

Development of a Decision Support Framework for Health Beverage Flavouring for the Ageing Society Using Artificial Neural Network

Athakorn Kengpol, Jakkarin Klunngien, and Sopida Tuamtee

Abstract—The objective of this research is to select health beverage flavour appropriate for the ageing people with the aid of a decision support framework by using the artificial neural network. The decision support framework's role is to gather information between consumers and manufacturers. The framework has the capability to compile the collected data and form the suitable model for selecting beverage flavouring of the products. In order to identify the preference of consumer, the artificial neural network has been applied to classify the beverage preference, i.e. taste, colour and odour of health beverages as well as the consumer groups. The questionnaire is used to gather the preference for taste, colour and odour from consumer groups which are separated into four groups such as the gender (male or female), age (60-65 years or over 65 years) health condition (healthy or unhealthy) and symptoms. The results of this research can benefit to consumers and manufacturers. The consumers can know the most preferred health beverage. In addition, the manufacturers can produce products that can match the consumer's preference.

Index Terms—Decision support system, artificial intelligence, artificial neural network, ageing society.

I. INTRODUCTION

Nowadays, the situation of the world population age structure is changing progressively with the population getting older and the child population declining. Consequently, the world becomes an ageing society. In Thailand, demographics show that a 2015 population of 68.66 million, a 2.11% increased from a 2010 population of 67.21 million. The elderly are likely to increase from 8.70 million in 2010 to 10.74 million in 2015 or increased by 18.99%. As a result, the proportion of the elderly population in Thailand will be 15.64%, leading to an ageing society [1]. For this reason, the ageing populations are concerned about their health [2]. Therefore, the demand for the health food and drink is increasing. Health awareness now focuses on individual feeling which affects purchasing and consuming of healthy food and drink behavior [3]. By evaluating consumer acceptance of healthy food and beverages, consumers have focused on taste, odour and texture. Furthermore, consumers

normally select their favourite beverage which is advised as good for health [4].

Due to different demands from consumers, the identification of flavours (taste, colour and odour) of health beverages can be difficult. This research proposes a decision support framework (DSF) with multi-layer perceptron neural network (MLPNN) to classify and select health beverage flavour (taste, colour and odour) which is suitable for the elderly.

II. LITERATURE REVIEW

A. Decision Support Framework

A decision support framework (DSF) is an information technology that supports decision-making activities. DSF supports the management, operations and organisation planning and help decision maker can make decisions about problems [5]. A decision-making process would be affected by the individual performance as the decision maker, their preferences and the criteria used to make the decision [6]. Therefore, DSF is a computer software system which can be implied in helping the decision makers in order to use models and data to solve the problems [7].

B. Artificial Neural Network

Modeling techniques which use artificial neural network (ANN) have been widely used and successfully over the last years [8]. ANN is another widely used tool in the classification. Such a model is developed of the problem to be solved. Hence, decision support system based on artificial neural network has been widely applied due to its simplicity and scalability [9]-[11]. Specifically, in classifying the complex of customer demand, ANN has been applied for classifying of the taste concentration with back-propagation algorithm (BP) [12]. After that, artificial intelligence system (AI) was developed with neural network algorithm through multi-layer perceptron architecture (MLPNN) with supervised learning by BP to classify the fragrance notes. Furthermore, ANN also has an ability to explore complex hidden patterns based on an involved input requirement on complex fragrance notes [13].

ANN is a computation method that simulates the work of biological neurons. The neurons are arranged in a defined structure which is created by the layer and defined by the number of neurons [14]. The advantage of ANN is learning for estimating information that has never been seen. At present, ANN is used in several ways such as forecasting, classification, pattern recognition and robotic control, etc. In

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this research, MLPNN with supervised learning is used to classify the health beverages flavours (taste, colour and odour) that are consumer's needs.

C. Evaluation the Model

Cross-validation [15] is a measurement of evaluating the performance of a forecasting model and statistical analysis will generalise to datasets. The datasets are divided into several parts such as K-fold cross-validation (K is sub-samples). After that, one of the datasets is used as the model's performance evaluation with confusion matrix. The confusion matrix contains information about actual and forecasted form the classification model [16].

Accuracy is the value that the model can forecast accurately.

$$Accuracy = \frac{\sum_{i=1}^n Y_{ii}}{\sum_{i=1}^n \sum_{j=1}^n Y_{ij}} \quad (1)$$

where Y_{ij} is the number of samples actually belong to class A_i , which is classified by class A_j .

Precision is the value that the model forecasts is correct.

$$Precision_i = \frac{Y_{ii}}{\sum_{k=1}^n Y_{ki}} \quad (2)$$

Recall is a measure of the forecasted model ability.

$$Recall_i = \frac{Y_{ii}}{\sum_{k=1}^n Y_{ik}} \quad (3)$$

III. METHODOLOGY

In order to obtain the decision support framework (DSF), the steps of this research are illustrated in Fig. 1, which consists of gathering the data, system designing, programming and testing, finally verifying and validating.

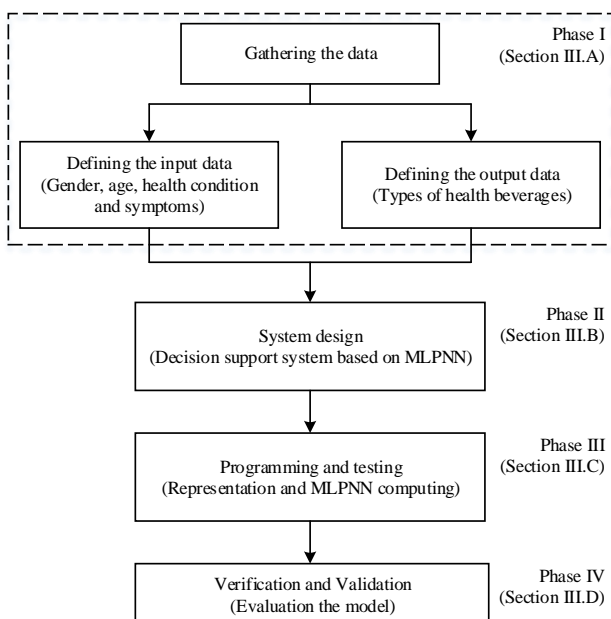


Fig. 1. DSF concept for health beverages flavouring.

A. Gathering the Data

Questionnaires were used to obtain the preferences of the 200 Thai elderly on health beverages flavour. The samples were divided into four groups, which were gender (male or female), age (60-65 or over 65 years), health condition (healthy or unhealthy) and symptoms of the elderly. Those symptoms related to the common problems elderly, which are Cardiovascular disease, Central nervous system, Gastrointestinal system, Urinary system, Endocrine system, Musculoskeletal system, Seeing and Hearing, and others. Then, the types of health beverages were selected from the properties that mitigate those symptoms and was investigate by experts. The beverages are Lingzhi drink, Lingzhi drink with honey, Germinated brown hom nin rice drink with cereal, Mangosteen juice, Mangosteen juice with longkong, Pomegranate juice, Passion juice, and Passion juice with gac fruit.

B. The Decision Support Framework Designing

The decision support framework (DSF) should have three main components, that are user interface, inference engine for decision making and database for storing the data and training the system [13]. Fig. 2 shows the DSF model based on MLPNN.

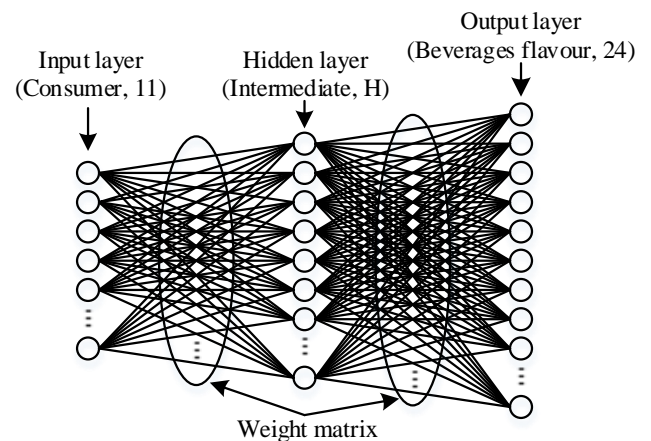


Fig. 2. The DSF model based on MLPNN.

1) User interface and database designing

The decision support framework program was designed by using HTML which features the input form for the user and shows the results of decision making. The PHP was developed to train the system by MLPNN through the data which was recorded in MySQL database. This framework was used to classify health beverage preference to the elderly. The welcome page for user interface shows in Fig. 3, which divides into consumer section, manufacturer section and administrator.

2) The artificial neural network designing

A suitable and simple structure to solve the classification problem employed a multi-layer perceptron neural network (MLPNN) which is a back-propagation algorithm (BP). The structure consists of the first layer (called input layer), the second layer (called hidden layer) and the third layer (called output layer).

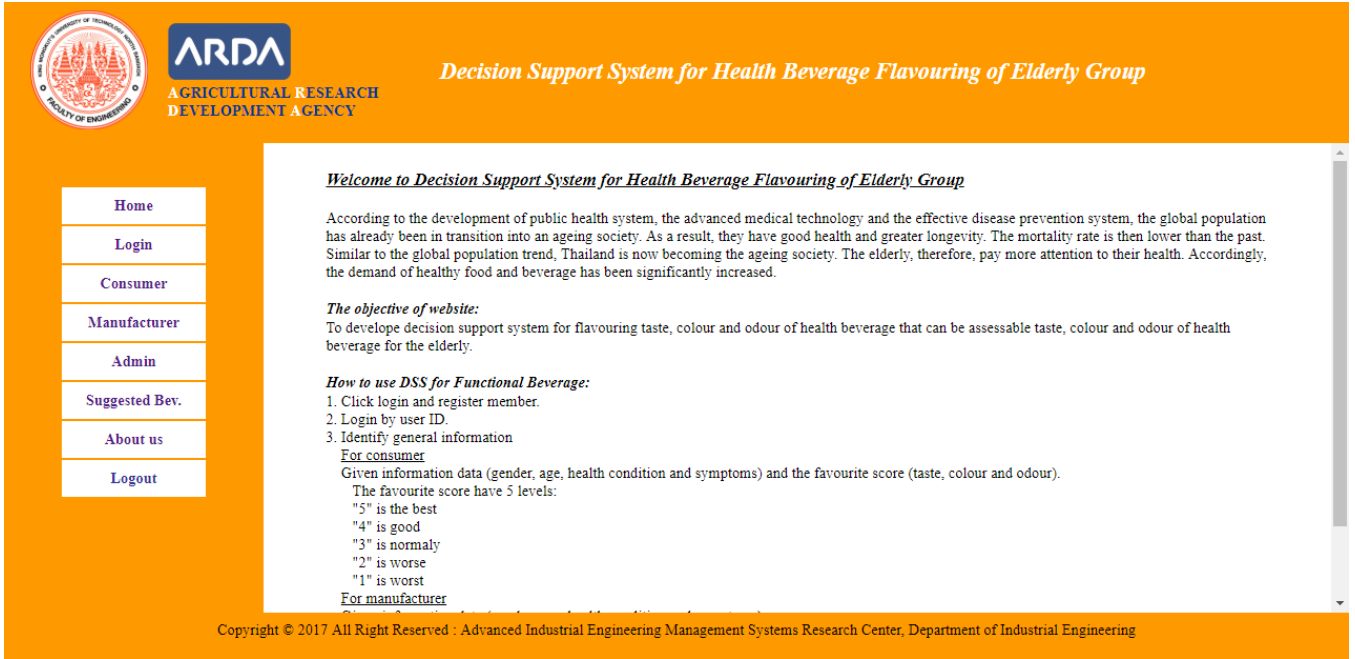


Fig. 3. Welcome page for DSF program, developed by the authors.

The number of neurons in the input layer should have 11 nodes (refer to the number of elderly groups), the number of neurons in the output layer should have 24 nodes (refer to the number of flavouring beverages) and the number of neurons in the appropriate hidden layer is the neurons number which is the lowest mean square error (MSE) as shown in (4). The function used to determine the output signal is called the transfer function or activation function which is shown in (5). The training function for consumer health beverage preferences is the back-propagation algorithm which can adjust the weight matrix as shown in (6) to (9). Mean square error (MSE)

$$MSE = \frac{1}{N} \sum_{n=1}^n [e_j(n)]^2 \quad (4)$$

where N is the number of neurons in output layers.

Transfer function

$$Y = \varphi(v) = 1 / (1 + \exp(-v)) \quad (5)$$

where Y is output value, φ is transformation function and v is sum of weights.

Weight update

$$W_{ji}^{(l)}(n+1) = W_{ji}^{(l)}(n) + \alpha [W_{ji}^{(l)}(n) - W_{ji}^{(l)}(n-1)] + \eta \delta_j^{(l)}(n) y_j^{(l-1)}(n) \quad (6)$$

whereas

$$e_j(n) = d_j(n) - o_j(n) \quad (7)$$

$$\delta_j^{(l)}(n) = e_j(n) b_j(n) [1 - o_j(n)] \quad (8)$$

$$\delta_j^{(l)}(n) = y_j(n) [1 - y_j(n)] \sum \delta_k^{(l+1)}(n) W_{kj}^{l+1}(n) \quad (9)$$

where W_{ji} is weight matrix, n is learning iteration (epoch), l is first and second (hidden) layer, α is learning rate, η is momentum constant, δ_j is slope at a layer, e is error, d is desire output, o is computation output, L is output layer, y is output at a layer and δ_k is previous slope.

According to input, hidden and out layer can simulate the structure of the MLPNN in Fig. 4.

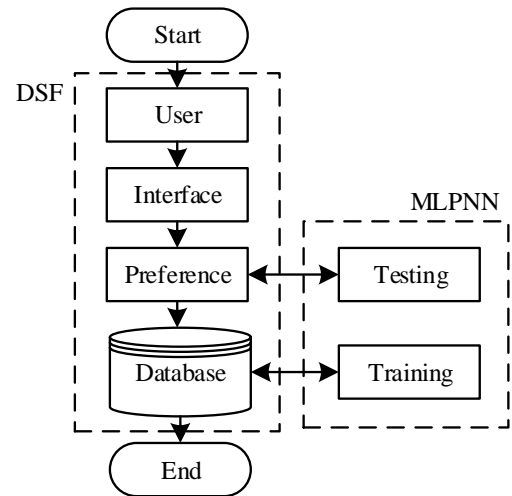


Fig. 4. MLPNN model for health beverages flavouring.

C. Programming and Testing

Within the DSF program, the buttons should be tested to show that they function correctly. For example, user interface, Fig. 5 shows consumer section page for input the data to DSF program.

After that, the number of nodes in the hidden layer was determined by the number of neurons that had the lowest MSE with MLPNN algorithm as shown in Fig. 6. The appropriate neural network structure in this research had 11 input layer nodes, 30 hidden layer nodes and 24 output layer nodes (11-30-24). The MSE in 30 hidden layer nodes was 0.01569.

Part I:

Please, identify your general information.

- Gender: Male
- Female
- Age: 60-65 years
- More than 65 years
- Health condition: Unhealthy
- Healthy
- Symptoms of the elderly: Cardiovascular disease
- Central nervous system
- Gastrointestinal system
- Urinary system
- Endocrine system
- Musculoskeletal system
- Seeing and hearing
- Other

Part II:

Please score of taste, colour and odour for your preference of health beverage.

	Taste:	Colour:	Odour:
Lingzhi drink	4 ▼	4 ▼	4 ▼
Lingzhi drink with honey	4 ▼	4 ▼	4 ▼
Germinated brown hom nin rice drink with cereal	4 ▼	4 ▼	4 ▼
Mangosteen juice	4 ▼	4 ▼	4 ▼
Mangosteen juice with longkong	4 ▼	4 ▼	4 ▼
Pomegranate juice	4 ▼	4 ▼	4 ▼
Passion juice	5 ▼	5 ▼	5 ▼
Passion juice with gac fruit	4 ▼	4 ▼	4 ▼

Fig. 5. The DSF program (consumer section page).

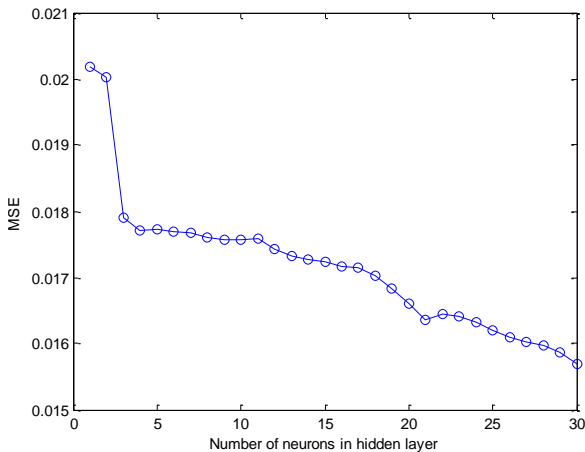


Fig. 6. MSE versus number of neurons in the hidden layer.

D. Verification and Validation

K-fold cross-validation is used to validating the MLPNN model. This research, K is 10 (10-fold cross-validation) [15] then the datasets are divided into 10 sub-samples. A single sub-sample is considered the validation data for the model testing and the K-1 sub-samples are used to training the data. The process is repeated K times (10 times) and K sub-samples used exactly as the validation data.

The results from 10-fold cross-validation are shown in the confusion matrix (Table IV). From the Table IV, the results show the forecasting data that are correctly and incorrectly. After that, the equation (1) and (2) are used to the computing recall and precision of each class of the forecasting data (Lingzhi drink with honey, Mangosteen juice, Mangosteen juice with longkong, Passion juice, and Passion juice with gac fruit). Finally, the equation (3) is used to the computing

accuracy form the overall class. The results of validating the MLPNN model are shown in Table I. The evaluating of the model, the average recall is 78.87%, the average precision is 82.01%, and the accuracy is 79.50%.

TABLE I: PERFORMANCE OF THE MLPNN MODEL

Class	Recall (%)	Precision (%)	Accuracy (%)
Lingzhi drink with honey	100.00	100.00	79.50
Mangosteen juice	55.00	68.75	
Mangosteen juice with longkong	66.67	90.32	
Passion juice	87.23	83.67	
Passion juice with gac fruit	85.37	67.31	

Verification of this research was conducted by using a single case for system training in order to determine the convergence of data. The input data was general information from the elderly for example gender is female, aged over 65 years, health condition is healthy (if the user picks on healthy, cannot picks on type of the symptoms). The output data (target data) is the score of preference in the flavour of beverages (for this example set the highest rating for passion juice). The test results are shown in Table V.

From Table V, the values in rows Y19 (taste of passion juice), Y20 (colour of passion juice) and Y21 (odour of passion juice) converged to one, which is the target value, when the epochs increased and the MSE decreased. This confirmed that the system had a correct computation.

IV. RESULTS

This research collected the data from the elderly northern, northeastern, southern, and central in Thailand by the questionnaire. The sample size is 200 samples. Data from the

questionnaire are shown in Table II. The results show that 75.5% of the samples are unhealthy. The symptoms found in the samples are Musculoskeletal system, Endocrine system, and Cardiovascular disease, respectively.

TABLE II: THE DETAILS OF COLLECTING DATA

No.	Description	Percentage	
1	Gender	Male	50.0
		Female	50.0
2	Age	60-65 years	48.5
		Over 65 years	51.5
3	Health condition	Healthy	24.5
		Unhealthy	75.5
4	Symptoms	Cardiovascular disease	23.0
		Central nervous system	1.0
		Gastrointestinal system	1.0
		Urinary system	1.0
		Endocrine system	24.0
		Musculoskeletal system	25.0
		Seeing and hearing	23.0
Other	2.0		

The program was then implemented for a case study. In the beginning, input the data (in this example were female aged over 65 years and healthy) was used to classifying favorite beverage by consumer group (for this example set the highest rating for Passion juice). Next, consumer preference data was stored in the database to be used for decision making. The program results of favourites beverage by the consumer (personal) were then compared to the overall favourites beverage (shown in Table III).

TABLE III: OUTPUT FORM OF PERSONAL AND OVERALL PREFERENCE

	Health beverage for consumer	Recommended health beverage
Taste	Passion juice	Mangosteen juice
Colour	Passion juice	Mangosteen juice
Odour	Passion juice	Mangosteen juice with longkong

The results from the data collection can be divided into eight groups: male aged 60-65 years and unhealthy, male aged 60-65 years and healthy, male aged over 65 years and unhealthy, male aged over 65 years and healthy, female aged 60-65 years and unhealthy, female aged 60-65 years and healthy, female aged over 65 years and unhealthy, and female aged over 65 years and healthy. In Table VI shows the most preferred health beverage for each sample. In addition, it shows the recommended healthy beverages according to the group of symptoms based on the nutrient of beverages.

V. CONCLUSION AND RECOMMENDATION

The resulted network architecture for classification of health beverages has 11 input layer nodes, 30 hidden layer nodes and 24 output layer nodes which were 100 epochs. MSE is 0.01569. The evaluated performance of the model with 10-fold cross-validation and confusion matrix, accuracy is 79.50%. The program can classify health beverages by consumer preferences successfully. Across manufacturer section, a variety of beverage flavouring in different products that make it a difficult and complicated task to identify the customer needs. Therefore, the objective of this research is to develop and design the decision support framework (DSF) in order to assess customer satisfaction on beverage flavouring by the DSF software.

For future study, consumers' preferences in large quantities should be performed but may take a long time when training. This is because of DSF design MLPNN by using a supervised learning method which allows a more accurate and appropriate result with a large scale data, and this is the reason DSF have to compare the output value and MSE versus epochs in Table V. Moreover, modifying the value of other variables such as learning rate can also affect the time of training.

APPENDIX

TABLE IV: PERFORMANCE OF THE MLPNN MODEL IN CONFUSION MATRIX

		Actual				
		Lingzhi drink with honey	Mangosteen juice	Mangosteen juice with longkong	Passion juice	Passion juice with gac fruit
Forecast	Lingzhi drink with honey	3				
	Mangosteen juice		11		4	1
	Mangosteen juice with longkong			28	2	1
	Passion juice				82	4
	Passion juice with gac fruit		9	2	6	35

TABLE V: THE CONVERGENCE OF SAMPLE DATA USED TO TEST THE PROGRAM

Test	Epochs	10	20	30	40	50	60	70	80	90	100
Y1	0.8	0.75175	0.79090	0.79782	0.79941	0.79971	0.79982	0.79980	0.79981	0.79981	0.79980
Y2	0.8	0.74131	0.78773	0.79740	0.79961	0.80003	0.80018	0.80015	0.80013	0.79996	0.79984
Y3	0.8	0.75074	0.79089	0.79787	0.79941	0.79969	0.79973	0.79976	0.79978	0.79982	0.79980
Y4	0.8	0.75117	0.79265	0.79881	0.80011	0.80026	0.80042	0.80041	0.80033	0.80022	0.80019
Y5	0.8	0.75782	0.79262	0.79872	0.79997	0.80019	0.80016	0.80018	0.80012	0.79995	0.79986
Y6	0.8	0.76786	0.79578	0.79899	0.79968	0.79983	0.79982	0.79982	0.79984	0.79984	0.79982
Y7	0.8	0.75187	0.79143	0.79822	0.79949	0.79974	0.79982	0.79983	0.79982	0.79983	0.79982
Y8	0.8	0.75730	0.79081	0.79766	0.79933	0.79983	0.79983	0.79984	0.79984	0.79984	0.79983

TABLE V: THE CONVERGENCE OF SAMPLE DATA USED TO TEST THE PROGRAM (CONT.)

Epochs		10	20	30	40	50	60	70	80	90	100
Test											
Y9	0.8	0.75352	0.79184	0.79787	0.79941	0.79983	0.79985	0.79991	0.79995	0.79992	0.79987
Y10	0.8	0.99827	0.82359	0.80556	0.80092	0.79989	0.79980	0.79984	0.79981	0.79983	0.79986
Y11	0.8	0.84424	0.81890	0.80464	0.80076	0.79995	0.79981	0.79983	0.79983	0.79983	0.79985
Y12	0.8	0.81883	0.80854	0.80210	0.80024	0.79976	0.79967	0.79963	0.79967	0.79977	0.79983
Y13	0.8	0.99948	0.99883	0.80810	0.80240	0.80062	0.80015	0.80014	0.80018	0.80016	0.80016
Y14	0.8	0.84606	0.82408	0.80789	0.80229	0.80065	0.80015	0.80015	0.80010	0.80006	0.80002
Y15	0.8	0.86025	0.82679	0.80749	0.80122	0.79974	0.79948	0.79952	0.79952	0.79954	0.79957
Y16	0.8	0.75189	0.79118	0.79840	0.80007	0.80033	0.80035	0.80020	0.80017	0.80017	0.80018
Y17	0.8	0.74744	0.78991	0.79821	0.79994	0.80023	0.80020	0.80018	0.80019	0.80019	0.80017
Y18	0.8	0.74442	0.79133	0.79947	0.80084	0.80084	0.80068	0.80049	0.80040	0.80019	0.80018
Y19	1	0.90397	0.92702	0.93846	0.94602	0.95141	0.95552	0.95882	0.96156	0.96386	0.96584
Y20	1	0.88795	0.91973	0.93448	0.94381	0.95022	0.95492	0.95854	0.96140	0.96374	0.96569
Y21	1	0.89710	0.92361	0.93661	0.94505	0.95093	0.95535	0.95883	0.96166	0.96400	0.96599
Y22	0.8	0.99784	0.81083	0.80588	0.80288	0.80158	0.80103	0.80079	0.80067	0.80054	0.80050
Y23	0.8	0.82378	0.81226	0.80438	0.80159	0.80078	0.80051	0.80047	0.80048	0.80046	0.80045
Y24	0.8	0.84790	0.82704	0.81035	0.80367	0.80156	0.80089	0.80067	0.80050	0.80049	0.80046
MSE		0.02125	0.01781	0.01618	0.01605	0.01597	0.01588	0.01580	0.01574	0.01570	0.01569

TABLE VI: THE RESULTS OF BEVERAGE PREFERENCE AND RECOMMENDATION FOLLOW THE CONSUMER GROUPS

Consumer groups	The most preferred health beverage by consumer group			Beverage recommended (by symptoms)
	Taste	Colour	Odour	
Male Age 60-65 years Unhealthy	Passion juice	Passion juice	Passion juice	-Lingzhi drink -Germinated brown hom nin rice drink with cereal -Passion juice
Male Age 60-65 years Healthy	Passion juice	Mangosteen juice with longkong	Passion juice with gac fruit	-
Male Age over 65 years Unhealthy	Passion juice	Passion juice with gac fruit	Passion juice	-Lingzhi drink -Germinated brown hom nin rice drink with cereal
Male Age over 65 years Healthy	Lingzhi drink with honey	Mangosteen juice with longkong	Lingzhi drink with honey	-
Female Age 60-65 years Unhealthy	Passion juice	Passion juice	Passion juice with gac fruit	-Mangosteen juice -Mangosteen juice with longkong -Passion juice
Female Age over 65 years Unhealthy	Passion juice with gac fruit	Passion juice	Passion juice with gac fruit	-Mangosteen juice -Mangosteen juice with longkong -Passion juice
Female Age over 65 years Healthy	Mangosteen juice	Mangosteen juice	Mangosteen juice with longkong	-

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