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Modeling Consumer Overall Acceptance for Traditional Spice-Based Ready-to-Drink Using Artificial Neural Network and Kansei Engineering

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***Abstract*—Measuring consumer acceptance of food products is challenging, primarily because the process is susceptible to bias. Several studies have reported that this challenge can be addressed through Kansei engineering through verbal and nonverbal response measurements. Therefore, this study aimed to predict consumer overall acceptance using artificial neural networks (ANN) and Kansei engineering. A total of 30 respondents participated in this study to test nine different samples of traditional spice-based ready-to-drink (RTD). The overall acceptance score and Kansei responses, including verbal and nonverbal, were then measured. Each sample was served cold in a 60-mL cup labeled with a three-digit random code, and the panelists were successfully presented with the nine drinks. All participants were asked to rank each Kansei word scale based on the intensity of their feelings during the assessment. The heart rate (HR) and skin temperature (ST) were also measured as nonverbal responses in real time. The results showed that Kansei's responses and respondent background best predicted overall acceptance. The optimal model architecture had ten input neurons, two hidden neurons, and one output neuron (10-2-1). The training, validation, and testing data showed that the performance of ANN was satisfactory, with a low error rate (RMSE) and a high coefficient of correlation value (R2). Based on the findings, the developed model could inspire and motivate further studies and development in industries to develop appropriate products for potential consumers, thereby revolutionizing the food industry.**

***Keywords*—Artificial neural network; consumer overall acceptance; Kansei responses.**

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I. INTRODUCTION

Over the years, traditional spiced drinks have increasingly gained popularity among Indonesians [1]. These drinks were typically characterized by including various spices in their composition. Furthermore, Indonesia is known to have multiple types of traditional spiced drinks, including *wedang uwuh, jamu, bandrek, and bir pletok* [2]. Among these, *wedang uwuh* has been developed to fulfill the needs of the young consumer generation, but the measurement of its consumer acceptance has proven to be a challenging endeavor [3]. This has led to the failure of several new spiced products to resonate with the younger demographic, leading to a notable increase in the number of product failures. Several reports have indicated that the failure rate of new food items ranged from 70% to 80%. [4]. The assessment of consumer acceptance of food products is often carried out using explicit methods, such as self-reported sensory evaluation [5]. Sensory evaluation has been extensively utilized in various studies due to its ease of application and cost-effectiveness [6], but this method has the potential to lead to biased results [7], [8].

Kansei Engineering offers a valuable means of measuring consumer acceptance while minimizing the potential bias [9], [10]. In this study, Kansei responses were used to predict consumer overall acceptance. These responses were divided into two categories, including verbal and nonverbal [11]. Verbal responses were related to stated adjectives or verbs that show consumer affective needs, while nonverbal responses were associated with measurable human body indicators. This approach is highly suitable for measuring the needs of millennials and Gen Z due to its association with the physical and psychological aspects of human affective needs [12].

Comprehending Kansei responses across various human parameters poses a complex and intricate challenge [11], [13]. In the context of food studies, artificial intelligence (AI) in the form of an artificial neural network (ANN) has been used to model these responses [14]. Furthermore, ANN is a critical, precise method that closely mimics the functionality of the biological neural system, which can distinguish complicated correlations across input and target data sets [11]. In recent times, there has been a growing interest in the application of Kansei engineering based on artificial intelligence in predicting group preference for the adoption of Industry 4.0 [15], customizing post-pandemic food service [14], and modeling Small and Medium Size Enterprises (SME) trust [11].

An artificial intelligence approach has not been used to analyze consumer acceptance based on Kansei's responses to traditional spice-based ready-to-drink (RTD) from Indonesia. Using Kansei responses to test food products can reduce bias, improving our understanding of public emotion. Therefore, this study aimed to predict the consumer overall acceptance score using ANN and Kansei engineering.

The findings were expected to support SMEs in measuring consumer acceptance, thereby increasing the number of product successes. Traditional spiced RTD was developed to support Indonesia in proposing the archipelago spice route as an intangible world cultural heritage to UNESCO. This endeavor aimed to obtain scientific evidence of spice product innovation. The consumer overall acceptance model can assist SMEs in competing in the global market and expanding the distribution of spiced products to the young generation market.

II. Materials and Method

A. Materials

Nine types of traditional spiced-based RTD were prepared using different processes and formulations. The processes consisted of other times and temperatures of pasteurization (10, 20, and 30 min; 65°C, 75°C, and 85°C), while the formulation included different sugar and milk compositions [3]. The spiced drink samples were then labeled as products I–IX. The panelists were not provided with information regarding the process and formulation of each product.

B. Method

1) Participants: A total of 30 young, healthy participants aged between 18-41 years who had previous experience with spiced drink products (defined as at least being incidental users) and reported no known food allergies, intolerances, or significant medical histories of major diseases were selected as participants. Viejo [16] utilized the same number of panelists to assess food acceptability based on sensory properties. All participants who completed the study were rewarded with financial compensation in appreciation for their assistance.

2) Experimental protocol: The experimental protocol was explained to each person, and informed consent indicating voluntary participation was obtained before the experiment. This study was approved by the ethics committee of Universitas Gadjah Mada, with reference No KE/UGM/021/EC/2023.

3) Consumer overall acceptance score: Participants were asked to measure the overall acceptance score for each product and sort their preferences starting from "extremely like" to "dislike" using the 9-point Likert scale. Subsequently, the participants individually filled in the scores after testing the samples.

4) Kansei Responses: All participants were requested to evaluate their preference for perceived Kansei words (verbal) on 7-point Likert scales ranging from 0 (dislike significantly) to 7 (like extremely). This scale has been commonly used to measure consumer liking of food or beverage items [1]. Kansei words, including "flavor," "easy," "fresh," and "rest" were utilized in this study. Nonverbal responses, including HR and ST, were measured in this study using Polar Verity Sense OH10 and thermocron DS1921H, respectively. The sensors were placed on the wrist of the nondominant hand of the participant to measure HR (unit: beat/minute) [17]. Meanwhile, ST (unit: °C) was measured by placing an electrode on the fingertip of the participant [18]. Data were collected at a sampling rate of 1-min intervals.

5) Instruction and Experimental Procedure: The experimental procedure used was described based on the modified method by Samant et al., [19]. Participants were requested to sit comfortably before the study began, and the experimental technique was thoroughly explained. Each sample was served in a 60-mL cup labeled with a three-digit random code at a chilled temperature. The panelists were then randomly presented with the nine samples successively. Furthermore, those who participated were asked to rank each Kansei word scale based on the intensity of their feeling. The HR and ST were also measured in real-time, while the participant rated the verbal questionnaire. In this case, the testing was divided into three stages, namely pre-consumption, consumption, and post-consumption within 3 min apart [20].

6) ANN Model Building: Artificial Neural Network (ANN) was performed using MATLAB R2022a Update 5 (9.12.0.2039608) (The MathWorks Inc., Natick, MA, USA). Figure 1 shows the methodology for building the ANN consumer overall acceptance model. The ANN used a feedforward architecture and supervised backpropagation learning [21]–[23]. The network was trained using the Levenberg–Marquardt (TRAINLM) algorithm. Furthermore, two distinct types of nonlinear sigmoid transfer functions were used to determine the relationship between input and output, namely logs and tansig [24]. The ANN design comprised an input stage, hidden layers, and an output layer [25].

The raw scores of the 24 panelists were mapped to the mean consumer overall acceptability scores. 80% of the data (i.e., nine samples × 19 participants = 171 data sets) were used for training, while the other 20% were used for validating the trained neural network (i.e., nine samples × 5 participants = 45 data).

Similar to regression modeling, the performance of the developed ANN model was tested with all samples (i.e., 9 samples × 6 participants = 56 data), which was not presented to the network during the training. Therefore, a total of 216 datasets were utilized as input and output of the ANN model, and 56 datasets were utilized for testing the model. Data sets were normalized between 0 and 1 using the min–max normalization before using them as inputs for the ANN.

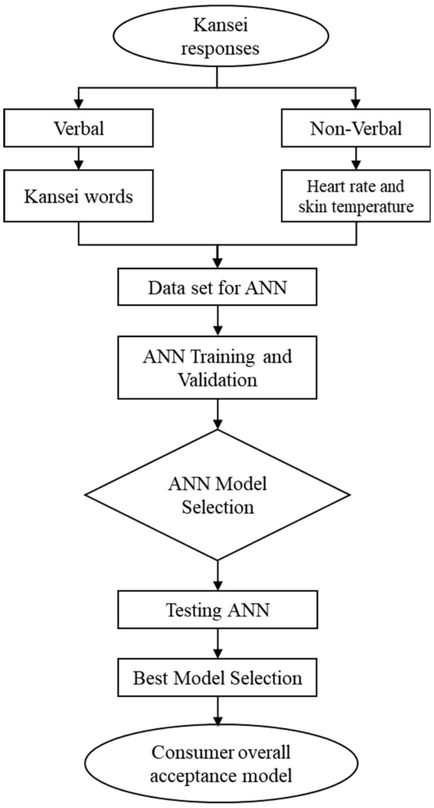

Fig. 1 Study methods for modeling consumer overall acceptance

Normalization was performed because neural networks used a sigmoid activation function with output values ranging from 0 to 1 to prevent the dominance of variables with large values over those with small values [26]. The normalization data could be calculated using the formula below:

$$X' = \frac{0{,}8(X - X_{min})}{(X_{max} - X_{min})} + 0{,}1 \tag{1}$$

where
X = actual data;
X' = data normalization.

The input data of the ANN model was divided into three data types, namely basic background information of participants, verbal questions, and nonverbal measurement. The basic information comprised body height, body weight, body mass index, sports activity, gender, and spiced beverage consumption frequency. The verbal data from the kansei questionnaire were collected using a 1–7 Likert scale, while the nonverbal data were measured using the HR and ST sensors. Meanwhile, the output of the ANN model was assessed using a 9-point Likert scale for the overall acceptability of the products. The parameters used to evaluate the ANN model were determined by the root mean square error (RMSE) and coefficient of correlation value (R2) [11].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}, \tag{2}$$

$$R2 = \sqrt{1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - y)^2}}. \tag{3}$$

III. Results and Discussion

A. Consumer Overall Acceptance Score

Figure 2 shows the average acceptance scores of the nine traditional spiced-based RTD and an overview of the ANOVA test results. The findings showed that the products differed significantly (p<0.05) in acceptance. Based on the results, three groups were identified from the most accepted sample to the strongly not accepted. Sample VIII had the highest acceptance score and likes. Samples I, II, III, IV, V, VI, and VII were liked, while IX was liked less. Therefore, the figure below illustrated that the data could be divided into three groups based on the acceptance score, where samples I to VII, VIII, and IX were presented as Group 1, Group 2, and Group 3, respectively.

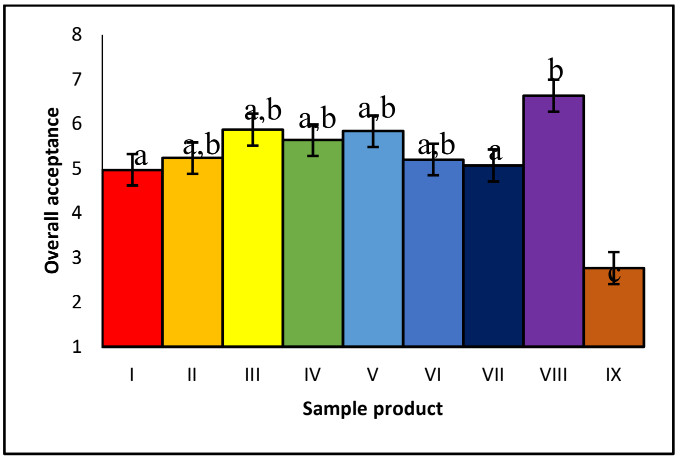

Fig. 2 Average overall consumer liking scores for traditional spiced-based RTD (n = 36). Error bars correspond to the standard deviations of the mean values (p<0.05).

B. Kansei Responses Measurement

1) Verbal Responses: The nine samples significantly differ in terms of kansei words "flavor," "easy," "fresh," and "rest" (P < 0.05). As shown in Figure 3, VIII elicited a higher kansei liking score compared to others. Moreover, participants felt more "fresh" and "rest" after consuming the product compared to others.

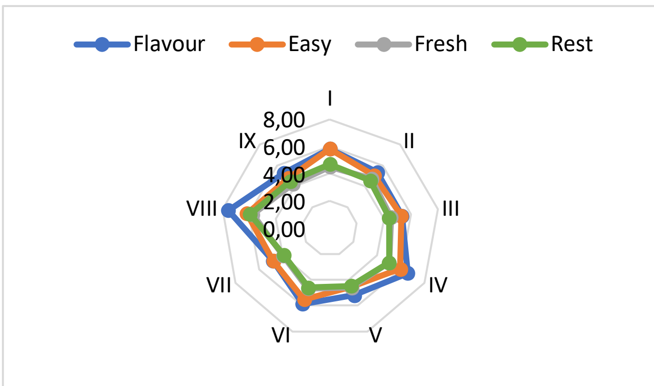

Fig. 3 Mean comparisons among nine spiced drink samples considering self-reported kansei words (p<0.05)

2) Nonverbal Responses: Figure 4 shows that HRs in Group 1 increased during the tasting period, followed by a gradual decrease. In Group 2, the HR slightly increased before tasting and decreased during the tasting period, followed by stagnant data, while Group 3 showed fluctuating data.

The results showed that the HR frequency did not vary significantly with traditional spice-based ready-to-drink. The dislike of certain foods was generally associated with a slightly increased HR, but this difference was not statistically significant. Furthermore, these results were consistent with Wijk [27], which also measured the HR of liked and disliked foods. The product associated with the “rest” and “fresh” emotions based on responses showed that the respondents felt highly relaxed by decreasing and stabilizing the heart rate [28].

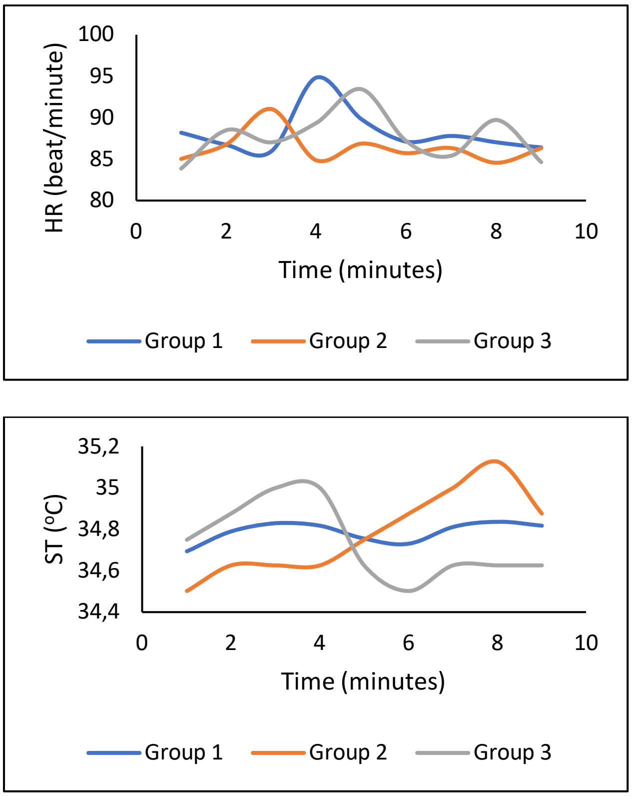

Fig. 4 Changes in (a) heart rate value (beats/min) and (b) skin temperature (°C)

Based on the results, ST was increased in the first 3 min before consumption. In Group 2, the chart showed a gradual increase after consumption, while the other group remained stagnant or decreased. The ST was probably slightly higher for liked foods than disliked foods despite reaching only a minimal difference. This ST trend was somewhat similar to Wijk [29], which showed that liking was associated with increased ST.

C. ANN Model Building

The ANN model was used to predict the consumer's overall acceptance score. The four best architectures were selected based on the criteria of RMSE and R2 [30], which measured the accuracy between the measured and predicted values using trial and error. Table 1 shows the four models of ANN architectures investigated to test the model sensitivity.

TABLE I
TRAINING AND VALIDATION OF ANN MODEL

Model	Archi-tectures	Itera-tion	Training		Validation	
			RMSE	R2	RMSE	R2
1	Model 10-2-1	1000	0.079	0.84	0.065	0.91
2	Model 10-4-1	1000	0.080	0.84	0.080	0.91
3	Model 10-6-1	1000	0.094	0.79	0.077	0.87
4	Model 10-8-1	1000	0.084	0.84	0.082	0.90

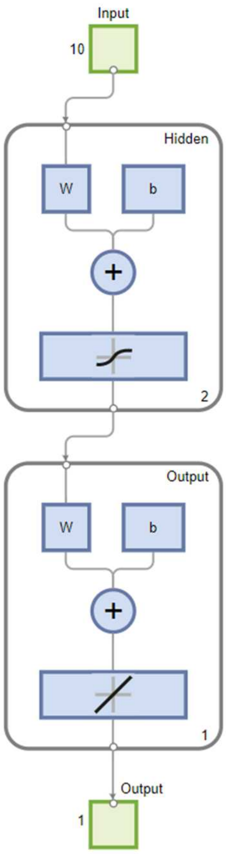

Fig. 5 ANN model architecture for prediction of overall acceptance score

Error-values were shown in the RMSE training and validation values. The lowest error value was obtained on the first model with RMSE training and validation values of 0.079 and 0.065, respectively, indicating a good performance [31]. Therefore, the lowest value was obtained in a 10-2-1 network structure, indicating ten inputs, two neurons in the hidden layer, and one output. The best neural network in this study is presented in Figure 5. This study also calculated R-values for the regression training, validation, and test sets. R represented the correlation between the output and target values in this situation. This value had a percentage indicating how the targets effectively accounted for the difference in production.

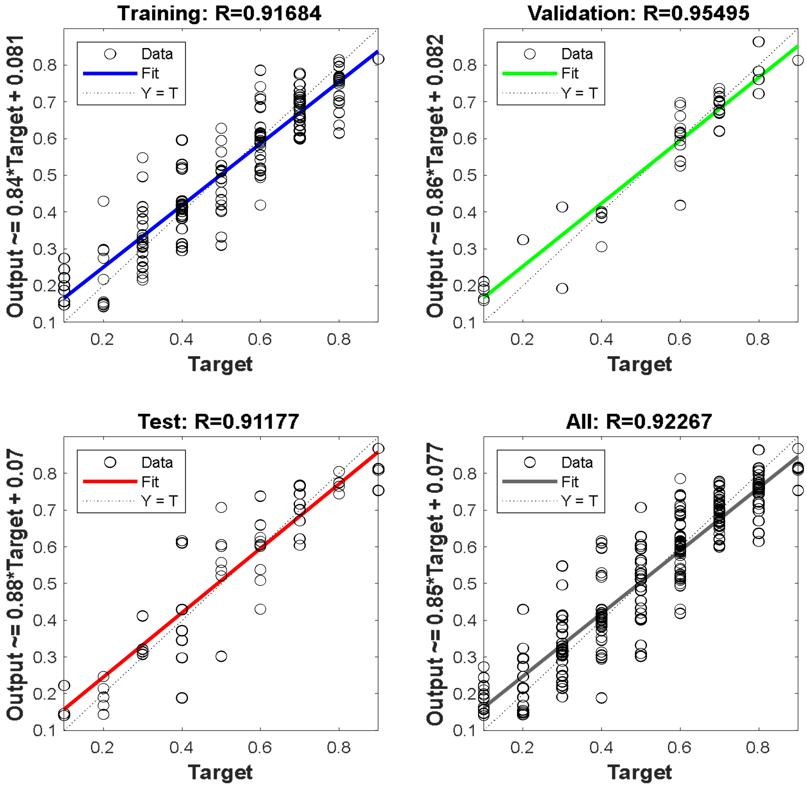

Fig. 6 ANN Regression plot for best model (10-2-1)

When R was equal to 1, a perfect correlation existed between targets and outputs, with the target being the actual value. Figure 6 showed that the R^2 (coefficient of determination) values for phases of training, validation, testing, and all were 0.84 (0.92), 0.91 (0.95), 0.83 (0.91), and 0.85 (0.92), respectively. The results showed a strong correlation between the observed and predicted values across all data for each group. The regression models above 80% showed the goodness of fit of the developed model [32].

D. Best Model Selected

Based on the results, the optimum ANN structure was 10-2-1. This ANN's inputs were Kansei, which comprised verbal and nonverbal responses, while the output was overall acceptance using a 9-point Likert scale. In this network, TRAINLM was chosen as the training function, and the weight and bias values were updated using Levenberg–Marquardt optimization, as shown in Table 2 [33].

TABLE II
ANN MODEL BASED ON TRAINING AND VALIDATION

Factors	**Parameters**
Input neurons	10
Hidden neurons	2
Output neurons	1
Type of network	Feedforward backpropagation
Training	TRAINLM (Levenberg–Marquardt)
Learning	LEARNDGM
Performance	Root Mean Squared Error
Transfer function	TANSIG
Epoch number	1000

Furthermore, TANSIG and LEARNDGM were selected as separate transfer and learning functions, respectively. The tested ANN model successfully predicted the overall acceptance score in traditional spice-based RTD using the feedforward backpropagation supervised learning method through the RMSE performance function.

E. Theoretical Contribution

The consumer overall acceptance model showed good performance using ANN. This model was specified for young consumers' acceptance of traditional spice-based RTD to strengthen the scientific evidence and support Indonesia's proposal to UNESCO to propose the archipelago spice route as an intangible world cultural heritage. It also enhanced several existing theoretical approaches for the consumer preference model based on nonverbal responses [27], [34] and the Kansei model [11], [15], [35].

F. Practical Implication

The consumer overall acceptance score model for traditional spice-based RTD was successfully used to predict product preference using Kansei responses. Other studies could utilize this model to develop spiced beverage products and increase the number of product successes after launching. Therefore, the consumer liking preference could be correlated with the willingness to pay [36], [37]. The findings of this study were also beneficial to industries and businesses in terms of reducing the time and expense of experimental trials before actual manufacturing [38], as well as developing the product based on the consumer needs of the young generation [39].

G. Limitation and Future Studies

The proposed model acknowledged several limitations. It only focused on Kansei's responses and disregarded sensory attributes. Although the sensory attribute was slightly biased, it could still strengthen the model. This study used excessive ANN inputs, but the experiment results showed a strong correlation between consumer acceptance and Kansei responses. Future studies were advised to comprehensively compare Kansei responses and sensory attributes to understand their differences. The sensory qualities included aroma, sourness, sweetness, astringency, flavor, aftertaste, and mouthfeel, as suggested by Rashid et al. [40]. Adding panelists was expected to reduce the number of inputs, providing a simple model. The findings of this study are beneficial to industries in terms of reducing the time and expense of experimental trials before actual production.

IV. Conclusion

In conclusion, the backpropagation supervised learning method could be used to model consumer acceptance of traditional spice-based RTD. The training, validation, and testing data showed that ANN performance was satisfactory with a low error rate. Based on the results, the lowest error value was obtained in the first model with RMSE training and validation values of 0.079 and 0.065, respectively, indicating good performance. The optimal model architecture (10-2-1) had ten inputs, two hidden neurons, and one output. The network also produces R2 between 0.8-0.95 for training, validation, and testing. The regression models above 80% showed the goodness of fit.

According to the model, respondents' fundamental information and verbal and nonverbal (Kansei) responses influenced consumer acceptance in the implementation of product design and development. Furthermore, the model could facilitate industry studies and development regarding producing appropriate products for potential consumers, particularly the young generation. The findings of this study are also beneficial to industries and businesses in terms of reducing the time and expense of experimental trials before actual production.

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Conflict of Interest

All authors declare no potential conflict of interest.

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