hidden correlation among the historical records of patients, this information is insufficient to deal with the problems of fluctuating demand of medical resources in replenishment. In view of that, the application of Artificial Intelligence techniques is essential for analyzing multi-factors in changing the frequency of the order and demand of medical resources.

C. Artificial Intelligence (AI) techniques for replenishment

Artificial Intelligence (AI) is defined as the ability of machines and computers to perform the characteristics of human activities and thoughts [30]. It is a useful tool in solving complicated problems such as modeling, optimization, prediction, forecasting and controlling [31].Yang et al. [32] applied Genetic Algorithm (GA) for optimizing replenishment policies in a single warehouse multi-retailer system. Yao and Chu [33] integrated GA and FL to figure out the replenishment schedule. Dua et al. [34] proposed a multiobjective Neural Network (NN) model to forecast the short-term replenishment in the fashion industry. However, researchers found that it is difficult for users to apply and obtain accurate results from GA and NN due to high dependence upon human judgment [35-37]. In contract with GA and NN, FL is useful in handling real life problems, which are ambiguous, imprecise and subjective. By transforming the different variables into linguistic form, the if-then statement, it allows to users easily access problems and fuzzy solutions in the application of a “human language” [38]. Leung et al. [39] applied FL to handle the replenishment problem in convenience store chain in order to have a simultaneous response to the fluctuating demands of customers. Furthermore, a fuzzy multi-objective joint replenishment inventory model was proposed by Wee et al. [40] to maximize the profit in a fuzzy demand and shortage cost environment. Lee et al. [41] adopted FL to a cloud based responsive replenishment system for managing the data in a franchise business. Therefore, it is shown that FL is a promising technique in handling the problems of decision making processes in replenishment.

To summarize, the review of the above literature shows that it is essential to have an intelligent decision support system to achieve the objective of optimizing the frequency and amount of medical resources while maintaining customer satisfaction. Healthcare workers not only need to rely on past records such as reordering points, costs and medical resources used in determining the amount of medical resources replenishment, but also take into the consideration of the historical diagnose of patients which may affect the medical resource needs. Therefore, an intelligent medical replenishment system (IMRS), integrating of FAR mining for hidden relationship discovery and FL techniques for decision support, is proposed to tackle the fluctuating demands of medical resources in the healthcare industry.

III. METHODOLOGY

To improve elderly satisfaction, the IMRS is designed for optimizing the quantity of medical resources in the replenishment process. Figure 2 shows the architecture of proposed IMRS, which consists of three modules, namely: (i) Data Collection Module (DCM), (ii) Knowledge Discovery Module (KDM), and, (iii) Decision Support Module (DSM).

A. Data Collection Module

In the DCM, a centralized data warehouse is applied to collect and store six types of relevant data, which are staff behavior, treatment data, patient data, medicine data, symptom data and supplier data. Table I shows examples of the six types of data. After gathering the relevant data and storing into the centralized data warehouse, all essential parameters are transmitted to the next module, KDM, for discovering the hidden relationships between parameters.

B. Knowledge Discovery Module

In order to generate useful association rules, the concept of FAR mining integrated data fuzzy set idea and the AR mining techniques is adopted in KDM [42]. In this module, historical records of patients are extracted from the data warehouse as input parameters. There are two keys factors, (i) minimum support count and (ii) confidence value, that affect the quality of association rules.

Therefore, in order to generate rules with high quality, these values are predefined by the doctors and healthcare experts for data mining purposes. Through the conversion of quantitative parameters in the historical records of patients into fuzzy sets, the data mining process can be started, and then useful association rules can be formed. Table II shows the notations of the FAR mining process and the detailed operations of the eleven step mining process are described as follows.

Step 1: Transform the quantitative value of the health status indicator Pj of each record of patient R_i into a fuzzy set f_{ij} using the predefined membership functions, and represent in as $(f_{ij1}/W_{ij1} + f_{ij2}/W_{ij2} + \ldots + f_{ijt}/W_{ijt})$

Step 2: Calculate the frequency (count) of each W_{ijk} of P_j in R_i, $count_{jk}$.

$$count_{jk} = \sum_{\forall i \in H} f_{ijk} \tag{1}$$

Step 3: Select the largest count among each P_j, Max-$count_{jk}$, and find the maximum fuzzy region Max-W_{ij} which indicate the corresponding fuzzy characteristics of Pj in the following mining process.

Step 4: Set the initial value of item s = 1 and compare the value of Max-$count_{jk}$ with the predefined minimum support threshold α_{jk}. Reject the Max-$count_{jk}$ in Ls if it is smaller than α_{jk}.

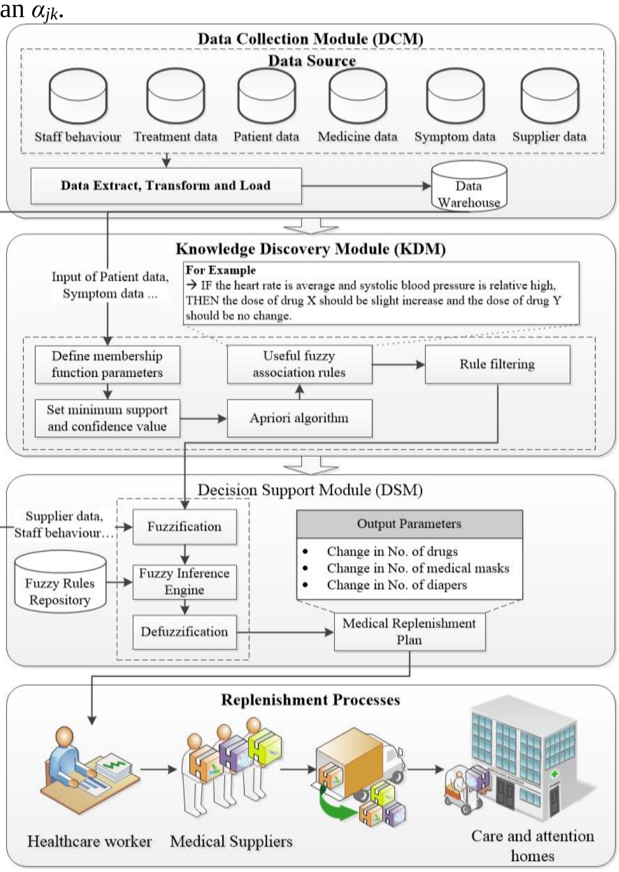

Fig. 2. The architecture of IMRS

TABLE I. Examples of six types of data in data warehouse

Type of Data	Examples
Staff behavior	Hygienic level of staff
Treatment data	Dose of drugs, appropriate drugs for recovering
Patient data	Heart rate, blood pressure, temperature
Medicine data	Existing amount of drugs stored in the inventory
Symptom data	Symptom of diseases, severity of diseases
Supplier data	Lead time of suppliers, order quantity of medical resources

TABLE II. The notation of FAR mining process

Notations	Description
h	The number of historical records of patients
$H = \{1,2, \dots ,h\}$	The set of index of historical records of patients
R_i	The ith historical records of patients, $\forall i \in H$
e	The number of health status indicators
$E = \{1,2, \dots ,e\}$	The set of index of health status indicators
P_j	The jth health status indicators, $\forall j \in E$
t	The number of fuzzy region for P_j
$T_j = \{1,2, \dots ,t\}$	The set of index of fuzzy region for P_j
W_{jk}	The kth fuzzy region of P_j, $\forall k \in T_j$
f_{ij}	The fuzzy set of quantitative value of P_j
f_{ijk}	The fuzzy membership of P_j in R_i in class W_{jk}
$count_{jk}$	The summation of f_{ijk} values
$Max\text{-}count_{jk}$	The maximum count value among $count_{jk}$
$Max\text{-}W_{jk}$	The fuzzy region of P_j with $Max\text{-}count_{jk}$
α_{jk}	The predefined minimum support threshold of P_j
λ	The predefined minimum confidence value
L_s	The set of itemsets contained s items

Step 5: Generate all possible itemsets of items in Ls. Reject items if the count of each itemset b is smaller than the maximum value of the minimum support threshold of items α_b. Put the items with sufficient count in the (s+1)-itemset.

Step 6: For the new (s+1)-itemset, identify the fuzzy value f_{ib} of b in R_i and sum up fuzzy counts $count_b$ of each itemset.

$$count_b = \sum_{\forall i \in H} f_{ib} \tag{2}$$

Step 7: Check the count value of each parameter among the (s+1)-itemset against its corresponding minimum support threshold. Reject $count_b$ if it is smaller than α_b.

Step 8: Check whether $L(s+1)$ is null. If s =1 and the value is null exists, leave the algorithm; If $s \geq 2$ and the null value is exists, move to Step 10. Else, move to the next step.

Step 9: Set $s = s + 1$ and repeat the Step 5 – 8.

Step 10: Extract and construct all possible association rules from k-itemset for k ≥ 2. Compute the confidence value of all possible association rules.

Step 11: Check the confidence value of the association rules against the predefined confidence threshold λ. Reject the association rules if the confidence value is smaller than λ.

The results of KDM are represented in ‘If-Then’ format which indicates the relationship between the health status of patients and the change in dose of drugs. The rules with output parameters in the ‘THEN’ part are selected and then input to the fuzzy system of DSM.

C. *Decision Support Module*

Apart from the outputs of KDM, other replenishment parameters, such as the existing drug level in the inventory and lead time of the supplier, from the data warehouse are transmitted to the DSM for decision making. These parameters with quantitative values are first converted into fuzzy sets, ‘IF-THEN’ format, in a fuzzification of fuzzy system. The equation for determining the membership function of the fuzzy sets is shown below.

$$S = \sum_{i=1}^{n} \frac{\mu_s(x_i)}{x_i} \tag{3}$$

where S is fuzzy set, x is the whole data set and $\mu_s(x_i)$ is the membership function of element x_i

Then, parameters with fuzzy sets are input into the fuzzy inference engine. Through matching of decision rules predefined by experts, the output fuzzy sets from the fuzzy inference engine can be generated. Finally, by calculating the center of area, these fuzzy sets can be transformed to numerical value through a defuzzification process. The equation of the center of area is represented as follows.

$$Y = \frac{\sum_{j=1}^{N} \overline{C_j A_j}}{\sum_{j=1}^{N} w_j \overline{A_j}} \tag{4}$$

where Y is replenishment change, w is the weight, C is the center of gravity and A is the area.

According to the output from the fuzzy system, the most appropriate order frequency and amount of medical resources can be determined in replenishment.

IV. CASE STUDY

A case study was conducted in the CF Care and Attention Home located in Hong Kong, in order to validate the feasibility of the IMRS in healthcare industry.

A. *Company background*

CF Care and Attention Home is a seven floor building and was founded in the 1980s. There are 95 staff, including doctors, nurses, healthcare assistants and cleaners, in the home. It provides healthcare services, such as personal care and nursing care, to 216 elderly patients who need care and suffer from chronic diseases such as hypertension and hyperglycaemia. The mission of the home is to provide a healthy and comfortable environment for the elderly residents through the staff professionalism and a high quality of service.

B. *Problems faced by the company*

Currently, healthcare assistants are responsible for the medical resources replenishment. Generally, they will check the existing inventory level and the last order quantity to estimate the amount of medical resources in the next replenishment. However, the case company is facing the following problems:

(i) Lack of a systemic approach to forecast the demands for drugs

Healthcare assistants order a fixed amount of drugs in replenishment. However, the demands of drugs is based on the health status of the patients. Healthcare assistants do not have sufficient knowledge about the relationship between the health status of the elderly and the symptoms of diseases;

between the symptoms of the disease and the dose of drugs in monitoring that disease. Once the health status of the elderly gets worse and the dose of drugs is increasing, the problem of drug shortage will result and hence delay the provision of treatment f.

(ii) High operation and medical costs

In order to prevent the problem of understocking, healthcare assistants order excessive amounts of medical resources in replenishment. Unnecessary medical resources are stored in the inventory and results in high operating and medical costs.

C. Implementation of IMRS

A case scenario is given to illustrate how the proposed IMRS helps healthcare assistants to make a decision on determining the order frequency and amount of medical resources in replenishment. At the beginning, related data, staff behavior, treatment data, patient data, medicine data, symptom data and supplier data, are collected and stored in the data warehouse. Then, data for illustration are retrieved from the data warehouse as inputs for the data mining process. The selected parameters, health status indicators and the change in the dose of drugs for hypertension and hyperglycaemia, are listed in Table III. Eight historical records of patients are extracted as an example for the data mining process and are shown in Table IV. After that, by using the Fuzzy Logic Toolbox in MATLAB software, the fuzzy logic is carried out for decision making support.

Before the data mining process, the minimum support count and the membership function of all the related parameters, as shown in Table V and VI, are predefined by doctors and healthcare experts in order to ensure the value suitability. At the same time, the confidence value λ for generating useful association rules is 0.70.

In KDM, 11 steps are involved in the FAR mining process.

Step 1: According to the predefined membership functions, convert the numerical values of all parameters into a fuzzy set. For example, through the conversion of the crisp values of the records into a fuzzy set, (0.25/Not Good + 0.75/ Poor), as shown in Figure 3, is used to present the crisp value of A in first record. All parameters in the eight records are transformed to fuzzy set by repeating this conversion and the result is listed in Table VII. The format of the 'parameter.fuzzy_region' is adopted to show the fuzzy set structure of the parameters.

Step 2: Compute the frequency (count) of the fuzzy region parameters. Take the fuzzy region of the 'Average' of parameter A as an example, there are 2 records containing the fuzzy region of 'Average' and then add them together, (0+0.5+0+0+1+0+0+0). The count of A.A is 1.5. This step is repeated for the remaining fuzzy regions of parameters.

Step 3: Select the maximum count of the fuzzy region of each parameter. For parameter A, there are five fuzzy regions which are 'Excellent', 'Good', 'Average', 'Not good' and 'Poor' and the count for these fuzzy regions are 0, 1.5, 1.5, 3.5 and 1.5. Therefore, the fuzzy region 'Not good' is selected for representing the parameter A.

TABLE III. The symbols of parameters

	Parameters	Symbol
Health status indicator (Input)	Heart rate (per min)	A
	Systolic blood pressure (mmHg)	B
	Diastolic blood pressure (mmHg)	C
	Blood glucose level (mmol/L)	D
	Body mass index (kg/m^2)	E
Change in dose of drugs (Output)	Calcium channel blockers (CCB) (%)	F
	Gliclazide (%)	G

TABLE IV. Historical records of the elderly

Patient ID	Health status indicators						
	A	B	C	D	E	F	G
1	79	142	95	6	25.3	+80%	+50%
2	69	112	72	5.1	18.5	+10%	+10%
3	77	125	85	6.5	25	+50%	+75%
4	74	118	75	6	21.5	+40%	+50%
5	72	132	90	5.5	22.5	+65%	+30%
6	66	105	70	5.7	18.9	-20%	+40%
7	74	120	80	4.9	22.5	+45%	-10%
8	78	136	91	4.2	24	+75%	-20%

TABLE V. Minimum support count of parameters

Parameters	A	B	C	D	E	F	G
Min. s.c.	1.7	1.5	1.75	1.5	2	1.7	1.6

TABLE VI. Membership functions of parameters

Parameters	Fuzzy class	Membership function	Type
A	Excellent	(58, 58, 64, 66)	Trapezoid
	Good	(64, 66, 68, 70)	Trapezoid
	Average	(68, 70, 72, 74)	Trapezoid
	Not good	(72, 74, 76, 80)	Trapezoid
	Poor	(76, 80, 84, 84)	Trapezoid
B	Low	(50, 50, 80, 100)	Trapezoid
	Normal	(80, 100, 110, 130)	Trapezoid
	Relatively high	(110, 130, 150)	Triangle
	High	(130, 150, 180, 180)	Trapezoid
C	Low	(50, 50, 55, 65)	Trapezoid
	Normal	(55, 65, 75, 85	Trapezoid
	Relatively high	(75, 85, 95)	Triangle
	High	(85, 95, 110, 110)	Trapezoid
D	Low	(2, 2, 3.5, 4.5)	Trapezoid
	Normal	(3.5, 4.5, 5, 6)	Trapezoid
	Relatively high	(5, 6, 6.5, 7.5)	Trapezoid
	High	(6.5, 7.5, 8.5, 8.5)	Trapezoid
E	Underweight	(15, 15, 17.3 ,19.7)	Trapezoid
	Normal weight	(17.3, 19.7, 22.2, 24)	Trapezoid
	Overweight	(22.2, 24, 26)	Triangle
	Obesity	(24, 26, 28.5, 28.5)	Trapezoid
F, G	Substantially decrease	(-100, -75, -50)	Triangle
	Significantly decrease	(-75, -50, -25)	Triangle
	Slight decrease	(-50, -25, 0)	Triangle
	No change	(-25, 0, 25)	Triangle
	Slight decrease	(0, 25, 50)	Triangle
	Significantly increase	(25, 50, 75)	Triangle
	Substantially increase	(50, 75, 100)	Triangle

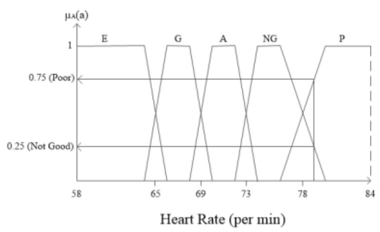

Fig. 3. An example of fuzzy set conversion

TABLE VII. The fuzzy set of parameters in historical records of the elderly

Patient ID	Conversion of quantitative values of health status indicators into fuzzy set
1	$\left(\frac{0.25}{A.NG}+\frac{0.75}{A.P}\right)\left(\frac{0.375}{B.RH}+\frac{0.625}{B.H}\right)\left(\frac{1}{C.H}\right)\left(\frac{1}{D.N}\right)\left(\frac{0.375}{E.OW}+\frac{0.625}{E.OB}\right)\left(\frac{1}{F.SuI}\right)\left(\frac{0.5}{G.SiI}+\frac{0.5}{G.SuI}\right)$
2	$\left(\frac{0.5}{A.A}+\frac{0.5}{A.G}\right)\left(\frac{0.92}{B.N}+\frac{0.08}{B.RH}\right)\left(\frac{1}{C.N}\right)\left(\frac{0.9}{D.N}+\frac{0.1}{D.RH}\right)\left(\frac{0.5}{E.UW}+\frac{0.5}{E.NW}\right)\left(\frac{0.7}{F.NC}+\frac{0.3}{F.SiI}\right)\left(\frac{0.7}{G.NC}+\frac{0.3}{G.SiI}\right)$
3	$\left(\frac{0.75}{A.NG}+\frac{0.25}{A.P}\right)\left(\frac{0.25}{B.N}+\frac{0.75}{B.RH}\right)\left(\frac{1}{C.RH}\right)\left(\frac{1}{D.RH}\right)\left(\frac{0.5}{E.OW}+\frac{0.5}{E.OB}\right)\left(\frac{0.5}{F.SiI}+\frac{0.5}{F.SuI}\right)\left(\frac{1}{G.SuI}\right)$
4	$\left(\frac{1}{A.NG}\right)\left(\frac{0.58}{B.N}+\frac{0.42}{B.RH}\right)\left(\frac{1}{C.N}\right)\left(\frac{1}{D.RH}\right)\left(\frac{1}{E.NW}\right)\left(\frac{0.8}{F.SiI}+\frac{0.2}{F.SuI}\right)\left(\frac{0.5}{G.SiI}+\frac{0.5}{G.SuI}\right)$
5	$\left(\frac{1}{A.A}\right)\left(\frac{0.92}{B.RH}+\frac{0.08}{B.H}\right)\left(\frac{0.5}{C.N}+\frac{0.5}{C.RH}\right)\left(\frac{0.5}{D.RH}+\frac{0.5}{D.H}\right)\left(\frac{0.83}{E.NW}+\frac{0.17}{E.OW}\right)\left(\frac{0.08}{F.SiI}+\frac{0.92}{F.SuI}\right)\left(\frac{0.08}{G.NC}+\frac{0.92}{G.SiI}\right)$
6	$\left(\frac{1}{A.G}\right)\left(\frac{1}{B.N}\right)\left(\frac{1}{C.N}\right)\left(\frac{0.33}{D.N}+\frac{0.67}{D.RH}\right)\left(\frac{0.45}{E.UW}+\frac{0.55}{E.NW}\right)\left(\frac{0.625}{F.SiD}+\frac{0.375}{F.NC}\right)\left(\frac{0.8}{G.SiI}+\frac{0.2}{G.SuI}\right)$
7	$\left(\frac{1}{A.NG}\right)\left(\frac{0.5}{B.N}+\frac{0.5}{B.RH}\right)\left(\frac{0.5}{C.N}+\frac{0.5}{C.RH}\right)\left(\frac{0.05}{D.L}+\frac{0.95}{D.N}\right)\left(\frac{0.87}{E.NW}+\frac{0.17}{E.OW}\right)\left(\frac{0.625}{F.SiI}+\frac{0.375}{F.SuI}\right)\left(\frac{0.3}{G.SiD}+\frac{0.7}{G.NC}\right)$
8	$\left(\frac{0.5}{A.NG}+\frac{0.5}{A.P}\right)\left(\frac{0.75}{B.RH}+\frac{0.25}{B.H}\right)\left(\frac{0.48}{C.RH}+\frac{0.5}{C.H}\right)\left(\frac{0.55}{D.L}+\frac{0.45}{D.N}\right)\left(\frac{1}{E.OW}\right)\left(\frac{1}{F.SuI}\right)\left(\frac{0.625}{G.SiD}+\frac{0.375}{G.NC}\right)$

Step 4: Check the largest counts of the fuzzy region parameters against the predefined minimum support threshold of each parameter. Reject the parameters if the maximum count is smaller than the minimum support threshold. In this case, all the largest counts of the parameters are greater than the minimum support threshold. Therefore, all parameters are kept.

Step 5: Generate all possible combinations of items and only the combinations with a sufficient number of counts, in which the minimum count of the related parameters is greater than or equal to the maximum value of their minimum support threshold, can be put in 2-itemset. For instance, in the combination of {A.NG, B.RH}, the minimum count value of A.NG (3.5) and B.RH (3.795) is selected and then compared with the maximum of the predefined support threshold of parameters A and B, 1.7 and 1.5. Since the minimum count of {A.NG, B.RH} is greater than their predefined support threshold, {A.NG, B.RH} is put in the 2-itemset.

Step 6: Identify the fuzzy value of each itemset in the 2-itemset through the calculation of the minimum count of items in each records. For example, {A.NG, B.RH} in the first record, the counts of A.NG and B.RH are 0.25 and 0.375, respectively and thus 0.25 is the minimum value. In the second record, only B.RH exists and thus the count of {A.NG, B.RH} is 0. This step is repeated for the rest of the records. Through the summation of count of {A.NG, B.RH} in eight records, (0.25+0+0.75+0+0.42+0+0.5+0.5), the count of {A.NG, B.RH} is 2.42. Table VIII shows the combination of the parameters in a 2-itemset, the maximum value of minimum support threshold and the fuzzy count.

TABLE VIII. Maximum value of minimum support threshold and fuzzy count in the 2-itemset.

Itemset	Max. v. of min. s.c.	Count	Itemset	Max. v. of min. s.c.	Count
{A.NG, B.RH}	1.7	2.42	{C.N, D.N}	1.75	1.73
{A.NG, C.N}	1.75	1.5	{C.N, E.NW}	2	2.55
{A.NG, D.N}	1.7	1.7	{C.N, F.SuI}	1.75	0.575
{A.NG, E.NW}	2	1.83	{C.N, G.SiI}	1.75	1.6
{A.NG, F.SuI}	1.7	1.825	{D.N, E.NW}	2	1.66
{A.NG, G.SiI}	1.7	0.75	{D.N, F.SuI}	1.7	1.925
{B.RH, C.N}	1.75	1	{D.N, G.SiI}	1.6	0.8
{B.RH, D.N}	1.5	1.505	{E.NW, F.SuI}	2	1.405
{B.RH, E.NW}	2	2.16	{E.NW, G.SiI}	2	2.18
{B.RH, F.SuI}	1.7	3.12	{F.SuI, G.SiI}	1.7	1.62
{B.RH, G.SiI}	1.6	1.795			

Step 7: Check the count of each parameter in the 2-itemset against its corresponding maximum value of the minimum support threshold. Reject the parameters if the count is smaller than the maximum value of the minimum support threshold. In table 7, the underlined itemsets are the parameters with a sufficient count.

Step 8: After reviewing the Ls, the null value does not exist, so move to step 9.

Step 9: Set s =3 and repeat Steps 5 – 8 until there are no available itemsets formed. Only a itemset {A.NG, B.RH, F.SuI} contains a sufficient count, 1.825, in the 3-itemset. Since no itemset can be put in the 4-itemset, therefore, the null value exists. Then move to step 10.

Step 10: Extract all possible association rules from the items in the k-itemset in which k should be greater than or equal to 2. Present the association rules in the 'IF-THEN' format and calculate the confidence value. The calculation of the confidence value of 'IF A.NG and B.RH THEN F.SuI is shown below:

$$\frac{(A.NG \cap B.RH \cap F.SuI)}{(A.NG \cap B.RH)} = \frac{1.825}{2.42} = 0.754$$

Step 11: Check the confidence value of the association rules against the predefined confidence threshold. In this case, 0.70 is set at the beginning of the data mining process. Reject the rules if the confidence value is smaller than the predefined confidence threshold. Table IX shows the useful association rules with a sufficient confidence value.

Only rules with output parameters in the 'THEN' part are extracted and then transferred to the DSM for determining the order frequency and the amount of medical resources. For the rule 'If {B.RH}Then {F.SuI}', since it involves the output parameter, change in dose of the drug, calcium channel blockers, in the 'THEN' part, therefore, this rule is transferred to the DSM. In contrast, the rule 'If {F.SuI}Then {B.RH}' does not contain the output parameter in the 'THEN' part and thus this rule is filtered out. Other than the outputs from KDD, data stored in the data warehouse, which is related to the replenishment, are also passed to DSM. In this case, five input and four output parameters in DSM are selected as shown in Table X.

TABLE IX. Useful association rule with sufficient confidence threshold.

Association Rules	Confidence value
If {B.RH}Then {F.SuI}	3.12/3.795 = 0.82
If {F.SuI}Then {B.RH}	3.12/3.995 = 0.78
If {C.N} Then {E.NW}	2.55/3.5 = 0.72
If {G.Sil} Then {E.NW}	2.18 / 3.02 = 0.72
If {A.NG, B.RH} Then {F.SuI}	1.825/2.42 = 0.75
If {A.NG, F.SuI} Then {B.RH}	1.825/1.825 = 1

TABLE X. Input and output parameters in DSM

Input parameters	Output parameters
Change in dose of calcium channel blockers	Change in no. of calcium channel blockers
Lead time of suppliers	Change in no. of marks
Existing inventory level	Change in no. of diapers
Hygienic level of staff	Change in no. of order frequency
Frequency of changing diapers	

In the DSM, there is a fuzzy rule repository for storing the predefined decision rules in the 'IF-THEN' format to identify the output values in the fuzzy inference engine. In order to enhance understanding of the relationship between the input and output parameters by healthcare workers, the decision rules are represented in statement form and a sample of decision rules is shown in Table XI.

With the reference to the decision rules, the hidden pattern between the input parameters and replenishment can be identified. In Table XI, the rule implies that if the dose of calcium channel blockers is substantially increased, the lead time of suppliers is medium, the existing inventory level is low, the hygienic level of staff is high and the frequency of changing diapers is normal. The healthcare workers should increase the amount of medical resources in the replenishment and they should order the medical resources more frequently. The recommendation is reasonable because the demands for medical resources is increased and thus the amount of medical resources in replenishment should be increased in order to prevent problems of shortages.

A Fuzzy Logic Toolbox in MATLAB is applied to facilitate the calculation of fuzzy logic. The membership functions of the replenishment parameters and the decision rules are entered and stored in the Fuzzy Logic Toolbox. Then, input the value as 60, 5, 30, 70 and 8 for five parameters into the software to obtain the output value. The result of fuzzy logic, and the combinations of individual fuzzy region in each rule, are shown in Figure 4,which means that when the dose of drugs for calcium channel blockers is increased 60%, the lead time of suppliers is 5 days, the existing inventory level is 30%, the hygienic level of staff is 70% and the frequency of changing the diapers is 8 per day. Healthcare assistants should increase calcium channel blockers by 68.5%, masks by 40.9%and diapers by 19.6%and the monthly order frequency should increase by 27.8% in replenishment.

TABLE XI. A sample of decision rule in the statement form.

IF	THEN
Dose of calcium channel blockers is substantially increase **AND** Lead time of suppliers is medium **AND** Existing inventory level is low **AND** Hygienic level of staff is high **AND** Frequency of changing diapers is normal	The no. of calcium channel blockers should be substantially increase **AND** The no. of marks should be significantly increase **AND** The no. of diapers should be slight increase **AND** The no. of order frequency should be slight increase

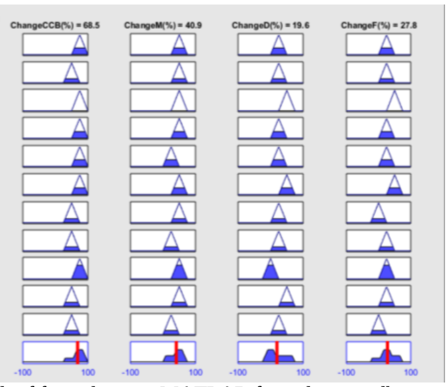

Fig. 4. Result of fuzzy logic in MATLAB fuzzy logic toolbox.

V. Results and Discussion

This paper proposes the IMRS for effective medical resources replenishment. Through the pilot study in the CF Care and Attention Home, the IMRS contributes to improving (i) the effectiveness of medical resources in replenishment, and, (ii) the healthcare service quality.

A. Improvemnet in the effectiveness of IMRS

Compared with the traditional replenishment method, which reviews the inventory and previous order quantity, IMRS provides a systemic approach for medical resources replenishment. Based on the demand for medical resources, healthcare assistants can easily estimate the appropriate amount of medical resources for replenishment. This can prevent the storage of excessive medical resources and hence solve the problem of overstock. At the same time, the cost for replenishing unnecessary medical resources can be significantly reduced.

B. Improvemnet in the service quality in CF care and attention home

By adopting the FAR mining technique, healthcare assistants can obtain relevant knowledge about the relationship between the health status of the elderly and the dose of drugs in controlling diseases. On the other hand, the use of fuzzy logic increases the reliability in determining the order frequency and the amount of medical resources in replenishment. Thus, the elderly can receive the proper treatment in time and be more satisfied with the service quality provided by the CF Care and Attention Home.

VI. Conclusion

This paper presents the IMRS which integrates the FAR mining technique and fuzzy logic to replenish medical resources in the healthcare industry. It helps healthcare workers extract the relationships between the health conditions of the elderly and the dose of drugs for controlling the particular disease by adopting the FAR data mining process. On the other hand, by considering the replenishment factors, including the change in dosage of drugs, the lead time of suppliers and the frequency of changing diapers, healthcare workers can determine the order frequency and the quantity of medical resources in replenishment. Through the implementation of IMRS in care and attention homes, the results showed that the system helps improve the healthcare service quality by providing the proper treatment to the elderly while reduce the operational and medical cost. However, the present study is applied to determine the amount of specific medical resources, i.e. masks, diapers and drugs. Further work will be conducted in determining the amount of other medical resources, such as needles, cotton balls and bandages, and in tackling different diseases, so as to further validate the IMRS model.

Acknowledgements

The authors would like to thank the Research Office of the Hong Kong Polytechnic University for supporting the project (Project Code: G-RU8J).

REFERENCE

[1] United Nations, Department of Economic and Social Affairs, Population Division (2011). World Population Prospects: The 2010 Revision, Volume I: Comprehensive Tables. ST/ESA/SER.A/313.

[2] D.E. Bloom, A. Boersch-Supan, P. McGee, and A. Seike, "Population Aging: Facts, Challenges, and Responses" Working Paper Series No. 71 pp. 1-10, 2011

[3] World Health Organisation (2013) Health Financing [Online]. Avaibable: http://www.who.int/gho/health_financing/en/

[4] M. Kaur, and S. Hall, "Medical Supplies and Equipment for Primary Health Care A Practical Resource for Procurement and Management," T. Roy. Soc. Trop. Med. H, vol. 96, pp. 461-461, 2002.

[5] E.M. Crimmins, and M.E. Levine, "Chapter 18 - Current Status of Research on Trends in Morbidity, Healthy Life Expectancy, and the Compression of Morbidity," Handbook of the Biology of Aging (Eighth Edition), San Diego : Academic Press, 2016, pp. 495-505.

[6] C.K.M. Lee, C.T.Y. Ru, C.L. Yeung, K.L. Choy, and W.H. Ip, "Analyze the healthcare service requirement using fuzzy QFD," Comput. Ind., vol. 74, pp. 1–15, Decemeber 2015.

[7] M. Mccellan, J. Kent, S.J. Beales, S.I.A. Cohen, M. Macdonnell and A. Thoumi et al. , "Accountable Care Around The World: A Framework To Guide Reform Strategies," Health Affair., vol. 33 pp. 1507-1515, September 2014.

[8] S. French, J.L.M. Lindo, E.W. Williams, and J. Williams-Johnson, "Doctor at triage – Effect on waiting time and patient satisfaction in a Jamaican hospital," International Emergency Nursing, vol. 22, pp. 123-126, July 2014.

[9] M. Spruit, R. Vroon, and Batenburg, "Towards healthcare business intelligence in long term care An explorative case study in the Netherlands," Computers in Human Behaviour, vol. 30, pp. 698-707, January 2014.

[10] G. Mohan, and P.O. Sinciya, "Real time healthcare system for patients with chronic diseases in home and hospital environments," International Journal of Science, Engineering and Technology Research, vol. 2, April 2013.

[11] S. Jeong, C.H. Youn, E.B. Shim, M. Kim, Y.M. Cho, and L. Peng, "An integrated healthcare system for personalized chronic disease care in home-hospital environments," IEEE Trans. Inf. Technol. Biomed., vol. 16, pp. 572–585, July 2012.

[12] C.R. Rosales, M. Magazine, and U. Rao, "The 2Bin system for controlling medical supplies at point-of-use," Eur. J. Oper. Res., vol. 243, pp. 271-280, May 2015.

[13] C.S. Grewal, S.T. Enns, and P. Rogers, "Dynamic reorder point replenishment strategies for a capacitated supply chain with seasonal demand," Computers & Industrial Engineering, vol. 80, pp. 97-110, February 2015.

[14] D. Talia, P. Trunfio, and F. Marozzo, "Chapter 1 - Introduction to Data Mining," Data Analysis in the Cloud, 1st ed, Elsevier, pp. 1-25, 2016.

[15] R. Henriques, C. Antunes, and S.C. Madeira, "A structured view on pattern mining-based biclustering," Pattern Recogn., vol. 48, pp. 3941-3958, December 2015.

[16] C.M. Hunt, N.A. Yuen, H.A. Stirnadel-Farrant, and A. Suzuki, "Age-related differences in reporting of drug-associated liver injury: Data-mining of WHO Safety Report Database," Regul. Toxicol. Pharm., vol. 70, pp. 519-526, November 2014.

[17] R.J. Urbanowicz, and J.H. Moore, "Chapter 9 – Learning Classifier Systems: The Rise of Genetics-Based Machine Learning in Biomedical Data Mining," Methods in Biomedical Informatics: A Pragmatic Approach, USA: Academic press, 2014, pp. 265–311

[18] E. Baralis, L. Cagliero, T. Cerquitelli, and P. Garza, "Generalized association rule mining with constraint," Inform. Sciences, vol. 194, pp. 68-84, July 2012

[19] C.K.H. Lee, K.L. Choy, G.T.S. Ho, K.S. Chin, K.M.Y. Law, and Y.K. Tse, "A hybrid OLAP-association rule mining based quality management system for extracting defect patterns in the garment industry," Expert Syst. Appl. , vol. 40, pp. 2435-2446, June 2013.

[20] R.Agrawal, and R. Srikant, "Fast algorithms for mining association rules in large databases," In Proceedings of 20th international conference on very large databases, Santiago de Chile, pp. 487–489, 1994.

[21] W. Chung, and T.L.B. Tseng, "Discovering business intelligence from online product reviews: A rule-induction framework" Expert Syst. Appl. , vol. 39, pp. 11870–11879, November 2012.

[22] R.J. Kuo, S.Y. Lin, and C.W Shih, "Mining association rules through integration of clustering analysis, and ant colony system for health insurance database in Taiwan," Expert Syst. Appl. , vol. 33, pp. 794–808, October 2007.

[23] A.H.L. Lim, C.S. Lee, and M. Raman, "Hybrid genetic algorithm and association rules for mining workflow best practices," Expert Syst. Appl. , vol. 39, pp. 10544–10551, September 2012.

[24] R. Chaves, J. Ramírez, and J.M. Górriz, "Integrating discretization and association rule-based classification for Alzheimer's disease diagnosis," Expert Syst. Appl. , vol. 40, pp. 1571-1578, April, 2013.

[25] M. Karabatak, and M.C. Ince, "A new feature selection method based on association rules for diagnosis of erythemato-squamous diseases," Expert Syst. Appl. , vol. 36, pp. 12500-12505, December 2009.

[26] A. Moustafa, B. Abuelnasr, and S.M. Abougabal, "Efficient mining fuzzy association rules from ubiquitous data streams," Alexandria Engineering Journal, vol. 54, pp. 163–174, June 2015.

[27] A.L. Buczak, and C.M. Gifford, "Fuzzy Association Rule Mining for Community Crime Pattern Discovery", In: ACM SIGKDD Workshop on Intelligence and Security Informatics, 2010.

[28] P. Rajendran, and M. Madheswaran, "Novel Fuzzy Association Rule Image Mining Algorithm for Medical Decision Support System," International Journal of Computer Applications, vol. 1, pp. 87-94, 2010.

[29] M.K. Muyeba, S. Lewis, L. Han, and J.A. Keane, "Understanding low back pain using fuzzy association rule mining," IEEE International Conference on Systems, Man, and cybernetics, Manchester, pp. 3265-3270, 2013.

[30] J.M. Ali, M.A. Hussain, M.O. Tade, and J. Zhang, "Artificial Intelligence techniques applied as estimator in chemical process systems – A literature survey," Expert Syst. Appl. , vol. 42, pp. 5915-5931, August 2015.

[31] A. Mellit, S.A. Kalogiroub, L. Hontoriac, and S. Shaarid, "Artificial intelligence techniques for sizing photovoltaic systems: A review," Renew. Sust. Energ. Rev., vol. 13, pp. 406–419. Febraury 2009.

[32] W. Yang, F.T.S. Chan, and V. Kumar, "Optimizing replenishment polices using Genetic Algorithm for single-warehouse multi-retailer system," Expert Syst. Appl. , vol. 39, pp. 3081–3086, February 2012.

[33] M.J. Yao, and W.M. Chu, "A genetic algorithm for determining optimal replenishment cycles to minimize maximum warehouse space requirements," Omega, vol. 36, pp. 619–631, August 2008.

[34] W. Dua, S.Y.S. Leung, and C.K. Kwong, "A multiobjective optimization-based neural network model for short-term replenishment forecasting in fashion industry" Neurocomputing, vol. 151, pp. 342–353, March 2015.

[35] G. Yang, S. Wu, Q. Jin, J. Xu, "A hybrid approach based on stochastic competitive Hopfield neural network and efficient genetic algorithm for frequency assignment problem," Appl. Soft. Comput., vol. 39, pp. 104-116, February 2016.

[36] C.K.H. Lee, K.L. Choy, G.T.S. Ho, and K.M.Y. Law, "A RFID-based Resource Allocation System for garment manufacturing," Expert Syst. Appl. , vol. 40, pp. 784-799, February 2013.

[37] A.F. Shapiro, "The merging of neural networks, fuzzy logic, and genetic algorithms," Insurance: Mathematics and Economics, vol. 31, pp. 115-131, April, 2002

[38] F. Aras, E. Karakas, and Y. Bicen, "Fuzzy logic-based user interface design for risk assessment considering human factor: A case study for high voltage cell," Safety Sci., vol. 70, pp. 387-396, December 2014.

[39] R.W.K. Leung, H.C.W. Lau, and C.K. Kwong, "On a responsive replenishment system: a fuzzy logic approach," Expert Syst., vol. 20, pp. 20-32, February 2003

[40] H.M. Wee, C.C Lo, and P.H. Hsu, "A multi-objective joint replenishment inventory model of deteriorated items in a fuzzy environment," Eur. J. Oper. Res., vol. 197, pp. 620-631, 2009.

[41] C.K.H. Lee, K.L. Choy, G.T.S. Ho, and C. Lin, "A cloud-based responsive replenishment system in a franchise business model using a fuzzy logic approach," Expert Syst., DOI: 10.1111/exsy.12117., July 2015.

[42] T.P. Hong, K.Y. Lin, and S.L. Wang, "Fuzzy data mining for interesting generalized association rules," Journal of Fuzzy Sets and Systems, vol.138, pp. 255-269, September 2003.