Extraction of Consumer Behavior Patterns Toward Quality Labels Using a Fuzzy Inference System Based on the Hierarchy of Effects Model

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https://doi.org/10.5109/7429614

出版情報：Evergreen. 13 (2), pp.673-689, 2026-06. Transdisciplinary Research and Education Center for Green Technologies, Kyushu University
バージョン：

Extraction of Consumer Behavior Patterns Toward Quality Labels Using a Fuzzy Inference System Based on the Hierarchy of Effects Model

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(Received May 19, 2025; Revised January 28, 2026; Accepted April 13, 2026)

Abstract: This study explores the influence of quality labels on consumer purchasing behavior using a Fuzzy Inference System (FIS) aligned with the Hierarchy of Effects (HoE) model. The methodology involved four main phases: primary data collection, fuzzy rule extraction from HoE-based attributes, model validation, and pattern interpretation. A total of 76 fuzzy rules were generated to classify consumer behavior across four HoE stages: Not Aware, Cognitive, Affective, and Conative. The overall model accuracy reached 78.59%. However, performance was uneven across stages, particularly in the not aware stage, which achieved only 45.5% accuracy, with 36.4% of its cases not covered by any rule. In contrast, the Cognitive, Affective, and Conative stages exceeded 80% accuracy. Statistical validation through literature review and multinomial logistic regression confirmed the significant roles of trust, perceived quality, and perceived risk as predictors of consumer transitions across HoE stages. At the same time, the model offers interpretable insights for strategic communication and label design. Limitations of methodology such as imbalanced class representation that causing local overfitting highlight the need for parameter simplification and future integration with adaptive learning models to enhance generalizability.

Keywords: decision making; fuzzy inference system; hierarchy of effects; perceptual reasoning; quality label

1. Introduction

Understanding consumer behavior is a central concern in marketing research, as it helps explain how, why, when, and what consumers buy[1,2]. Manufacturers who can understand consumer behavior in the buying decision process will be able to support the success of product sales in the market[3]. This behavior is shaped by factors such as consumer profiles, product knowledge, and exposure to marketing stimuli, such as advertisements or product labels. Among the many touchpoints influencing consumer decisions, product labels—particularly those conveying quality assurance—play a crucial role in forming perceptions and influencing purchasing behavior.

Consumers need or have the right to have adequate information before they buy a product[4–6]. Consumers often seek product insights from online reviews, social media, or advertisements. However, when making quick decisions at the point of sale, many rely on product labels as their primary source of information. Labels function not only as identifiers but also as tools of communication, mainly when they include trusted quality markers. Therefore, the label should convey information in an effective and straightforward communication[2]. This information will serve as stimuli and strengthen consumers' perceptions of a product, enabling them to make a decision[7]: buy it or leave it.

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In Indonesia, the Indonesian National Standard (SNI) label signifies product conformity to nationally endorsed safety and quality standards. The quality label is one of the markers consumers need to be concerned about, as it signifies the product is safe[8]. To obtain the SNI label, a product must pass a conformity assessment, or so-called certification, according to the referenced standards. When the requirements have been met, the company will receive a certificate for the product, indicating that it has the right to include the SNI mark on the product to communicate to consumers that it has met the standards. Despite its importance, there is limited research or a research gap in examining whether, and how, such labels influence consumer decisions.

This study addresses that gap by investigating the impact of the SNI quality label on consumer purchasing behavior using a classification approach. Prior research has employed various predictive models, such as Regression (LR), Decision Tree (DT), Support Vector Classifier (SVC), Random Forest (RF), and Neural Network (NN), 10 to classify consumer behavior. Although NNs often yield high accuracy, they lack transparency in explaining consumer decision pathways and in interpreting the underlying factors influencing consumer behavior. In contrast, FL offers interpretability by handling ambiguity and approximating human reasoning, making it suitable for modelling complex psychological processes. Sadikoglu[11] classified consumer buying behavior using FL with consumer profile variables, marketing, sociocultural, psychological, and personal factors. Like other approaches, FL is often used in classification problems[11–14] or clustering[15, 16].

In recent years, machine learning and artificial intelligence (AI) have been widely applied to model and predict consumer behavior, particularly in purchasing decisions. AI techniques such as machine learning, natural language processing, and expert systems are now widely utilized to analyse consumer purchasing behavior to improve sales performance, customer satisfaction, and loyalty[17]. Several studies have compared various machine learning algorithms for modelling and forecasting consumer purchase behavior[18–20]. Among the available methods, the Fuzzy Inference System (FIS) offers a compelling alternative to conventional black-box algorithms due to its capability to handle ambiguity and subjectivity effectively[21–24]. Moreover, FIS does not require large datasets[25], making it particularly advantageous in contexts where data are limited, or transparency is essential, and it is well-suited for analysing purchase behavior in which labelling influences are fuzzy, context-dependent, and culturally influenced.

This study adopts the Hierarchy of Effects (HoE) model as the conceptual framework to understand consumer decision-making processes. Generally, HoE is used to measure the effect of advertising or certain information[26,27], to design communication strategies[26], or to assess consumer awareness of specific information[28]. This approach categorizes the consumer behavior into three psychological stages: cognitive (awareness and knowledge), affective (liking and intention), and conative (purchase and loyalty)[26,29,30]. Integrating Fuzzy Inference Systems (FIS) with the HoE model enables nuanced classification of consumers based on their perceptions and responses to quality labelling.

FIS was selected in this study primarily due to its inherent interpretability and its capacity to emulate human reasoning, especially under conditions of uncertainty, an essential characteristic when modelling complex psychological processes such as those embedded in the HoE model[21]. Unlike black-box approaches such as neural networks, which often yield high accuracy but lack explanatory power, FIS enables transparent decision-making by translating input-output relationships into human-readable rules. This transparency is particularly valuable in behavioral research where understanding the cognitive transition from awareness to action is as important as prediction accuracy[23]. By providing linguistic if–then rule structures and visualizable membership functions, FIS offers stakeholders, including policymakers and marketers, a way to interpret not only what consumers decide but also why they make those decisions. Such interpretability fosters not only trust in the model outputs but also greater applicability in designing communication strategies that align with consumers' perceptual and emotional responses.

Its utility in developing contexts like Indonesia also allows potential extrapolation to other regions with similar consumer literacy and regulatory conditions. Indonesia offers a relevant case due to its growing consumer base, expanding Implementation of national quality labels, and varied levels of public awareness. The country's socio-economic diversity and evolving regulatory frameworks provide a rich context to examine how consumers perceive and respond to quality certifications. Insights gained here may apply to other emerging economies facing comparable challenges in building trust and behavioral response toward quality assurance systems. The Indonesian context represents a setting where data are scarce, and interpretability is critical, hence offering a useful model applicable to similar emerging economies[31].

The specific objectives of this study are to: (1) Classify consumer responses to the SNI label across the cognitive, affective, and conative stages of the HoE model; (2) develop an interpretable fuzzy rule-based system that models consumer decision patterns regarding quality-labeled products; and (3) provide insights for policymakers and businesses to improve labeling strategies and promote quality-conscious consumption. The research question to answer is: To what extent does the SNI quality label influence consumer purchasing behavior at each stage of the Hierarchy of Effects, and how can this influence be modelled and interpreted using a Fuzzy Inference System? By addressing this question, the study contributes to a deeper understanding of perceptions of quality labels in Indonesia. It supports efforts to align consumer protection strategies with effective communication and behavioral insight. The FIS approach is often used in ambiguous, unclear, and imprecise models of human factors[32,33]. Using a mathematical approach, the concepts and knowledge of human factors can be well-defined and have clear boundaries[14,33].

2. Literature Review

2.1. Hierarchy of Effects (HoE)

The theoretical basis for stage differentiation in the HoE model is the conceptualization of consumer responses to marketing as a sequential transition from awareness to action[34], which is further elaborated through the historical development of communication effectiveness models[30]. The HoE model explains the psychological processes by which consumers respond to information or marketing stimuli. In practice, measuring the HoE stages typically uses a Likert-scale questionnaire, in which cognitive indicators reflect the level of awareness or understanding of a product or label, affective indicators measure attitudes, interests, and beliefs, and conative indicators represent purchase intentions and decisions[28,29]. Validation of classification into each stage is based on quartile distributions, which require a strong theoretical basis to reduce the potential for categorization bias[26].

To contextualize our model choice, we also incorporated a comparative analysis with other established consumer behavior frameworks such as the Theory of Planned Behavior (TPB) and Information Signalling Theory (IST). TP emphasizes intention formation through cognitive evaluations like attitudes and subjective norms[2], while IST focuses on how consumers interpret informational cues under conditions of uncertainty[29]. However, these models are primarily designed to predict single-point decisions or trust dynamics, rather than to capture the gradual psychological engagement process central to the HoE model. HoE, in contrast, offers a structurally layered view of consumer decision-making that aligns more closely with the aim of this study: to extract interpretable behavioral rules across psychological stages. Nonetheless, a notable limitation of the HoE model is the absence of empirically validated threshold values that distinguish one stage from another. This ambiguity has been highlighted in the literature, underscoring the relevance of our exploratory, data-driven approach, which seeks to infer stage boundaries inductively from observed behavioral patterns. Several studies with unclear stage boundaries have employed exploratory techniques as initial research. Menezes and Roth[35] detect human mobility using multilevel partitions by determining the percentile scale. This experiment is purely exploratory without building initial assumptions—Akhuseyinoglu and Brusilovsky[36] model student behavior using questionnaire data. The exploratory approach is used when the student's learning labelling process is based on calculating the median label for all students, and when repeated labelling corrections are performed. Menaker et al.[37] classify animal behavior using the trajectory method, based on questionnaires and video data, as support. The boundaries of the experiment are determined exploratively from both datasets. Although less explored, studies using exploratory techniques, particularly unsupervised methods, can uncover meaningful patterns before forming hypotheses [37].

2.2. State of The Art

The novelty of this research is that it seeks to address HoE's weakness of failing to consider the influence of advertising by incorporating consumers' understanding of quality marks through indicators of knowledge of SNI application and the urgency of implementing SNI. Another weakness of the HoE model, which ignores differentiation between product types with different advertising approaches, is that consumers can choose products marked with SNI that they feel are closest, thereby conveying concrete, relevant conditions based on their knowledge and experience.

Other studies that use Fuzzy Logic functions generally formulate IF-THEN rules that depend on human knowledge to determine a phenomenon[32,38]. Meanwhile, this research was conducted backwards. IF-THEN rules are obtained from actual phenomena through an extraction process, thereby minimizing subjective human bias.

3. Methodology

In general, this study has three main stages: data collection, model development, and validation. The workflow in Figure 1 outlines the stages, parameters, and tools used. This study used a survey method with a five-point Likert-scale questionnaire as the research instrument. The questionnaire questions covered consumer socio-economics, understanding of the SNI mark, and consumer perceptions and experiences of SNI-marked products. Primary data were collected from 456 respondents aged 15-64 years. Respondents must meet the requirements of productive age because they are considered able to make good decisions[39].

The survey was conducted using purposive sampling, with the public (70% of the sample) assumed to have low, medium, and high levels of understanding. The remaining activists are assumed to have medium and high understanding. This aims to obtain representation from respondents with low, sufficient, and good understanding of quality labels, so that the four stages of HoE are achieved. Each respondent has filled out the consent form. The demographics of research respondents are shown in

Table 1.

The questionnaire trial was conducted with expert validation and five members of the general public. The questionnaire trial included tests of ease of understanding the questions and the clarity of their substance[40]. After data collection, the primary data was tested for validity and reliability. The validity test used the Pearson test with a significant value of 5%. The result was that all range and Cronbach alpha values were greater than the correlation (r table), so that all questionnaire items were valid and reliable. While the questionnaire's overall reliability was assessed using Cronbach's alpha of 0.92, this indicates that it is reliable. The test data are statistically sufficient because the research aims at interpretation and knowledge discovery, not at prediction[41].

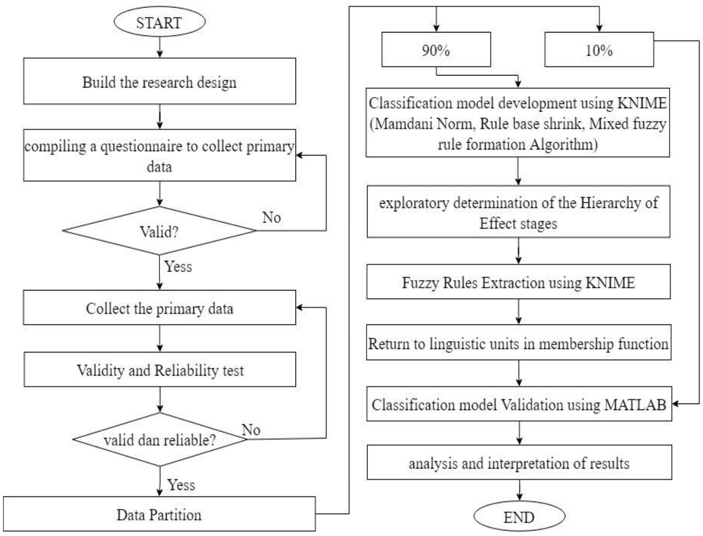

Fig. 1: Workflow of the study

Table 1: Demographics of Research Respondents

Variable	Categories	Distribution (%)
Age	15-30	43.64
	31-45	48.25
	46-64	8.11
Gender	Male	41.45
	Female	58.55
Education	Senior High School and before	17.76
	Diploma	6.80
	Bachelor	54.61
	Master	19.52
	Doctor	1.32
Job	Student	21.71
	Government employees	42.55
	Private employees	16.23
	Self-employed	3.95
	Housewife	3.95
	Others	11.62

Table 2: Specification of primary data

No	Indicator Type	Indicator Name	Data		
			Type	Min.	Max.
1	Input	Age	Integer	16	63
2		Economic capability	Integer	1	3
3		Education	Integer	1	5
4		Knowledge: Purpose of the quality label	Integer	0	6
5		The urgency of applying the quality label	Decimal	1	5
6		Image of quality label	Decimal	1	5
7		The trust in the quality label	Decimal	1	5
8		Perceived Quality	Decimal	1	5
9		Perceived Risk	Decimal	1	5
10	Output	Class HoE categories: Not aware, Cognitive, Affective, Conative	Decimal	1	5

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An exploratory study is good to use when you want to understand a phenomenon, but not many have discussed the problem in depth. This method is generally used in initial research[42]. Exploratory in this study by conducting experiments and model replication so that it can evaluate and obtain the best model[43]. Modelling is done to determine the threshold value of each HoE stage. Each model will be tested fifty times[44] to obtain the average Cohen Kappa value and accuracy. This threshold was determined because there is no literature on this, and according to Lavidge (34), the purchasing threshold will vary and depend on the object.

System modelling with a Fuzzy Inference System (FIS) uses the Konstanz Information Miner (KNIME) software to derive fuzzy rules from primary data. The specifications of raw data are shown in Table 2, which shows the specifications for primary and indicator data and is used as input to the FIS system. 90% of primary data is used as training data, and 10% as test data, because the data representation in each classification is not ideal. Three validation methods were used: k-fold cross-validation, multinomial logistic regression, and expert consultation. The objectives were as follows:

1) Validate the threshold and model using k-fold cross-validation on KNIME and expert consultation.
2) Validate the fuzzy rule pattern using multinomial logistic regression.

The k-fold cross-validation specification is k=10, each fold contains 46 or 45 data sets and stratified sampling is used. Validation with expert consultation was conducted with three experts with over 10 years of experience (see Table 3).

Three experts with complementary expertise were involved in the validation process. This panel size is consistent with prior methodological studies employing expert judgment for conceptual validation in exploratory research. The experts evaluated the psychological plausibility of the following HoE thresholds derived from the FIS model (Section 4.1). Experts were asked to assess the extent to which each threshold configuration reflects the theoretical definition of the corresponding HoE stage using a five-point Likert scale:

1 = Strongly inconsistent
2 = Inconsistent
3 = Moderately consistent
4 = Consistent
5 = Highly consistent

4. Result

The KNIME is a publicly accessible software for integration, processing, analysis, and exploration[45,46]. The KNIME operational system is modular, user-friendly, and open source.

KNIME is widely used for data mining and machine learning[46]. This study uses KNIME for data processing with FIS to obtain fuzzy rules from existing data. The workflow system consists of five components: input, processing, and output data in the form of predictions and accuracy scores (Figure 2).

In forming fuzzy rules, the KNIME software uses a Mixed fuzzy rule formation algorithm with several stages, from determining random points to forming an initial pattern by accessing rows. Each epoch system was compared to patterns through three steps: cover, commit, and shrink[47]. The epoch will stop when the rules do not overlap; in other words, there is no conflict or overlap among the rules.

Table 3: Expert Panel

No	Expert Code	Area of Expertise	Background
1.	E1	Consumer Behavior	Academic researcher in consumer decision-making and quality label studies
2.	E2	Marketing Psychology	Senior lecturer and marketing research consultant specializing in attitudes and purchase intention
3.	E3	Marketing Communication	Researcher and practitioner in brand communication and label effectiveness

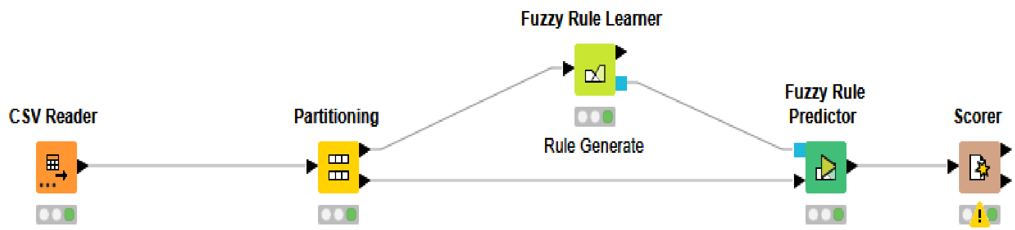

Fig. 2: Configuring Basic FIS using KNIME

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4.1. Determination of Hierarchy of Effect Stages

Data collection used a 5-point Likert scale, ranging from Strongly Disagree (1) to Strongly Agree (5). The output of this data is to classify respondents' responses into 4 four classes according to the HoE stage. The modelling data will be treated according to the exact specifications in the conFigured FIS, and data will be selected based on average accuracy and model reliability.

The development of this model is carried out in an exploratory manner by building several models with different parameter sets to evaluate the models and identify the best one[43)]. This classification is determined based on experimental results, which are compared with the data of non-quartile, quartile 1, and quartile 2. Each model will be tested 50 times[44)] to obtain average epoch values, form fuzzy rules, calculate Cohen's kappa, and assess accuracy. Each model simulation has different parameter values because the system randomly selects the training data. This is done because the threshold value for each stage in HoE has not been derived from the literature.

The fundamental differences in the experimental results without quartiles, quartile 1, and quartile 2 are the amount of training data at each HoE stage, model accuracy, Cohen's kappa value, and the number of fuzzy rules formed. The amount of training data at each HoE stage is related to the initial or raw data distribution, which impacts the fuzzy rules formed. The parameters considered are the model's accuracy and Cohen's Kappa value. Table 4 shows that classification without quartile determination achieves the best accuracy, with an average accuracy of 89.27% and an average Cohen kappa value of 0.32.

Compared to other models, the non-quartile model required fewer fuzzy rules (87.08 on average) while maintaining high performance. This indicates that the non-quartile setting produces a more efficient rule base without sacrificing accuracy or generalizability. On the other hand, quartile-based models resulted in more complex rule sets—188.5 fuzzy rules for quartile 1 and 236.32 for quartile 2—but the accuracy significantly declined to 67.57% and 48.70% respectively. This suggests that a larger number of fuzzy rules does not always equate to better model performance and may lead to overfitting or lower generalization capacity.

The values obtained in the non-quartile model in Table 4 are based on the recapitulation experiment, which yielded 26 possible models with more than 90% accuracy and 24 with less than 90% accuracy. At an accuracy of less than 90%, the average accuracy is 85.42%, with an average Cohen's kappa of 0.26 and an average number of fuzzy rules of 88.45. While the accuracy is more than 90%, the highest is 97.3% and the lowest is 90% (across three models), with an average accuracy of 92.83%. The highest Cohen's kappa was 0.789, the lowest was -0.036, and the average was 0.39. These variations show that a high accuracy value is not always consistent with a high Cohen's Kappa score. For instance, models with 94.74% accuracy can have an antagonistic Kappa (-0.027), while a lower accuracy of 91.89% could yield a better Kappa (0.539). Therefore, the evaluation must consider both accuracy and inter-rater agreement simultaneously.

From various experimental simulations with non-quartile thresholds, it was decided to choose a fuzzy rule model with an accuracy value of 93.3% and kappa value of 0.673. Then, the threshold of HoE classification follows this specification:

- Not aware: if cognitive value < 4 and affective value < 3.5 and conative value < 3.75
- Cognitive: if cognitive value > 4 and affective value < 3.5 and conative value < 3.75
- Affective: if cognitive value > 4 and affective value > 3.5 and conative value < 3.75
- Conative: if cognitive value > 4 and affective value > 3.5 and conative value > 3.75

4.2. Fuzzy Inference System (FIS)

The Fuzzy Rule Learner component demonstrates the Fuzzy Inference System in KNIME. Several parameters can be set in this component: the dimensions of the input and class (output), the norm, and the shrink function. The input and class (output) dimensions are shown in Table II, which contains the system dimensions. The fuzzy rule used is the Mamdani method. Mamdani's method is widely accepted for capturing expert knowledge and can describe expertise more intuitively[22,48)]. Selecting this norm will

Table 4: Recapitulation of experimental results, determination of classification boundaries

Specifications/Parameters	Without Quartile	Quartile 1	Quartile 2
Sum of Fuzzy Rules	87.08	188.5	236.32
• Not aware	4.58	23.68	44.46
• Cognitive	16.62	38.7	53.82
• Affective	7.1	26.2	52.36
• Conative	58.78	99.92	85.68
Average epoch	4.6	4.82	4.84
Average Accuracy	89.27%	67.57%	48.70%
Average Cohen Kappa	0.32	0.29	0.27
Average Correct Classified	34.4	21.44	13.64
Average Wrong Classified	4.14	10.34	14.38

affect both the degree-of-membership calculation and the defuzzification process. The shrink function used in this system is the rule-based volume shrink. This shrinkage function is performed by weighing the volume loss across the entire set of fuzzy rules[49]. Determination of the fuzzy membership function in this study using a literature study, as presented in Table 5, for the input. The membership function is used when the fuzzy rules are obtained from KNIME, and then the limits of the rules in the form of the fuzzy set are returned in the membership function to be known linguistically.

4.3. Fuzzy Rule Extraction

A mixed fuzzy rule formation algorithm in KNIME results in a fuzzy set in the form of a trapezoidal function for each dimension[47, 50]. In addition, the software has defined the membership degree function. Prince[51] said that the trapezoid function performs better than the triangular membership function in terms of accuracy and complexity of data classification.

Parameters in the trapezoidal membership function consist of the lower limit (a), the upper limit (d), the lower support limit (b), and the upper support limit (c), where $a < b < c < d$. Gabriel 49) conveys the trapezoidal function parameters consisting of (a, b, c, d), where (a, b) and (c, d) are support-region boundaries and (b, c) are core-regions of fuzzy sets (Figure 3). The fuzzy set in each of these dimensions is the output of the Fuzzy Rule Learner component. The rules are formed based on the classification of the training data.

In this study, a pessimistic classification based on the core region limitation is used to determine the rules, considering a narrow range of membership functions. In addition, using optimistic classification will produce fuzzy rules that are too general[47]. The fuzzy rule uses experimental results with an accuracy value of 93.33% and

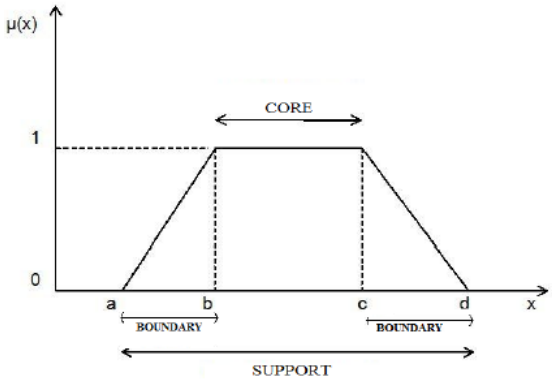


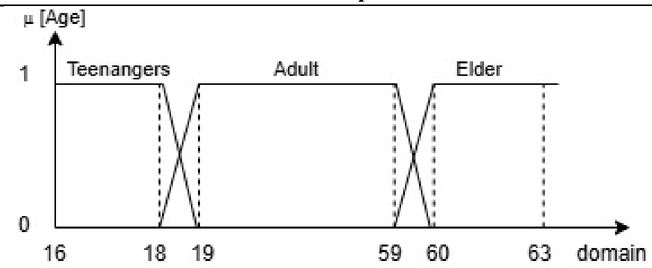
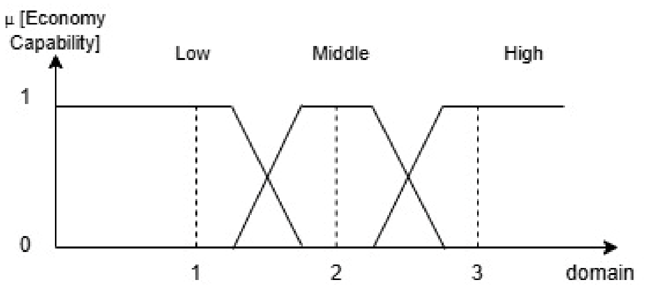
Fig. 3: Trapezoidal fuzzy set[51]

a Cohen's kappa value of 0.673. Based on the nine inputs and the specifications of the built system, 76 rules were formed covering four output classifications. In the classification of not aware, there are five rules: cognitive (19), affective (6), and conative (46).

4.4. Fuzzy Rules Validation

According to Varshney and Tora[52], the use of fuzzy methods for knowledge discovery prioritizes the structure of fuzzy rules over accuracy. Validation can be done by measuring the number of rules, coverage, and consistency of reasoning with the literature. However, to strengthen the analysis, three validations were conducted. First, validating the coverage of fuzzy rules against the data obtained using MATLAB (Toolbox[53]), because KNIME cannot set the fuzzy rules. Second, validating the model using K-fold cross validation by KNIME and expert consultation. The last, validating the fuzzy rule patterns generated by KNIME using the multinomial logistic regression test.

Table 5: Input dimension fuzzy membership function

No	Indicator (dimensions)	Curve Representation	Ref.
1	Age		54)
2	Economic capability		55)

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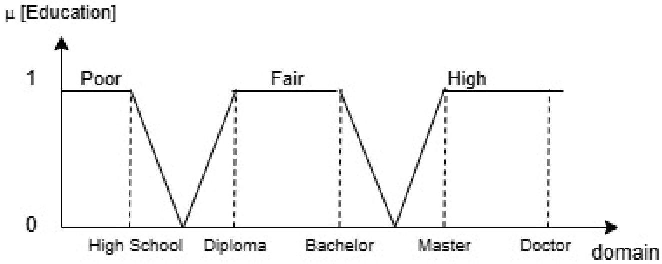
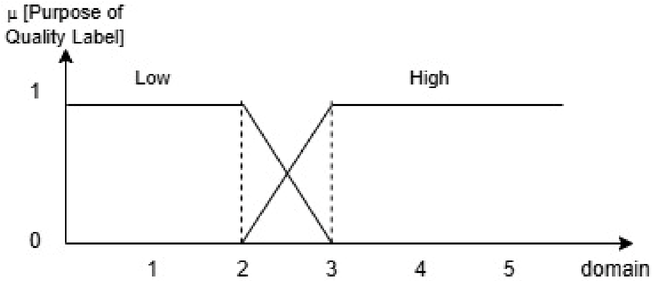
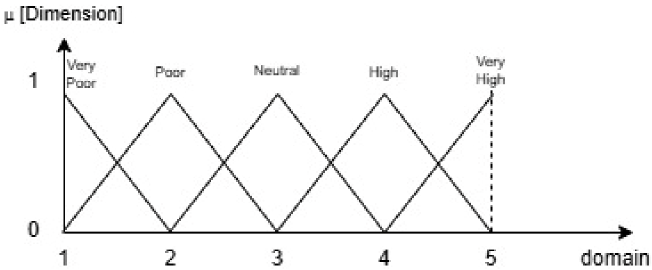
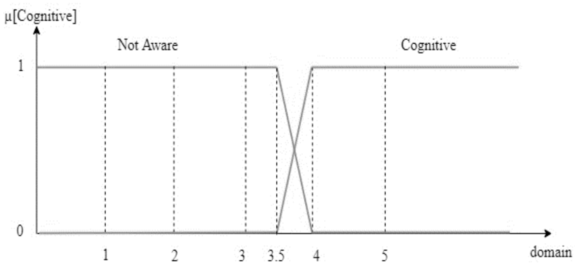
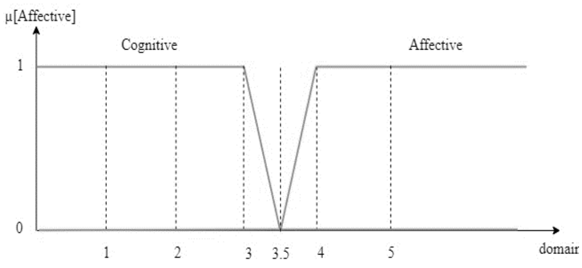
3	Education		56)
4	Knowledge: Purpose of the quality label		57)
5	The urgency of applying quality labels, Image of quality labels, trust in quality labels, Perceived quality, and Perceived risk.		11)

4.4.1. Validate the Coverage of Fuzzy Rules

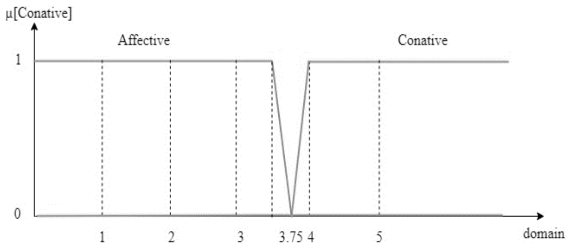
The specifications will follow the settings in KNIME. Several parameters will be set in the FIS editor: 9 inputs, three classification classes as system outputs, trapezoidal membership types, Mamdani norms, and fuzzy rules based on the KNIME results. The membership function for the HoE stage (output) is shown in Figure 4.



(a)



(b)



(c)

Fig. 4: Membership function of (a) Cognitive, (b) Affective, (c) and Conative

After the system model is built, the rule validation stage is done by randomly entering 57 data sets. The validation of fuzzy rules shows that the accuracy of the formed rules is 78.59%, the prediction error is 5.26%, and no rule includes data of 15.79%. Table 6 shows the level of accuracy of fuzzy rule validation at each HoE stage. The data show that fuzzy rule coverage is lowest at the not aware stage (45.5%), with 36.4% of rules not covered and a prediction error of 18.2%. The high error in the not aware stage leads to low overall accuracy for fuzzy rules. While the highest accuracy is Affective at 100% followed by Conative at 89.9%, then Cognitive at 80.5%. The discrepancy between training (93.33%) and validation (78.59%) accuracies indicates overfitting, particularly due to underrepresentation in the not aware class, leaving 36.4% of cases uncovered by fuzzy rules.

Table 6: Confusion matrix fuzzy based on data validation

		Actual			
		Not Aware	**Cognitive**	**Affective**	**Conative**
Prediction	**Not Aware**	**45,5%**	0	0	0
	Cognitive	0	**80,5%**	0	1,1%
	Affective	18,2%	0	**100,0%**	0
	Conative	0	1,7%	0	**89,8%**
	No Rules	36,4%	17,8%	0	9,0%

Much data needs to be covered in the new data. This is because the FIS approach lacks a learning process, so predictions depend on the rules that have been formed. In addition, the lack of data in some segments leads to insufficient fuzzy rule coverage, even though several important insights have been obtained at this stage. For example, at the not aware stage, there are only five fuzzy rules, indicating that the number of people who are not aware of quality labels is the least among the other three stages.

An interesting thing is that at the cognitive stage, the error rate for guessing to become conative is 1.1%. Likewise, at the conative stage, there is an error in predicting that it will become cognitive at 1.7%. This can be caused by a combination of incomplete or overly rigid rules, especially in high-dimensional data, leading to underfitting[38,58].

4.4.2. Validate the Model

4.4.2.1. K-Fold Cross Validation

The FIS-HoE model validation and thresholding stage uses k-fold cross-validation to evaluate model performance more accurately and reliably, reduce bias from a single data split, prevent overfitting, and ensure the model's generalization ability to new data. This is done by dividing the dataset into k parts (folds) and alternating them as training and test data.

K-fold cross-validation is performed by adding an X-Partitioner node to determine the number of folds and sampling type. The results of each fold are then displayed through an X-aggregator.

Table 7 shows the cross-validation results, which include the mean squared error (MSE) and total squared error (TSE) for each fold. The data shows the highest MSE in fold 1 (0.565) and the lowest in fold 6 (0.089). Four folds have moderate interpretations (MSE >0.400). A lower MSE value indicates a more accurate model[59].

Table 7 presents the K-fold cross-validation results (k = 10), reporting the TSE and MSE for each fold based exclusively on the corresponding test subsets. The fold numbering follows the sequential output generated by the X-Partitioner node in KNIME. Slight variations in test set size occur because the total dataset size (456 datasets) is not perfectly divisible by the selected number of folds.

The MSE values ranged from 0.089 to 0.565, with an average of 0.398. This indicates that the most folds produced fair-to-moderate prediction errors. The lowest error is observed in Fold 6 (MSE = 0.089), indicating very good predictive performance for that subset, while the highest error occurs in Fold 1 (MSE = 0.565), suggesting localized modeling challenges for certain data partitions. Generally, the MSE values in this range indicate that the FIS model is capable of capturing the main patterns in the data, but still faces challenges in modelling local variations and uncertainty in some subsets of the test data.

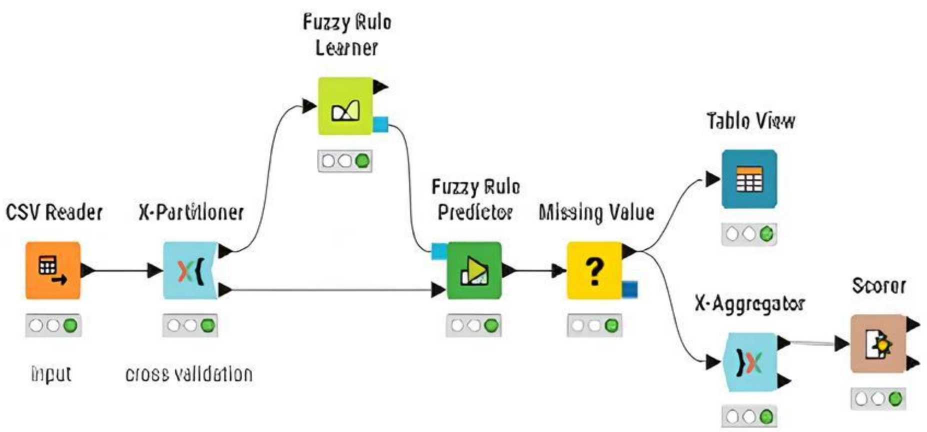


Fig. 5: Workflow of K-Fold Cross Validation on the FIS System in KNIME

Table 7: Evaluation value on each fold (k=10)

Fold	Size of Test Set	TSE	MSE	Interpretation
0	46	21	0.457	Moderate
1	46	26	0.565	Highest Error
2	46	18	0.391	Fair
3	46	19	0.413	Moderate
4	46	22	0.478	Moderate
5	46	22	0.478	Moderate
6	45	4	0.089	Very Good
7	45	18	0.400	Fair
8	45	12	0.267	Fair
9	45	20	0.444	Moderate
Mean		18.2	0.398	

The model's standard deviation of the MSE was 0.133, with a Mean Absolute Error (MAE) of 0.090. The MSE standard deviation of 0.133 indicates that the variation in prediction errors between folds is relatively small. This indicates that the model's performance is relatively stable against changes in the training and test data at each iteration of K-fold cross-validation. In other words, the model is not overly dependent on any particular data subset and does not exhibit extreme performance fluctuations.

4.4.2.2. Expert Consultation

To address concerns regarding the theoretical grounding of the HoE thresholds, an expert-based validation was conducted to assess whether the proposed numerical boundaries are consistent with the psychological meaning of each HoE stage. This validation aimed to ensure construct validity beyond model accuracy optimization.

These results indicate that all HoE stages achieved mean scores above 3.5, suggesting acceptable to strong conceptual alignment between the thresholds and the underlying psychological theory (Table 8). To further quantify expert agreement, the Item-Level Content Validity Index (I-CVI) was calculated as the proportion of experts assigning a rating of 4 or higher. For a panel of three experts, an I-CVI value of 0.67 or above is generally considered acceptable, indicating that all HoE stages meet the criterion for content validity (Table 9).

Table 8: Threshold–Theory Alignment Scores

HoE Stage	E1	E2	E3	Mean
Not Aware	4	4	3	**3.67**
Cognitive	4	5	4	**4.33**
Affective	5	4	4	**4.33**
Conative	5	5	4	**4.67**

Table 9: Content Validity Index (CVI)

HoE Stage	Experts ≥ 4	I-CVI
Not Aware	2 of 3	**0.67**
Cognitive	3 of 3	**1.00**
Affective	3 of 3	**1.00**
Conative	3 of 3	**1.00**

In addition to numerical ratings, the experts provided qualitative feedback that further supports the validity of the proposed thresholds. The consumer behavior expert noted that the thresholds adequately capture the gradual progression from awareness to purchase intention, emphasizing that the higher conative requirement for the final stage is theoretically consistent with established consumer decision-making models. The marketing psychology expert highlighted that requiring a sufficiently strong affective response prior to conative classification is psychologically sound, as positive attitudes typically precede behavioral intention. Meanwhile, the marketing communication expert acknowledged that although the not aware stage is inherently difficult to quantify, the proposed thresholds remain reasonable as an operational approximation in an exploratory modelling context.

The convergence of quantitative ratings and qualitative expert feedback indicates that the HoE thresholds are not arbitrary but represent a defensive operationalization on the cognitive–affective–conative sequence. While the thresholds should not be interpreted as universal psychological cut offs, they are conceptually acceptable within the exploratory scope of this study.

4.4.3. Validate The Fuzzy Rules Pattern

Some assumptions must be met before conducting a multinomial logistic regression: the data must not exhibit multicollinearity. To test this assumption, a multicollinearity test is conducted using tolerance and VIF values. The test results show that all input data (independent variables) have a tolerance value greater than 0.10. Meanwhile, the VIF values for all input variables are <10.00. The conclusion is that there are no multicollinearity issues in the regression model, and it meets the requirements for the multinomial logistic regression test.

Table 10: Partial test results

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intersept	260.012	0.000	0	.
SNI Aims	261.790	1.779	3	0.620
Urgency	262.240	2.228	3	0.526
Image	271.469	11.458	3	0.009
Trust	270.029	10.018	3	0.018
Perceived Quality	276.112	16.100	3	0.001
Perceived Risk	272.613	12.601	3	0.006
Age	262.969	2.958	6	0.814
Economy	267.177	7.165	6	0.306
Education	261.526	1.514	6	0.959

Table 11: Results of indicator category prediction for the hoe stages

Indicators		Cognitive		Affective		Conative	
		Sig.	Exp(B)	Sig.	Exp(B)	Sig.	Exp(B)
Intersept		1.000		0.191		0.324	
SNI Aims		0.243	0.577	0.530	0.706	0.243	0.583
Urgency		0.299	0.243	0.480	0.300	0.207	0.172
Image		0.831	1.285	0.557	2.309	0.172	4.938
Trust		0.184	4.243	0.250	4.601	0.031	10.460
Perceived Quality		0.493	2.040	0.308	3.545	0.059	7.125
Perceived Risk		0.039	0.286	0.052	0.211	0.003	0.162
Age	(Adult)	1.000	8.916	.	51.184	.	1.758
	(young)	0.998	140.928	1.000	2.672	1.000	7.608
	(old)	.	.	.	.	.	.
Economy	(middle)	0.072	49.280	0.158	32.366	0.068	52.331
	(poor)	0.267	4.784	0.446	4.007	0.120	8.855
	(rich)	.	.	.	.	.	.
Education	(average)	0.682	1.754	0.478	3.477	0.477	2.651
	(low)	0.604	2.291	0.718	2.171	0.596	2.301
	(high)	.	.	.	.	.	.

Note: Ref. category: Not Aware

Based on Table 10, the independent variables in the form of image indicators, trust, perceived quality, and perceived risk statistically significantly influence the dependent variable, the HoE stage. This can be seen from the sig. value are <0.05. Table 11 shows the tendencies of the independent variables at each stage of HoE, with the Ref. category not aware. The tendency of consumers to be at the HoE stage is evident from the Exp(B) value.

Consumers who have confidence in quality labels tend to be at the cognitive and affective stages 4 times as often as at the not aware stage, and at the conative stage 10 times as often. Although it does not have a significant effect, the better the experience consumers have with products with quality labels, the 7 times greater at the conative stage, 3.5 times greater at the affective stage, and 2 times greater at the cognitive stage compared to the not aware stage. The perceived risk indicator has a significant effect on all stages, although the tendency to be at the HoE stage is not too different.

In demographic indicators, the data shows that there are prominent results among young consumers, who tend to be at the cognitive stage, 140 times more than those at the not aware stage. Middle-income consumers tend to consider the presence of quality labels on products.

5. Discussion

5.1. The Influence of Quality Labels on Product Purchases

This study identified nine indicators, resulting in a high-dimensional model. The object of this research is a quality label in Indonesia, for which limited literature is available, so a fuzzy inference system approach is used to achieve the objectives of this study. This problem uses the KNIME software to analyse high-dimensional data and extract rules that other software cannot. However, based on MATLAB validation of the rules, several areas for improvement were identified: the heuristic model showed decreased accuracy, especially on new data. Ideally, the fuzzy rules formed with nine indicators (dimensions) and 36 degrees of membership are 160,750; thus, 160,674 rules remain to be obtained. The number of regulations that have yet to be formulated indicates that the raw data collected does not fully reflect the conditions in the community, especially for older respondents and for reproducing datasets at all stages of HoE.

Based on k-fold cross-validation, the MSE standard deviation indicates that the FIS model's generalization capability is adequate but still requires improvement, particularly for underrepresented data such as the not aware and affective categories. These standard deviation and MAE values reinforce the conclusion that the model's complexity with nine parameters remains within sufficient limits for the amount of data used.

According to the confusion matrix, the decreasing accuracy of the training and test data indicates overfitting, where the model is too well-suited to the training data[60]. Tetko et al.[61] indicate that although the model results have good accuracy on both training and test data—even in cross-validation—it is important to note that high-dimensional or hyperparameter models have the potential to overfit, although overfitting is challenging to prove. Generally, overfitting occurs when the data in the test set all come from the same distribution[61]. In this study, it is believed that overfitting occurs in specific categories not represented in the data (local overfitting)[61,62] and this is indicated by a difference between training accuracy (93.33%) and validation accuracy (78.59%) up to 15%, which means that methodological limitations occur. So that these categories cannot be generalized, such as the not aware category. This is shown in the high overall model accuracy of 93.33%, but the Cohen's kappa value is 0.673. The observed gap of approximately 15% is acknowledged as a methodological limitation of the proposed model. This discrepancy indicates susceptibility to overfitting, primarily driven by class imbalance and sparse representation in early HoE stages, rather than model instability. Although k-fold cross-validation shows relatively stable error variation across folds, the accuracy gap suggests that the rule-based FIS may fit the dominant classes more effectively than underrepresented categories. This limitation highlights the need for more balanced data collection in future studies to improve generalization performance.

There are several steps to avoid overfitting by considering the complexity of the data and the interpretation of phenomena, including reducing the number of dimensions that do not have a significant effect[60] and collecting data with more proportional segmentation[60]. Based on statistical analysis and fuzzy patterns, the dimensions that can be reduced because they do not have a significant effect are the understanding of SNI, the urgency of SNI, and the level of Education. Meanwhile, for ease of data segmentation, the respondent can be specific, such as age group, focusing on teenagers, young adults, and so on.

The distribution of fuzzy rules across the four stages of the HoE model is uneven. The dominance of fuzzy rules occurs at the conative stage, followed by the cognitive, affective, and not aware stages. However, the accuracy at the not aware stage is relatively low compared to other stages so that this discussion will focus on the Cognitive, affective, and conative stages. This shows that Indonesian people consider quality labels when purchasing. With the identification of new patterns related to demographic aspects, a clearer understanding of the purpose and urgency of quality labels, and other indicators, the following will encourage people to make quality labels a determinant in decision-making.

Based on statistical testing, fuzzy rules generally follow the same pattern as the multinomial logistic regression results. Indicators of Image, trust, perceived quality, and perceived risk influence the categorization of HoE. Analyzing more deeply, the trust indicator significantly influences the conative stage and simultaneously influences the cognitive and affective stages. In addition, the perceived risk indicator significantly influences all three stages of HoE.

The findings indicate that young consumers are 140 times more likely to be at the Cognitive stage and 7 times more likely to be at the Conative stage than at the not aware stage. Likewise, with Education, the higher the level of Education, the more likely they are to be aware of and choose products with quality labels.

This rule extraction was undertaken due to insufficient literature on consumer behavior toward quality labels in Indonesia. Although there are areas for improvement in the heuristic approach, it can be an alternative to get an overview or pattern of consumer behavior in general, based on demographics, understanding of quality labels, and consumer perceptions and knowledge, to achieve the research's objectives. Increasing the model's accuracy can be achieved using methods that learn, such as Neural Networks or metaheuristic approaches. By obtaining fuzzy rules, beneficiaries can be used as decision support in determining quality culture target strategies and can build predictions to engineer related indicators.

Consumer patterns towards quality labels in Indonesia have several findings. Demographically, education indicators do not significantly influence consumers' product choice with quality labels. However, they show that consumers with better Education tend to be at the affective and conative stages because they have better perceptions of quality[63]. Interestingly, in terms of age, teenager consumers were found in the cognitive (21%) and conative (14.28%) stages, with no one in the not aware or affective stages. This finding shows that teenagers and youth consumers (mean age 25 years) tend to be more selective in their reading of product information before deciding to buy, suggesting they are at the cognitive stage[64]. Another insight into economic indicators is that the middle class pays more attention to product quality labels.

Quality labels should be understood as indicators of SNI's purpose and the urgency of implementing SNI. Fuzzy rules with indicators of the urgency of applying SNI that have very low or low membership degrees account for 2.6%. At the same time, the SNI knowledge indicator is very low, with a membership of only 47.36%. This shows that they need to understand the benefits and quality assurance of products, and their understanding remains partial[65].

The public already has a good image of and perception of the quality label. Images with a very low degree of membership are found in the not aware stage, and perceived quality has a low and very low membership degree found in the not aware stage (40%) and the cognitive stage (36.8%). At the conative stage, 12.2% of the rules are of low value. At the same time, the affective stage of all the rules regarding the perceived quality indicators is high. Interestingly, the trust and perceived risk indicators sufficiently influence consumers at the affective and conative stages. The confidence indicator showed a very low degree only at the not aware stage, and low values were observed at the not aware and cognitive stages. In other stages, the confidence indicator is neutral to very high. That is, the trust indicator is very influential at the conative stage. Likewise, regarding perceived risk, the indicator showed a very high degree of membership (40%) at the not aware stage. This finding shows that consumers who buy a product tend to avoid uncertainty.

Based on these findings, the relevant agencies can disseminate standard culture to students, as 49% of respondents do not know the purpose of implementing the quality label. Students in the adolescent and early adulthood age range may also be in the cognitive and conative stages. Agencies must also build quality label communication so that products marked with SNI have added value in quality assurance [6]. This communication aims to enhance consumer recognition and improve consumer image[29,66)] and reduce consumer uncertainty perception[39,67)]. Building trust is an important element for reducing uncertainty, triggering consumer purchase intention[39, 66, 68)], and increasing loyalty[66, 69)]. Trust can also be built by providing traceable and credible information that consumers can easily access. Important product information is provided to minimize perceived purchase risk, as potential consumers are likely to collect and consider more information from reliable sources when a relatively high perceived risk is involved[70)].

5.2. Implication and Generalization of Influential Variables

The significant influence of trust, perceived quality, and perceived risk variables on consumer responses to quality labels underscores the importance of building a transparent, trustworthy product communication system. This finding shows that trust is a key factor, especially at the conative stage, indicating that consumers who have confidence in quality labels such as SNI tend to have higher purchase intentions and loyalty. This finding is consistent with previous studies that emphasize that trust in the certification system can increase consumer confidence in product safety and quality[31,71)].

Young consumers, especially those aged 15–30, are more likely to be at the cognitive and conative stages of the decision-making process. This responsiveness is thought to stem from this age group's high exposure to digital information and their tendency to make more rational decisions based on available data. This group is also more accustomed to using gadgets and social media to compare product information, including quality labels. Meanwhile, although education levels do not always have a statistically significant effect on all HoE stages, there is a tendency for individuals with higher Education to have better perceptions and knowledge of the meaning of quality labels[72)].

This finding implies that quality label communication strategies need to be adjusted to demographic characteristics. For example, campaigns for young consumers can be carried out through digital media and interactive visual approaches. In contrast, for older consumers, a direct approach emphasizing risk reduction and high-quality evidence can be more effective. Furthermore, the patterns of consumer responses to the SNI label identified in this study may generalize to other regional contexts or label systems. Cognitive and affective responses to quality labels are universal mechanisms that are also reflected in studies of European consumers towards the Ecolabel, Organic, and Fair Trade labels, which show that the variables of trust, perceived value, and perceived risk are cross-cultural behavioral constructs[73,74)]. However, applying these findings to other regions or systems still requires adjustments to local contexts, such as consumer literacy levels, the credibility of certification bodies, and label recognition. The rule-based, fuzzy-inference approach used in this study provides an analytical framework that can be expanded and adapted to understand consumer segmentation across contexts. Policymakers and certification authorities can utilize this model to establish segmentation strategies, predict market acceptance, and design more effective label communications.

5.3. Limitation Model

The model's performance exhibited notable limitations in accurately classifying consumers within the "Not Aware" stage—a phenomenon that reflects deeper structural and methodological challenges. This underperformance can be attributed to a combination of interrelated factors. First, the fuzzy inference system generated only a limited number of fuzzy rules for this class, resulting in sparse rule coverage that reduced the model's ability to recognize the full spectrum of behavioral variation present among not aware consumers. Second, the dataset's demographic representation was imbalanced, particularly the underrepresentation of older age groups, who are more likely to be at earlier stages of the decision-making process. This lack of demographic diversity limited the training data's ability to generalize effectively across consumer segments. Third, the rule boundaries established by the fuzzy model were relatively rigid due to the trapezoidal membership functions and the heuristic rule-extraction process, potentially limiting the model's flexibility in handling unstructured or borderline responses. These combined factors not only reduced classification accuracy for the not aware stage but also highlight the need for improved segmentation strategies and adaptive modelling techniques in future studies to enhance model responsiveness and inclusivity [38)].

This study acknowledges the limited number of experts involved in the validation process. However, given the exploratory nature of the research, expert consultation was intended to assess conceptual alignment rather than to ensure statistical generalizability, and this was reinforced through the consistency of expert evaluations and triangulation with quantitative validation methods. Future studies may strengthen this aspect by involving a broader panel of experts.

6. Conclusion

This study demonstrates the potential of a Fuzzy Inference

System integrated with the Hierarchy of Effects (HoE) model to extract interpretable consumer behavior patterns toward quality labels. A total of 76 fuzzy rules were derived, yielding an overall model performance of 78.59%. The findings consistently indicate that trust, perceived quality, and perceived risk are key determinants shaping consumer progression across the Cognitive, Affective, and Conative stages, which exhibit robust classification accuracy and rule coverage, thereby supporting reliable behavioral interpretation and practical insights.

In contrast, the Not Aware category shows limited predictive reliability, as reflected by low classification accuracy (45.5%) and a substantial proportion of not covered cases (36.4%). Accordingly, results for this category should be interpreted as exploratory rather than inferential, and no statistically robust conclusions are drawn at this stage. This limitation is primarily associated with class imbalance and sparse rule representation in early HoE stages.

Future research should address these limitations by expanding data collection for early-stage consumers, particularly through targeted sampling of underrepresented demographic groups, and by integrating adaptive or learning-based approaches, such as neuro-fuzzy systems or hybrid machine learning–fuzzy models, to enhance rule coverage and generalization. Additionally, cross-contextual validation across different product categories, certification schemes, or cultural settings would help assess the transferability of the extracted behavioral patterns and refine stage-specific thresholds. Such extensions would strengthen the methodological robustness and practical applicability of interpretable models for quality label communication strategies.

Acknowledgements

The authors thank the Ministry of Research and Technology-BRIN for facilitating this research through the 2020 SAINTEK program. B/9/P3.2/KD.01.00/2020.

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