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RESEARCH ARTICLE OPEN ACCESS

Rule-Based Adaptive Chatbot on WhatsApp for Visual, Auditory, and Kinesthetic Learning Style Detection

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Abstract **Adapting learning methods to individual learning styles remains a major challenge in digital education due to the static nature of traditional questionnaires and the absence of adaptive feedback mechanisms. This study aimed to develop a rule-based adaptive WhatsApp chatbot capable of automatically identifying users' learning styles, visual, auditory, and kinesthetic, through a weighted questionnaire enhanced with probabilistic refinement. The proposed system introduces an adaptive decision framework that dynamically manages conversation flow using score dominance evaluation, early termination, and selective question expansion. Bayesian posterior probability estimation is employed to strengthen decision confidence in borderline cases, ensuring consistent and interpretable results even when user responses are ambiguous. The chatbot was implemented using WhatsApp-web.js and MongoDB, supported by session validation and activity log monitoring to ensure operational reliability and data integrity. System validation involved white-box testing using Cyclomatic Complexity to verify logical accuracy and 20-fold cross-validation using a Support Vector Machine (SVM) to evaluate classification performance. The adaptive model achieved an accuracy of 80.2% and an AUC of 0.902, supported by a balanced precision (0.738), recall (0.662), and F1-score (0.698). These results demonstrate stable discriminative capability and confirm that the adaptive scoring mechanism effectively reduces redundant questioning, lowers cognitive load, and improves interaction efficiency without compromising reliability. In conclusion, the study successfully achieved its objective of developing an adaptive, efficient, and mathematically transparent learning style detection system. The findings confirm that adaptive rule-based logic reinforced by probabilistic reasoning can significantly enhance the efficiency and reliability of digital learning assessments. Future research will extend this framework by incorporating multimodal behavioral indicators and personalized learning content to further strengthen adaptive learning support.**

Keywords **Chatbot; Learning Styles; Adaptive System; Personalized Learning; Bayesian Inference**.

I. Introduction

Advances in artificial intelligence (AI) technology have led to the emergence of various innovations in digital interactive systems, one of which is chatbots [1]. A chatbot is a computer program designed to simulate a human conversation through text or voice, enabling automatic two-way interaction between the user and the system [2]. In recent years, the adoption of chatbots has expanded in various fields, including customer service, healthcare, and education. In the world of education, chatbots are used to answer students' questions, provide subject matter, and guide the learning process independently [3]. The presence of this technology creates opportunities to build a more flexible, responsive, and accessible learning environment for users without space and time limitations [4].

In the realm of education, chatbots present new opportunities for creating more interactive and adaptive learning experiences. This system can provide instant learning assistance, guide students in understanding the material, and provide personalized feedback in real-time [2]. The role of chatbots in learning is very relevant in the context of distance education, online learning, and blended learning models that are currently developing [5]. However, to provide optimal benefits, chatbots are not enough to convey information, they must be capable of adapting instructional delivery to the characteristics of individual learners [6].

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One approach that has proven effective in increasing student learning engagement and retention is learning personalization, a strategy that adjusts learning methods and media according to the needs and characteristics of each individual [7]. In this context, learning style is an important aspect that needs to be identified early. A learning style refers to an individual's preference in receiving, processing, and retaining information[8]. One widely used model is the VAK (Visual, Auditory, Kinesthetic) learning style model, which categorizes individuals into three groups based on the way they most effectively absorb information [9].

The application of learning style-based instruction has been shown to increase the effectiveness of the learning process [10]. Students with visual learning styles, for example, tend to understand information more easily through pictures or diagrams; auditory students respond better to verbal explanations or discussions, and kinesthetic students are better suited to physical activity-based learning or hands-on practice [11]. When the learning system can accommodate these differences, the learning process becomes more meaningful and relevant for each individual [12]. Unfortunately, in practice, many digital platforms still employ a one-size-fits-all approach, despite the diverse learning preferences.

While there is great potential in integrating chatbots and learning styles, research and development that combine the two in an easily accessible platform are still very limited. Moreover, the use of popular platforms, such as WhatsApp, which has been utilized by billions of users worldwide and has high penetration in Indonesia, is still not fully maximized in an educational context [13]. WhatsApp offers a variety of advantages, such as high accessibility, ease of use, real-time communication, and no additional app installation, making it ideal for reaching students in various regions, including those with limited infrastructure [14].

However, until now, the integration of an automatic learning style detection function in WhatsApp-based chatbot platforms remains relatively rare. Most digital learning systems still rely on conventional or manual approaches in identifying student learning preferences. This creates significant research opportunities in designing systems that are able to recognize learning styles in real-time through automated mechanisms, as well as presenting relevant materials following the identification results [15].

In response to this gap, this study aims to design and develop a WhatsApp-based educational chatbot that can detect users' learning styles through a series of questions in the form of questionnaires based on the VAK model [16]. These chatbots not only serve as a communication tool, but also as a proactive and adaptive learning. This system is designed to identify the dominance of learning style scores from the beginning of the questionnaire-filling process, so that results can be obtained efficiently. In addition, a dynamic approach is implemented to allow the addition of questions in real-time if the initial results are not significant enough [17]. To ensure the quality of the system, testing is conducted using a white-box approach to evaluate the logic and performance of the algorithms employed. Thus, the contribution of this research includes the development of personalized, adaptive, and inclusive learning technologies, as well as the use of popular communication platforms to support smarter and more equitable digital education.

II. Design

A. Architecture

The system architecture developed in this study is designed to support the automatic, quick, and efficient identification of user learning styles through the WhatsApp instant messaging platform. The system utilizes whatsapp-web.js library-based chatbot technology that enables real-time two-way communication between the user and the system. This approach was chosen considering that WhatsApp is one of the most widely used communication platforms in Indonesia, thus providing easy access and convenient interaction for users from various backgrounds.

Fig. 1 shows that the first main component in this system is the WhatsApp Client, which functions as a communication interface. The WhatsApp Client is in charge of receiving messages from users and forwarding them to the system logic module. On the other hand, WhatsApp Client is also a channel for sending responses from the system back to the user. Through this real-time two-way communication, users can participate in quiz sessions naturally, like an ordinary conversation.

The second component is the Chatbot Engine, which serves as the logic control center of the system, managing the entire course of the quiz. This module is responsible for displaying questions in stages, recording the answers given by the user, calculating provisional scores for each category of learning styles (visual, auditory, kinesthetic), and making decisions related to the identification of learning styles. The Chatbot Engine is also equipped with an adaptive mechanism to handle cases of balanced scores between categories. In such situations, the system automatically adds additional relevant questions to more clearly differentiate the user's learning preferences. In addition, the chatbot also inserts a sequence number on each question to provide context and facilitate easier navigation for users.

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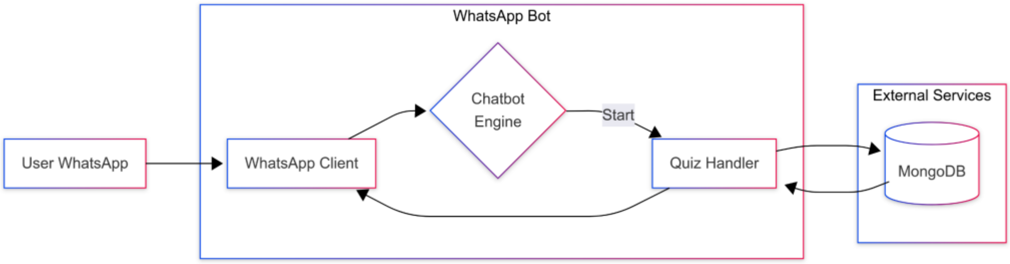

Fig. 1. The system architecture required in developing adaptive chatbots for learning style detection.

The third component is the MongoDB Database, which acts as a permanent store for user interaction data. The information stored includes the user's identity (name, NIM, class), a list of questions that have been answered along with the scores of each category, as well as metadata such as start time, finish time, and quiz duration. This time-based data storage is an important aspect for analyzing the effectiveness of interactions, measuring user participation levels, and serving as supporting data if the system is to be further developed for response time-based adaptive learning.

The fourth component is the Learning Style Quiz Module, which comprises a collection of 27 structured questions compiled based on learning style theory. The questions are classified into three main domains, namely visual, auditory, and kinesthetic, each representing the user's tendency to absorb information. The initial questions were drawn evenly from all three categories, while additional questions were selected based on the category with the highest score or a tied score, allowing for a more personalized and reflective identification process that better reflected the user's mindset.

Overall, as shown in Fig. 1, the system is designed with a modular and dynamic approach, allowing for flexibility in adaptation and further development. The advantage of this architecture lies in its ability to combine ease of access through WhatsApp, adaptive decision-making based on scores, and the ability to record complete and accurate data. This allows the system not only as a tool for identifying learning styles, but also as a starting foundation for the development of a learning system that is smarter and responsive to the individual needs of users.

B. Flow System

The system built in this study is designed to support two-way, adaptive, and efficient interaction between users and educational chatbots on the WhatsApp platform. All stages of the process are centered on a personalized user experience and supported by a score-based dynamic logic mechanism to generate accurate identification of learning styles.

Based on Fig. 2, the initial stage of the system begins when the user initiates the interaction by sending a key message, such as "start a quiz", to the WhatsApp account connected to the chatbot. The response to this initiation is processed in real-time by the system, which builds a new conversation session marked by a quiz start timestamp. In this phase, the chatbot will systematically ask users to fill in identity information, namely name, student identification number (NIM), and class. This information is not only useful as administrative data, but also part of the metadata that will be recorded in the database.

After the identification process is complete, the system proceeds to the quiz-filling stage. Users will be presented with nine initial questions that have been proportionally curated from three main categories of learning styles, namely visual, auditory, and kinesthetic. The selection and preparation of questions are carried out alternately to maintain diversity and avoid order bias. Each question has an answer scale ranging from 0 (never) to 4 (always), and these scores are cumulatively added to their respective categories. The system also stores the entire answer trail as part of the interaction data.

After the user answers the initial nine questions, the system evaluates the scores of each category. If one of the categories has a striking advantage with a difference of at least five points over the second-highest category, then the system considers that the learning style preference is clear enough. In this condition, the system immediately concludes the results and ends the quiz, while recording the completion time and calculating the duration of the work.

However, if the score results show that there are two or even three balanced categories or the difference is no more than 5, the system will activate the refinement mechanism by automatically giving additional questions. A total of six questions from each of the drawn categories will be selected from a set of questions that have not been used before. These additional questions are still presented alternately to avoid boredom and to maintain consistency in interaction. In this phase, the system also activates a dynamic evaluation feature that checks if there are categories that are no longer possible for other categories to pursue, based on the number of remaining questions and the maximum score that can

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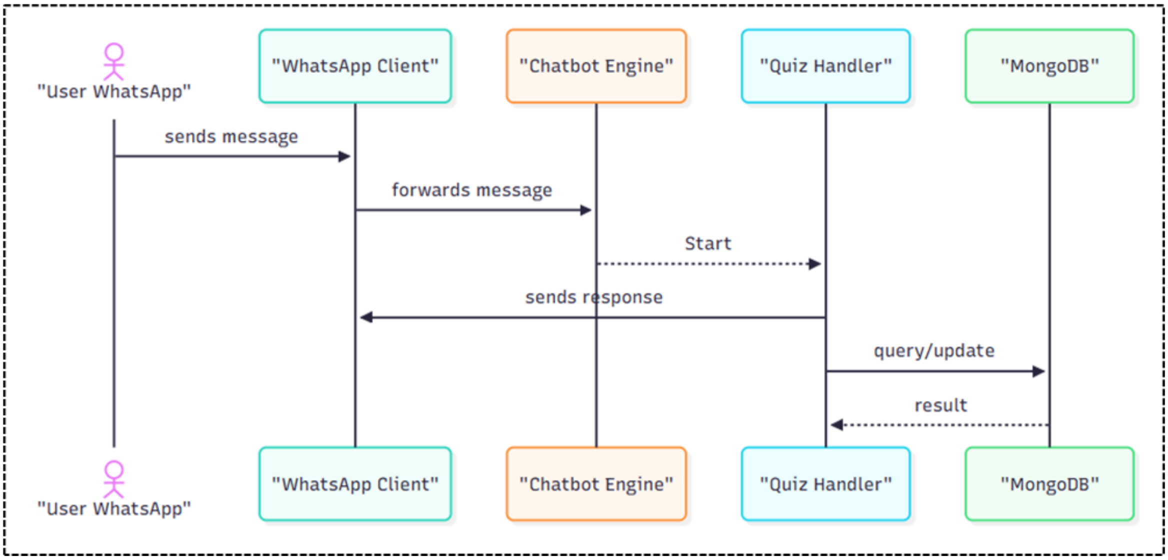

Fig. 2. The research method workflow in developing adaptive chatbots for learning style detection.

be achieved. If these conditions are met, the system will efficiently stop the quiz early. Once the quiz session is over, either due to the depletion of the number of questions or due to dynamic termination, all relevant data, including start time, completion time, total duration, and the entire question and answer trail, will be stored in the MongoDB database. This data storage enables further analysis, historical tracking, and integration into a learning system based on user profiles.

Finally, the chatbot conveys the results of learning style identification directly through WhatsApp messages. If the user has a dominant category, the system displays the results for that single learning style. However, if two or more categories have the same high final score, the system will display the combined results. The chatbot will then invite users to continue learning by mentioning the material they wish to learn, tailored to their identified learning style. With this flow, the system is not only responsive but also capable of intelligently adapting the process to the user's characteristics and needs. This approach offers a more adaptive and personalized learning experience, demonstrating the flexibility of implementing chatbots in the context of digital education.

C. Quiz Module Design

The design of the quiz module in this system is designed to support the process of identifying learning styles in an adaptive and conversation-based manner [18]. These modules are developed in a modular manner so that each function has specific responsibilities that can be managed and tested separately. The first function that forms the core of this module is the Query Taking Function. This function has adaptive selection logic, in which the system selects nine initial questions arranged sequentially and proportionally from three categories of learning styles (visual, auditory, and kinesthetic). Preparation is carried out in an alternating pattern to ensure a balanced initial distribution. If the score from the initial results indicates ambiguity or a balanced score between two or more categories, the system will trigger an additional question retrieval function. This function will accept a maximum of six new questions for each category whose score is still tied, while also considering questions that have not been asked in the session. This aims to ensure accuracy without compromising the user experience due to repetitive queries.

The second function is the Scoring Function, which calculates the cumulative score based on each answer provided by the user. Each question is associated with a single category of learning styles, and answers are graded between 0 and 4 on a frequency scale (from "never" to "always"). This function also stores a historical record of each answer, allowing the data to be used in the evaluation process as well as for future longitudinal analysis of learning behavior. The system is designed to perform real-time score weighting after the user answers the question, which then becomes the basis for evaluation in the next function.

The Score Dominance Evaluation function determines whether the final result can be concluded or if additional questions are still required. The evaluation is conducted after the user completes the first nine questions. If one category has an advantage of at least five points over the other category, the system immediately decides the user's main learning style. However, if there are two or three categories that have the same score or a minimal difference in score, then the system will activate the question addition mode. In the advanced process, this function also has feature advanced evaluative logic: the system will stop the quiz

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process early if it detects that the category with the highest score can no longer be pursued by other categories based on the remaining questions and the potential maximum score that can be obtained.

The fourth function is the Result Store Function, which stores the quiz result data in a structured manner in the MongoDB database. The stored data includes user information (name, NIM, class), a list of questions and answers, total scores per category, and time information (start, finish, and duration in seconds). This storage scheme is designed to be flexible and compatible with user interfaces as well as analytical dashboards that allow the results to be used in further academic evaluations. Saving is done automatically after the quiz session is over, either because the results have been concluded or because the user has passed the deadline.

The Timer function is an important complement to this module. The system records the time when the first question is displayed to the user as the start time, and records the time when the system concludes the result as the completion time. From these two-time values, the system calculates the duration of the work automatically in units of seconds. This function is not only responsible for taking notes, but also for supervising the duration of the quiz. If the user exceeds the maximum time limit, for example, 10 minutes (600 seconds), the system will cancel the active session and ask the user to restart from the beginning. This mechanism is designed to avoid cases of the system not responding due to delayed interactions, as well as encourage users to complete the quiz in one continuous session.

Overall, the design of this quiz module demonstrates a systematic approach that not only adjusts the flow based on user responses but also integrates aspects of time validation, data storage, and in-depth evaluative logic. The combination of all these functions forms an intelligent quiz system that can adapt to the dynamics of user interaction, yielding more accurate and efficient identification results. This module is also designed with the principle of openness to further development, such as the addition of new categories, the integration of machine learning, or adaptation to other conversational platforms other than WhatsApp.

III. Implementation

A. Adaptive Implementation

To ensure that the quiz system can accurately and efficiently identify the user's learning style, several evaluation and calculation logics are employed. Each formula has an important role in determining the flow of the system adaptively, here is the full description.

1. Accumulated Score per Category

Each question in the questionnaire has a score weight ranging from 0 to 4 and is associated with one of three learning style categories: Visual (V), Auditory (A), and Kinesthetic (K). To generalize the score computation process, user responses and category mappings are represented in a matrix–vector formulation.

Let the response vector be defined as shown in Eq. (1) [19]:

$$R = [r1, r2, \dots, rn], ri \in \{0,1,2,3,4\} \tag{1}$$

where r_i denotes the score given by the user to the i^{th} question.

Let $W \in \mathbb{R}^{n\times 3}$ be the category weight matrix, defined in Eq. (2) [19]:

$$W = \begin{bmatrix} w_{1,V} & w_{1,A} & w_{1,K} \\ w_{2,V} & w_{2,A} & w_{2,K} \\ \vdots & \vdots & \vdots \\ w_{n,V} & w_{n,A} & w_{n,K} \end{bmatrix} \tag{2}$$

where $w_{i,j} = 1$ if question i belongs to category j, and 0 otherwise.

The accumulated score vector for each learning style category is then computed as shown in Eq. (3) [19]:

$$S = R \times W \tag{3}$$

Where the score results follow Eq. (4) [16]:

$$S = [S_V, S_A, S_K] \tag{4}$$

Eq. (4) represents the total accumulated scores for the visual, auditory, and kinesthetic categories, respectively. This process allows the system to form a profile of the learning preferences of each user based on their interaction in answering the questions provided.

2. Early Termination Based on Score Dominance

The system accommodates efficiency by evaluating after the user answers the initial 9 questions. If there is one category that has a score significantly higher than the other category (at least a 5-point difference), the system immediately concludes the results and ends the quiz. This condition is formulated in Eq. (5) [20].

$$f(S) = \begin{cases} 1, & |S_{top} - S_i| \geq t \\ 0, & otherwise \end{cases} \tag{5}$$

In this Eq. (5), S_{top} represents the highest-scoring category, S_i denotes the score of the remaining categories, and t refers to the predefined threshold value set to 5. When $f(S) = 1$, the system immediately finalizes the result and ends the quiz because one learning style is clearly dominant. Conversely, when $f(S) = 0$, the quiz continues with additional questions for the top categories to further refine the distinction between learning styles.

3. Addition of Additional Questions

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If the result of the decision function is $f(S) = 0$, indicating that the score gap is below the threshold, the system selects categories with top or near-top scores for further clarification. Six additional questions are added for each selected category. The selection rule is defined in Eq. (6) [20]:

$$S_{selected} = \{S_i \in S \mid S_{top} - S_i < t\} \quad (6)$$

If more than one category is included in S_{selected}, the system proceeds with follow-up questions to clarify the dominant learning style. If only one category remains, the system terminates the quiz and classifies the user accordingly.

4. Early Termination If Not Exceeded

The system includes a real-time evaluation mechanism that enables early termination of the quiz when the category with the highest score is unlikely to be surpassed by the others, even if all remaining questions are answered with the maximum possible value. This ensures that the system operates efficiently without unnecessary question delivery. Let S_{top} represent the current score of the category with the highest value, S_i denote the score of the other categories, and s_i indicate the number of remaining questions for category i. Since each question can yield a maximum score of 4, the early termination condition is defined as follows in Eq. (7) [21].

$$S_{top} - S_i > 4 \times s_i \qquad \forall i \neq top \quad (7)$$

The system can conclude that the quiz does not need to be resumed because the results will not change significantly so that it can be stopped efficiently.

5. Determination of the Final Result

Once all evaluations have been completed and the final scores are obtained, the system determine the final result based on the number of categories with the highest scores. If there is only one category that has the highest score, then the final result only lists that learning style. However, if there are two or more categories with the same highest score, then the system will give a combined result. The formula for obtaining the final result is given by Eq. (8) [20].

$$result = \begin{cases} \{S_{top}\}, & if\ S_{top} > S_i\ \forall i \neq top \\ \{i \mid S_i = S_{top}\} & if\ multiple\ max\ score \end{cases} \quad (8)$$

This formulation reflects the model's flexibility in identifying not only a single dominant learning style but also mixed tendencies in user learning behavior.

6. Probabilistic Learning Style Estimation

To enhance the reliability of learning style detection, especially in conditions where category scores are close, the system integrates a Bayesian inference approach as a probabilistic decision mechanism. This model estimates the posterior probability of each learning style category $C \in \{V, A, K\}$ (Visual, Auditory, Kinesthetic) given the cumulative user responses R.

Each category score is represented as in Eq. (9) [16]:

$$S = [S_V, S_A, S_K] \quad (9)$$

Assuming a uniform prior distribution due to the absence of any initial preference, as in Eq. (10) [22]:

$$P(C = i) = \frac{1}{3} \quad (10)$$

A softmax-based likelihood approximation is employed to convert score differences into probability values in Eq (11) [22]:

$$P(R \mid C = i) \propto \exp(\beta S_i) \quad (11)$$

In Eq. (11), S_i denotes the accumulated score of category i, while β represents a sensitivity constant that controls the steepness of the confidence distribution.

Thus, the posterior is computed using Bayes' rule as Eq. (12) [22]:

$$P(C = i \mid R) = \frac{\exp(\beta S_i)\, P(C = i)}{\sum_{j \in C} \exp(\beta S_j)\, P(C = j)} \quad (12)$$

The final decision follows Eq. (13) [21]:

$$C^{*} = \arg\max_{i \in C} P(C = i \mid R) \quad (13)$$

If the resulting posterior probability meets the confidence threshold, such as Eq. (14) [21]:

$$P(C^{*} \mid R) \geq \theta \quad (14)$$

With Eq. (14), the system concludes the dominant learning style. Otherwise, the system triggers the adaptive Additional questioning to further reduce uncertainty. In this context, the parameter $\beta = 0.5$ serves as the empirical sensitivity constant that controls the steepness of the confidence response, while $\theta = 0.75$ represents the confidence threshold that must be achieved for a category to be considered dominant. This Bayesian mechanism allows the system to properly quantify uncertainty and prevents premature classification during closely balanced scoring scenarios.

7. Performance Metrics and Algorithmic Flow

To validate the reliability of the proposed adaptive detection mechanism, its performance was benchmarked using a statistical classification model, specifically the Support Vector Machine (SVM). The SVM was employed to learn the decision boundaries between the learning style categories (Visual, Auditory, and Kinesthetic) based on the accumulated score vectors $S = [S_V, S_A, S_K]$. This approach provides measurable and interpretable decision parameters, complementing the rule-based and Bayesian mechanisms described earlier.

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Table 1. Summary of System Implementation Processes and Pseudocode Workflow

No	Proses Description	Pseudocode

1	**Initial Questions** – The system displays 9 initial questions consisting of 3 questions each from the visual, auditory, and kinesthetic categories. The user answers using numbers from 0 to 4.	`FUNCTION InitialQuiz():`
		`SELECT 9 questions (3 visual,3 auditory ,3 kinesthetic)`
		`DISPLAY each question to user`
		`FOR each question i:`
		`RECEIVE response X[i]`
		`UPDATE S = W * X`
		`RETURN S`

2	**Dominance of the Score** – After 9 questions are answered, the system checks whether any category has a ≥5-point advantage.	`FUNCTION CheckDominance(S, t):`
		`topIndex ← index of max(S)`
		`secondVal ← second highest value in S`
		`IF S[topIndex] - secondVal ≥ t:`
		`RETURN (1, topIndex)`
		`ELSE:`
		`RETURN (0, topIndex)`

3	**Addition of Additional Questions** – If no category is dominant, the system adds 6 new questions for tied categories.	`FUNCTION SelectFollowUpCategories(S, t):`
		`topVal = max(S)`
		`I_selected = {}`
		`FOR i in [1..3]:`
		`IF topVal - S[i] <= t:`
		`ADD i to I_selected`
		`RETURN I_selected`
		
		`I_selected = SelectFollowUpCategories(S,t)`
		`FOR each i in I_selected:`
		`ADD 6 new questions related to category[i] to Q_remaining`

4	**Early Termination** – During additional questions, the system checks if the leading score can no longer be surpassed.	`FUNCTION EarlyStop(S, remainingQuestions):`
		`topIndex = index of max(S)`
		`FOR i in [1..3]:`
		`IF i ≠ topIndex:`
		`maxPossible = remainingQuestions[i] * maxScore`
		`IF S[topIndex]- S[i]<= maxPossible:`
		`RETURN False`
		`RETURN True`

5	**Determination of Finish and Storage** – After completion, the system determines the final learning style result and stores it in the database.	`FUNCTION FinalResult(S):`
		`maxScore = max(S)`
		`resultCategories = {}`
		`FOR i in [1..3]:`
		`IF S[i] == maxScore:`
		`ADD category[i] to resultCategories`
		`RETURN resultCategories`
		`result = FinalResult(S)`

The mathematical representation of the SVM decision function follows Eq. (15) [23]:

$$f(x) = w \cdot x + b \tag{15}$$

where w is the weight vector and b is the bias term that defines the decision boundary.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$
$$\text{Precision} = \frac{TP}{TP + FP} \tag{16}$$
$$\text{Recall} = \frac{TP}{TP + FN}$$
$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where in Eq. (16) TP, FP, FN, and TN represent the standard confusion matrix components [23]. The evaluation was performed using synthetic questionnaire response data from 200 participants to ensure the statistical validity of the adaptive mechanism. The obtained performance metrics confirm that the adaptive model achieves consistent

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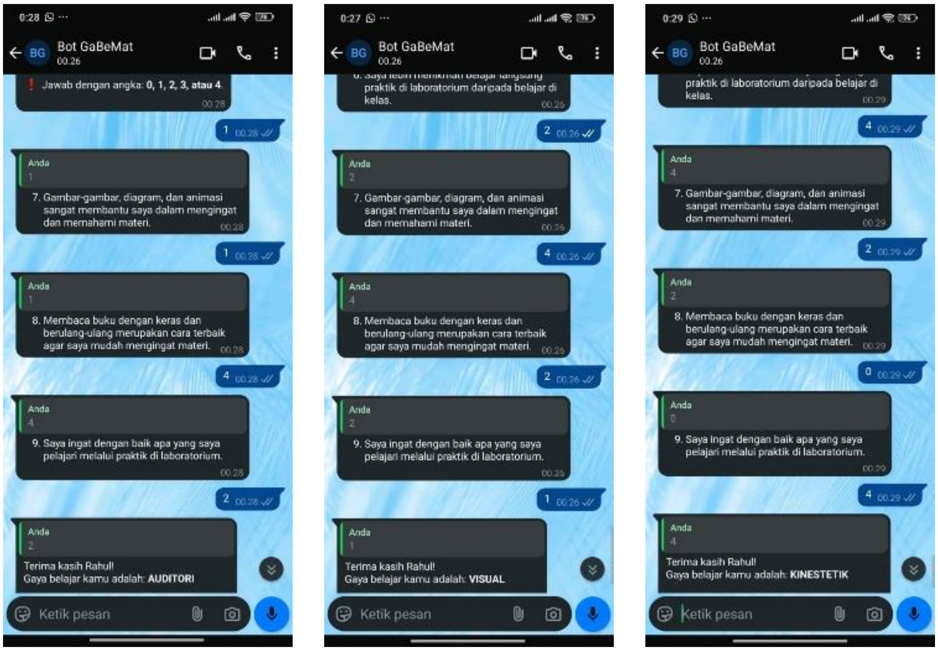

Fig. 3. The early detection function test for each learning style which can stop at the ninth question if the score is dominated

and interpretable classification across different user response scenarios.

B. System Implementation

To ensure that the mathematical formulation aligns with the technical execution, the adaptive quiz logic was implemented into the chatbot workflow using structured pseudocode. This approach provides clarity, reproducibility, and consistency between theoretical models and their operational behavior. The complete process is summarized in Table 1.

IV. Result

A. Functionality Testing

Functionality testing was carried out after the entire system programming process was completed. This test aims to ensure that every pre-designed function operates as planned. The main focus in this trial was to observe whether the system had worked adaptively as expected. The tests are carried out sequentially to evaluate the likelihood that each function is executed correctly or not. The results of the tests show that the entire system function has been operating properly and covers all possible scenarios.

Fig. 3 shows the results of the test on the first function, namely the early detection of learning style. This function is designed to stop the questionnaire process faster if the system has identified a significant predominance of scores in one of the learning style categories. In such cases, the system does not need to display all additional questions because the user's learning style can already be definitively determined.

This trial was conducted thoroughly across all three categories visual, auditory, and kinesthetic to ensure that the early detection function works consistently, not just in one category. The test results showed that when one of the categories obtained a significantly higher score from the start, the system was able to recognize this dominance and stop the process appropriately without needing to proceed to the additional question stage. This demonstrates that the function is effective in reducing the number of questions that need to be answered without compromising the accuracy of identifying the user's learning style.

Fig.4 shows the results of the test of the additional question addition function. This function will be active if, after the initial nine questions, there are still two or three categories of learning styles with balanced scores. This balance is defined as a score that is equal or has a difference of no more than five points. In such a situation, the system will add six additional questions for each category whose value differs slightly.

The addition of questions aims to clarify the dominance of one learning style within an almost balanced category. With a larger amount of data, the system can make more accurate assessments. This process enhances the reliability of determining the user's learning style. The final result is expected to be able to avoid ambiguity in the determination of dominant categories. The test is performed on several possible combinations of categories. These combinations include visual and auditory, visual and kinesthetic, and auditory and kinesthetic. Each test is

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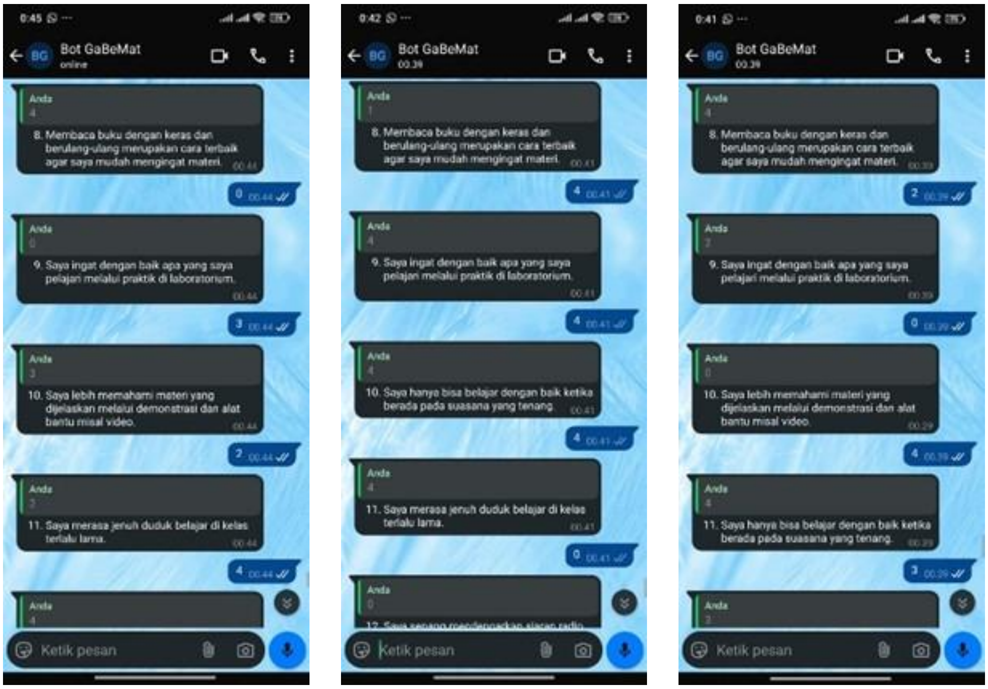

Fig. 4. The Additional question function test when there are two or three with balanced scores

designed to ensure that the addition function runs consistently across a variety of scenarios. It also ensures that the system doesn't just work on one specific type of category balance.

Fig. 5 shows the results of a trial of the early termination function applied to the supplementary question session in the Learning Style Questionnaire system. This function is designed to identify a user's learning style faster when there is one category with a score that the other categories can no longer pursue. Under these conditions, the system does not need to display all additional questions because decisions can be taken early. This aims to save user time and improve the efficiency of the identification process.

The test was conducted with various variations of score combinations between categories to ensure the

Fig. 5. Early Early stop function test when two or three categories can no longer be exceeded

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function ran according to the expected logic. In some cases, the system stops additional questions midway through the session because the dominance of scores from one of the categories has become apparent. This proves that the function is able to evaluate the score in real-time and establish the final result accurately. Thus, the system becomes more adaptive to situations that do not require complete evaluation.

B. White Box Testing

White box testing is a software testing method that focuses on the internal structure of program code. In this method, the tester possesses a thorough understanding of the program logic and the control flows employed within the system. The purpose of this test is to ensure that each execution path in the code has been tested and works as expected. This test is highly effective in detecting logic errors, branching, and repetition that do not function as intended [24].

1. Basic Path Testing-Cyclomatic Complexity

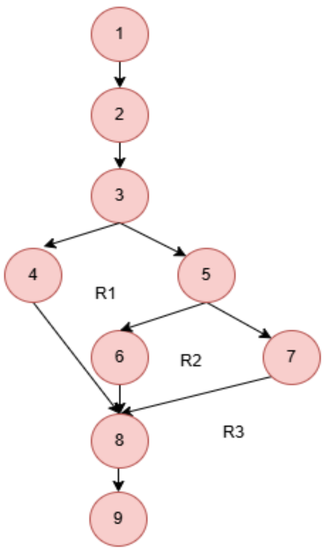

Fig. 6. Test Flow Graph uses McCabe's theory to calculate Cyclomatic Complexity (CC)

Basic Path Testing is a white-box technique that utilizes McCabe's theory to calculate the Cyclomatic Complexity (CC) of a program's control flow graph. From the pseudocode that previously could be used as a flow graph for white box testing using cyclomatic Complexity. The sequence of the program is made in sequence numbers to facilitate the formation of a flow graph, starting from initialization and then determining the node statement of the loop, branching statement, the output [25]. The flowgraph form used is based on the previous pseudocode, as shown in Fig. 6.

Circulating Fig.6 can determine the cyclomatic complexity of the resulting flow chart, by using the Cyclomatic Complexity formula.

1) The number of regions on the flow graph corresponds to Cyclomatic Complexity, as shown in Eq. (17) [26].

$$\begin{aligned} V(G) &= Region \\ V(G) &= 3 \end{aligned} \tag{17}$$

2) The cyclomatic complexity for the flow graph can be calculated using this formula, in Eq. (18) [26].

$$\begin{aligned} V(G) &= E - N + 2 \\ V(G) &= 10 - 9 + 2 \\ V(G) &= 3 \end{aligned} \tag{18}$$

The value of cyclomatic complexity presents the number of linear independent paths through the program's control structure. So, there are 3 paths, namely:

1) 1-2-3-4-8-9
2) 1-2-3-5-6-8-9
3) 1-2-3-5-7-8-9

From the path generated above, it can be seen that 3 and 5 are predicate nodes.

2. Coverage Testing- Condition Coverage

Condition Coverage is a test criterion that ensures each Boolean sub-expression on a condition statement is evaluated as true and false at least once during the test [27]. In the implementation of the learning style identification chatbot system, there are several possibilities that occur, condition coverage is carried out on several main functions, such as questionnaire processing, score assessment, selection of additional questions, to early termination mechanisms. Each function is tested by browsing the code flow, evaluating the logical (if-else) conditions, and ensuring that each block of code is executed under various input conditions. For example, testing is conducted under conditions where the score is balanced, when one category dominates the score, and when additional questions need to be administered or stopped early. Thus, all branches in the system were successfully reached through this test.

Based on Table 2 of the white box test results with condition coverage, it can be concluded that the system has met all the main execution lines that were previously designed. No logic errors or path-specific omissions were found in this test. Important functions, such as dividing scores based on answers, selecting dominant categories, and evaluating termination conditions, have been carried out accurately as planned. Therefore, white box testing provides confidence that the internal structure of the program has worked optimally and is free from logical errors[28].

C. Case Study

1. Bayesian simulation

To demonstrate the probabilistic reasoning of the proposed adaptive model, a simple inference simulation was conducted using a representative

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Table 2. Test cases on each functional condition coverage.

No	Function Name	Tested Conditions	Score Input	Execution Path	Expected Output	Status
1	checkDominant()	One of the dominant categories by more than 5 points	{V: 10, A: 4, K: 3}	Entering into a state of dominance	Direct identification to "Visual"	Pass
2	checkBalance()	The two categories have the same score	{V: 7, A: 7, K: 5}	Add 6 questions for V and A	Skip to additional questions	Pass
3	checkBalance()	Three categories have the same score	{V: 6, A: 6, K: 6}	Add 6 questions for all three	Skip to additional questions	Pass
4	checkBalance()	The score of the two categories is only 1–4 points	{V: 8, A: 5, K: 4}	Add 6 questions for V and A	Skip to additional questions	Pass
5	checkFinal()	One of the significant superior scores after the additional questions	{V: 14, A: 9, K: 8}	Output final "Visual"	System stops, show final results	Pass
6	checkFinal()	Additional questions still result in a draw score	{V: 12, A: 12, K: 9}	Re-evaluation or re-evaluation	Show a draw score, ask for a re-evaluation	Pass
7	testduration ()	Save the start and end times of the questionnaire	Start time: 12:00, finish: 12:03	Calculate the duration of the work	Save and show duration: 3 minutes	Pass
8	Numbering()	Sequential numbering of questions	Questions 1 to 27	Looping questions	Questions are displayed with the correct number	Pass

response pattern. In this example, the scores were Visual = 12, Auditory = 8, Kinesthetic = 7.

A uniform prior was assumed, $P(C=i)=\frac{1}{3}$for $i \in \{V, A, K\}$, reflecting the absence of initial bias toward any learning style category. The sensitivity parameter was empirically set to $\beta = 0.5$, representing moderate confidence steepness in the softmax-like likelihood function.

The unnormalized posterior for each category is computed following Eq. (19) [22]:

$$u_i = \exp\,(\beta S_i)\, P(C=i) \tag{19}$$

This produces the following results, as shown in Eq. (20) [22]:

$$u_V = \frac{e^6}{3} \approx 134.476,$$
$$u_A = \frac{e^{4.5}}{3} \approx 30.006 \tag{20}$$
$$u_K = \frac{e^{1.5}}{3} \approx 1.494$$

The normalization constant was obtained in Eq. (21) [22]:

$$Z = u_V + u_A + u_K = 165.976 \tag{21}$$

The normalized posterior probability were then calculated, as shown in Eq. (22) [22].

$$P(V \mid R) = \frac{134.476}{165.976} = 0.810,$$
$$P(A \mid R) = \frac{30.006}{165.976} = 0.181, \tag{22}$$
$$P(K \mid R) = \frac{1.494}{165.976} = 0.009$$

This Eq. (22) indicates that the Visual learning style dominates with a posterior probability of approximately 81.0%, which exceeds the predefined confidence threshold ($\theta = 0.75$). Therefore, the system confidently concludes the user's dominant learning style as Visual, while the remaining probabilities for Auditory (18.1%) and Kinesthetic (0.9%) represent marginal tendencies.

2. Model evaluation

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The adaptive detection model was further evaluated using a Support Vector Machine (SVM) to validate its classification performance across the three learning style categories: Visual, Auditory, and Kinesthetic. Evaluation was conducted using a 20-fold cross-validation method to ensure reliable estimation of generalization ability. The results showed that the SVM achieved a classification accuracy of 80.2% with an AUC of 0.902, indicating strong discriminative performance. The F1-score (0.698), precision (0.738), and recall (0.662) values were relatively balanced, confirming that the model performs consistently across folds. Overall, these results demonstrate that the adaptive detection mechanism achieves stable, interpretable, and statistically reliable classification outcomes for identifying dominant learning styles.

V. Discussion

The adaptive detection model demonstrated strong and balanced performance, yielding an overall accuracy of 80.2% with an AUC of 0.902, confirming its reliable discriminative capability. With a precision of 0.738, a recall of 0.662, and an F1-score of 0.698, the system achieved a well-balanced trade-off between sensitivity and specificity, ensuring stable classification across different learning style categories. These findings highlight that the adaptive mechanism not only performs consistently but also preserves interpretability, allowing educators and researchers to trace how each score contributes to the final classification outcome [29].

When compared to previous research employing traditional machine learning models for learning style detection based on the Theory of Multiple Intelligences, the proposed model exhibits superior performance. In that study, the Support Vector Machine (SVM) achieved an accuracy of 75.55%, while other algorithms such as Logistic Regression (73.33%), Random Forest (73.33%), and Naïve Bayes (70.55%) demonstrated lower levels of accuracy [23]. By contrast, the adaptive SVM integration in this research reached 80.2%, reflecting an improvement of approximately 4.65% over the conventional SVM implementation. This enhancement can be attributed to the adaptive scoring formulation and the early-termination logic, which reduce redundancy in user responses and improve the representativeness of feature weighting during classification.

Moreover, unlike static questionnaires that require users to complete all items before producing an outcome, the developed system employs score-dominance evaluation and Bayesian refinement to dynamically determine when sufficient evidence has been reached. This design allows the chatbot to terminate interactions early without compromising reliability, significantly reducing user fatigue and response time. Consequently, the proposed model not only improves accuracy compared to prior SVM-based approaches but also enhances efficiency and interpretability, key aspects for practical deployment in adaptive digital learning environments [30].

Despite its effectiveness, several limitations may affect the accuracy of the results. The system still relies heavily on numerical responses without accounting for contextual user behavior such as response timing patterns, learning media preferences, or emotional cues in message texts. These unmeasured variables may create bias, particularly for users whose behavior does not fully align with selected numeric responses [31]. Additionally, the limited dataset size used in evaluation may not fully represent the broader population diversity, potentially affecting the generalization of classification.

Another limitation lies in the lack of error analysis on misclassified and borderline cases. Some users may exhibit overlapping characteristics across categories, leading to lower confidence in the final decision, especially when insufficient score separation is detected [32]. While Bayesian inference reduces ambiguity, further algorithmic refinement is still needed to handle highly uncertain profiles. The adaptive mechanism adopted in this system could provide a significant impact on personalized learning ecosystems. By offering real-time learning style identification directly through an accessible platform like WhatsApp, educators can dynamically adjust teaching strategies, deliver multi-modal materials, and support learner autonomy without requiring additional applications [33]. The efficiency demonstrated in testing also highlights its potential use in large-scale digital learning settings where user attention and responsiveness are critical.

Theoretically, the system's threshold-based decision approach aligns with cognitive load theory, which suggests that unnecessary tasks should be minimized to prevent mental fatigue. Early termination of the quiz reflects this principle, helping maintain user engagement while still achieving valid results [34]. Although performance metrics indicate high success, the system may produce incorrect predictions under certain conditions. For example, users who respond randomly or select moderate values across categories can trigger near-equal score distributions that reduce certainty in decision-making. Furthermore, single-session interaction without historical feedback prevents the system from learning user behavior patterns over time, which could otherwise improve prediction confidence.

Therefore, future development should incorporate uncertainty modeling, such as confidence intervals and posterior probability thresholds, to more effectively

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express classification reliability and enhance decision-making transparency. Future research should focus on several important directions to enhance the performance, scalability, and real-world applicability of the proposed system. One promising improvement lies in the integration of multimodal data, where incorporating audio and visual interactions could better represent auditory and visual learning behaviors, thereby overcoming the limitations of a purely text-based evaluation approach. In addition, the implementation of machine learning–based personalization, such as continual learning models using algorithms like Naïve Bayes or Support Vector Machine, can utilize users' historical interaction data to refine detection accuracy over time. Expanding large-scale validation to more diverse participant groups is also essential to ensure that the system remains scalable, inclusive, and fair across different educational contexts. Furthermore, practical and ethical considerations, including data privacy, transparency of consent, user experience design, and connectivity reliability, must be thoroughly addressed before deployment in real academic environments.

Overall, this study contributes a novel adaptive mechanism for identifying learning styles through everyday communication platforms. The findings highlight that rule-based adaptive systems supported by probabilistic logic can effectively advance digital personalization strategies while maintaining efficiency and user-friendliness. With these future developments, the system has the potential to become a more impactful and practical educational tool within the modern digital learning landscape [35].

VI. Conclusion

This This study successfully developed a rule-based adaptive WhatsApp chatbot designed to identify users' learning styles, visual, auditory, and kinesthetic, through a weighted questionnaire enhanced with probabilistic refinement. The system demonstrated its capability to adaptively manage conversation flow by evaluating score dominance, performing selective question expansion, and applying Bayesian posterior estimation to resolve uncertainty in balanced-score scenarios. Experimental validation confirmed that the model achieved an accuracy of 80.2% and an AUC of 0.902, supported by a balanced precision (0.738), recall (0.662), and F1-score (0.698). These results indicate that the system operates reliably across learning style categories, maintaining a stable trade-off between sensitivity and precision. Compared to conventional static questionnaires, the adaptive mechanism effectively reduces redundant questioning, minimizes cognitive load, and improves response efficiency while preserving interpretability and transparency. White-box testing using Cyclomatic Complexity further verified the logical correctness and operational robustness of the implemented algorithm, confirming that the system performs consistently under real-time interaction conditions. Future work will focus on integrating multimodal behavioral cues such as response timing, text sentiment, and message interaction patterns to enhance detection depth. In addition, the chatbot will be expanded to include personalized learning content recommendations and broader dataset validation across diverse learner populations to improve further generalization and adaptive learning support within digital education ecosystems.

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Data Availability

No datasets were generated or analyzed during the current study.

Author Contribution

Muhammad Rahulil initiated and conceptualized the research, designed the framework for chat-based learning style identification, carried out data collection, and led the analysis and interpretation of the results. Yuni Yamasari provided support in refining the research methodology and offered academic guidance throughout the study. Ricky Eka Putra assisted in system implementation and integration of the chat application. I Made Suartana contributed to the validation process and provided constructive feedback for improving the model. Anita Qoiriah reviewed the manuscript, provided critical suggestions, and assisted in finalizing the written report. All authors reviewed and approved the final version of the manuscript, agreeing to take responsibility for the accuracy and integrity of the work.

Declarations

Ethical Approval

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This study utilized primary data collected directly through a learning style questionnaire distributed via WhatsApp chatbot. Participation was voluntary, and the data were used solely for research purposes. Therefore, this study did not require additional ethical approval.

Consent for Publication Participants.
Consent for publication was given by all participants

Competing Interests
The authors declare no competing interests.

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