Expert System for Learning Styles Diagnosis Using Dempster–Shafer and Bayesian Network

Tesalonika Palilingan[1], Krismiyati[2], Teguh Wahyono[3]
[1,2,3]Universitas Kristen Satya Wacana; Jl. O. Notohamodjojo, Sidorejo Salatiga, Jawa Tengah - Indonesia 50711, 08562981374
[1,2,3]Magister Sistem Informasi, Fakultas Teknologi Informasi, Universitas Kristen Satya Wacana, Salatiga
e-mail: [1]palilinganecha@gmail.com, [2]krismiyati.krismiyati@uksw.edu, [3]teguh.wahyono@uksw.edu

Abstract

The lack of intelligent diagnostic tools for determining the learning styles of students at STMIK Multicom Bolaang Mongondow is the subject of this study. The absence of reliable and flexible diagnostic techniques makes it difficult for teachers to modify their lesson plans. To address this, a hybrid inference approach that combines Bayesian Networks (BN) and Dempster–Shafer Theory (DST) is proposed, because BN effectively handles probabilistic reasoning while DST manages uncertainty, making the integration of both suitable for adaptive learning diagnosis. The research contributes mainly by creating and confirming a new framework that combines probabilistic and belief-based inference. System development follows the Expert System Development Life Cycle (ESDLC). The method's internal consistency and reliability are demonstrated through accuracy evaluations and white-box testing of the core inference mechanism. Stable performance across devices is demonstrated by functional testing. An 86.67% match rate is found through accuracy testing based on comparisons with expert evaluations. The findings support the usefulness of combining BN and DST to manage uncertainty and enhance adaptive learning suggestions. This method-focused contribution provides a useful framework for individualized learning systems in the future that do not rely on massive datasets.

Keywords— Learning Style, VAK, Dempster-Shafer, Bayesian Network, Expert System

1. INTRODUCTION

Learning style is the way people understand and recall new knowledge by using their senses, influencing their processing of information. Though there are several models, this paper focuses on the Visual, Auditory, and Kinaesthetic (VAK) model, which is especially helpful for improving instruction in Indonesian schools [1] – [9].

Lack of diagnostic tools causes many teachers at STMIK Multicom Bolaang Mongondow difficulty in determining the learning preferences of their pupils [6][9][10]. Although earlier studies have used Dempster–Shafer theory to manage uncertainty in learning style diagnostics, these methods are hardly included in web-based, real-time expert systems, particularly those using Bayesian Networks for adaptive recommendations [1][9][11].

More consistent findings than Certainty Factor or Fuzzy Logic approaches, Dempster–Shafer theory was selected to reconcile unclear and contradicting facts rationally. Bayesian networks enhance this by allowing probabilistic thinking and effective VAK indicator categorisation, thereby providing tailored learning recommendations [1][4][9][12][13][14].

Previous studies have demonstrated that the Dempster–Shafer theory is effective for reasoning under uncertainty. For example, Anggrawan et al. [15] reported an accuracy of 87% in detecting learning problems, highlighting DST as a reliable method for handling unclear input and combining evidence in expert systems, particularly in educational contexts.

This effort intends to build a web-based expert system for higher education that uses the VAK model to identify student learning styles, controls uncertainty with Dempster–Shafer theory, and delivers tailored suggestions by Bayesian Networks. This solution closes a significant void at STMIK Multicom by giving teachers an interactive platform to modify their lesson plans appropriately.

The main objectives of this study are to develop, integrate, and assess inference techniques—particularly Dempster-Shafer Theory and Bayesian Network—for identifying students' learning styles in the face of uncertainty.

2. RESEARCH METHODS

This research adopts a structured and systematic approach to develop an expert system that diagnoses students' learning styles using the VAK (Visual, Auditory, Kinesthetic) model, the Dempster–Shafer theory, and Bayesian Network inference. The research process was designed to follow a sequential flow starting from problem identification to system evaluation, ensuring that each step contributes directly to the system's reliability and effectiveness.

2.1. Research Framework and Approach

The research stages begin with identifying the problem [8], which is the absence of a personalized system to diagnose learning styles among students at STMIK Multicom Bolaang Mongondow. After defining the focus, the knowledge acquisition process is conducted by gathering information from educational experts and scientific literature [1]. This knowledge is organized and formalized into a knowledge base that underpins the reasoning logic of the expert system [16][17]. The system is then implemented using inference mechanisms and finally evaluated to ensure its accuracy and functional reliability [16]. It should be noted that several processes shown in Figure 1 may involve multiple iterations to refine the knowledge base and improve the expert system's reliability.

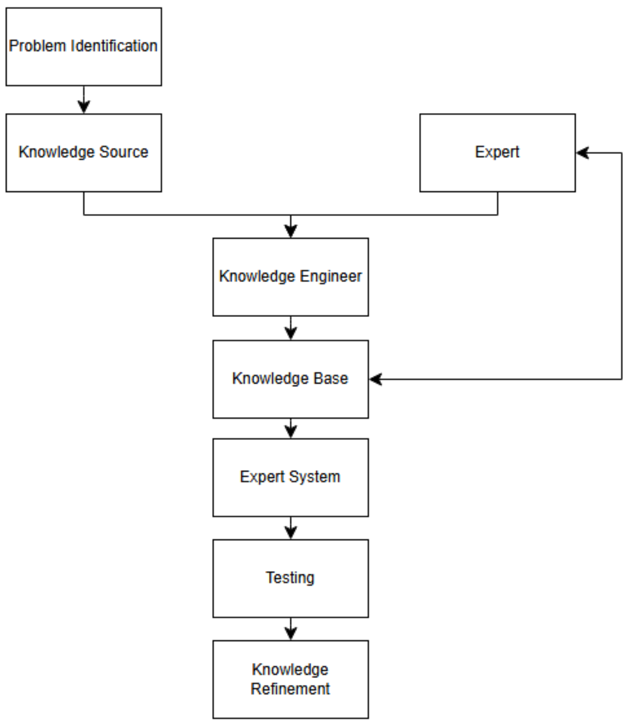


Figure 1. Research Stages

2.2. *Expert System Development*

To guide the development process, this study adopts the Expert System Development Life Cycle (ESDLC), which consists of four major phases: planning, knowledge acquisition, implementation, and evaluation [1]. In the planning phase, the researcher defines the system requirements, analyzes existing solutions, studies relevant literature, and designs the development strategy. The knowledge acquisition phase involves collecting learning style indicators and expert insight. In total, 30 indicators were identified, each mapped to one or more learning style categories and assigned belief and plausibility values based on the Dempster–Shafer theory.

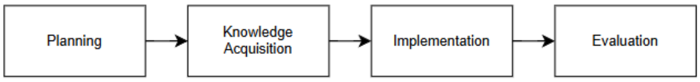


Figure 2. ESDLC Model

2.3. *Dempster-Shafer Theory*

The Dempster–Shafer Theory (DST) combines pieces of evidence (belief functions) to calculate the degree of belief in a hypothesis [1][9]. For two independent belief functions m1and $m2$ over the same frame of discernment, below is more information about the Dempster–Shafer formula and how to use it.

$$m_3(Z) = \frac{\sum_{X \cap Y = Z} m_1(X) \cdot m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) \cdot m_2(Y)} \quad (1)$$

Where:

- $m1\ (X)$: belief value for hypothesis X from the first indicator.
- $m2\ (Y)$: belief value for hypothesis Y from the second indicator.
- $X \cap Y = Z$: only intersecting (consistent) beliefs contribute to the final belief $m3\ (Z)$.
- K: total conflict — sum of all conflicting mass assignments where there is no intersection.
- $1 - K$: normalization factor to ensure the result stays within [0, 1].
- $m3\ (Z)$: the combined belief mass for hypothesis Z.

This formula allows the system to merge evidence from multiple indicators, even when some of the data is uncertain or conflicting.

2.4. *Bayesian Network*

To combine the belief values obtained from the Dempster–Shafer theory with the probabilistic reasoning of the Bayesian Network [13], the system uses the total probability theorem to compute the final recommendation likelihood for a given learning material or method M.

$$P\ (M) = \sum_{i=1}^{3} P\ (C_i)\ \cdot\ P\ (M|C_i) \quad (2)$$

Where:

- $P\ (Ci)$: belief value of learning style class Ci (Visual, Auditory, Kinesthetic) as calculated by the Dempster–Shafer theory.
- $P\ (M \mid Ci)$: conditional probability of recommending material or strategy M given learning style Ci, as defined by the Bayesian Network.

This approach integrates DST and BN by using the belief values $P(Ci)$ as soft priors, which are then weighted against the BN's internal probabilistic structure. The result is a more adaptive and personalized recommendation mechanism that reflects both the uncertainty in user inputs and the structured relationships among learning attributes.

2.5. *Data Processing Workflow*

Students begin the Data Processing Workflow by completing a VAK (Visual, Auditory, Kinesthetic) learning type assessment. To cope with uncertainty and get the belief values for each learning method, we employed Dempster-Shafer theory to process these answers. After that, the information was submitted to a Bayesian Network, which used the information to figure out the possibilities of each learning style and give personalised learning suggestions. The system finally indicated the student's learning style and gave them ideas, which are tailored ways for them to study better, as seen in Figure 3.

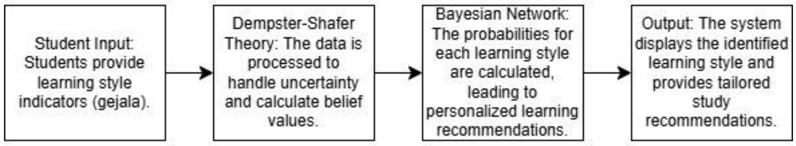


Figure 3. Data Processing Workflow

2.6. *Inference Mechanism Pseudocode*

The main reasoning logic used by the expert system is shown in this section in the form of structured pseudocode. Based on user-selected indicators, the reasoning process combines Bayesian Network (BN) and Dempster-Shafer Theory (DST) to determine the best learning strategy.

```
Algorithm 1: Integrated DST-BN Inference Mechanism
Input:
        S ← Set of selected indicators (e.g., s1, s2, ..., sn)
        DST_Table ← Belief mass values for each indicator
        BN_Map ← Conditional probabilities for learning methods given class
Output:
        M ← Recommended learning method (video, audio, practice)
Begin
1. Initialize:
        combinedMass ← {C1: 0, C2: 0, C3: 0, U: 1}
2. For each indicator si in S:
        a. massi ← DST_Table[si]
        b. combinedMass ← Combine(combinedMass, massi)
        // Use Dempster’s rule of combination
3. Determine dominantClass:
        maxBelief ← 0
        For each class ∈ {C1, C2, C3}:
        if combinedMass[class] > maxBelief:
        maxBelief ← combinedMass[class]
        dominantClass ← class
4. Compute BN probabilities:
        For each method m ∈ {video, audio, practice}:
        prob[m] ← 0
        For each class ∈ {C1, C2, C3}:
        prob[m] ← prob[m] + (combinedMass[class] × BN_Map[class][m])
5. Normalize probabilities:
        total ← prob[video] + prob[audio] + prob[practice]
        For each m ∈ {video, audio, practice}:
        prob[m] ← prob[m] / total
6. Determine recommendation:
        M ← method m with the highest prob[m]
7. Return M
```

End

The system's internal inference mechanism is reflected in this pseudocode. In order to make sure the system adheres to the desired belief combination and probabilistic reasoning logic, it also acts as a guide for white-box testing.

2.7. Comparison of Learning Style Diagnostic Methods

Previous research has investigated a number of diagnostic techniques, such as Bayesian approaches, Certainty Factor, and fuzzy logic, to ascertain students' learning styles. A comparison of these techniques with Dempster-Shafer Theory is given in Table 1, which also explains why DST and BN were chosen for this investigation. Dempster–Shafer Theory has also been effectively implemented in educational expert systems for diagnosing learning-related conditions such as learning disorders in children [16].

Table 1. Comparative Analysis of Learning Style Diagnostic Methods

Criteria / Method	Fuzzy Logic	Dempster–Shafer (DST)	Bayesian Network (BN)	Certainty Factor
Handling Uncertainty	Moderate	Strong (via belief)	Strong (via probability)	Weak
Transparency	Moderate	High	Moderate	High
Dataset Requirement	Low	Low (rule-based)	High (data-driven)	Low
Adaptability	Limited	Flexible via rule update	Dynamic via probability	Static
Implementation Complexity	Moderate	Moderate	High	Low
Prior Studies	[17]	[1]	[13]	[18]

The Dempster–Shafer method is good for dealing with student response data that is unclear or missing, while the Bayesian Network adds adaptive recommendation features to the system. This mixed approach strikes a balance between being easy to understand and using probabilistic reasoning, which is important in personalized learning systems.

2.8. System Architecture and Flow

During the implementation stage, the expert system was designed as a web-based application composed of several interconnected modules. Figure 4 shows the overall system flow, illustrating how input from students is processed through rule-based reasoning and probabilistic inference.

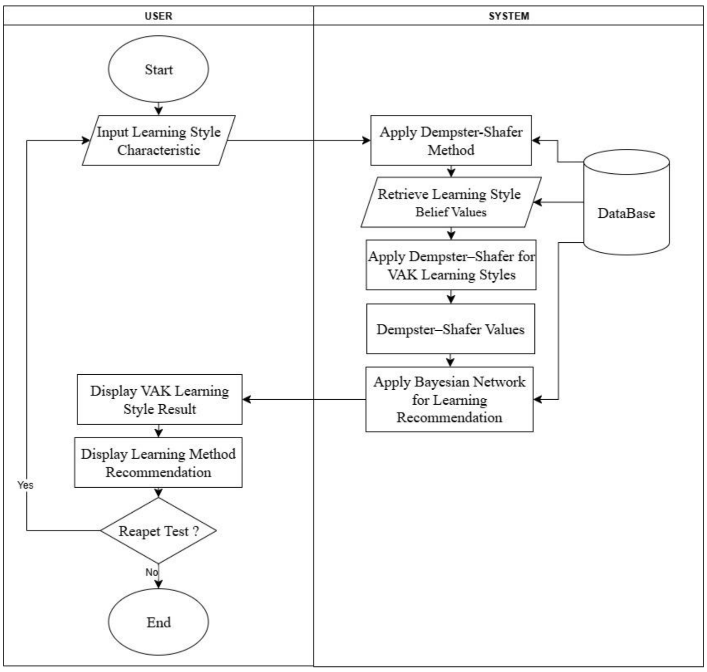


Figure 4. Expert System Flowchart

Student responses were evaluated using Dempster–Shafer theory, and the resulting belief values were passed into a Bayesian Network for final recommendation. The system architecture includes components for questionnaire management, inference engine, result visualization, and rule management by administrators.

2.9. Data Storage

To help put the Dempster–Shafer theory and Bayesian Network-based diagnostic algorithm into action, the system uses structured data storage to keep track of the indicators and diagnostic results that users choose. This study does not provide details about the database's structure because the main focus is on creating and testing the inference methods.

2.9.1. Rule-Based Reasoning and Indicators

Input from professionals and past research helped determine the three basic learning styles—visual, auditory, and kinesthetic—of the VAK model. Summarising the learning kinds, Appendix A (Tables D1-D3) includes thirty indicators with belief scores and displays the IF-THEN rules applied in the system's logic. Visual learners "remember what they see," for instance; auditory learners "prefer vocal instructions; kinaesthetic learners "learn best by doing." Education professionals like Dr. Rusli Wali from Kotamobagu validated these indications and guidelines. This validation was conducted by experts in educational methodology, ensuring the appropriateness and reliability of the applied rules for the student context. Inspired by several scholarly sources [1][4], this method guarantees that the diagnosis of the system is accurate and useful for developing appropriate learning resources.

2.9.2. Evaluation Method

Using two main approaches—functional testing and accuracy testing—we evaluated the dependability and performance of our web-based expert system. The aim was to ensure that the system performed as expected in several contexts and that its diagnostic findings complemented professional evaluations.

2.9.3. Blackbox Testing

We applied a black-box method for functional testing, emphasizing the system's performance without considering internal code. We evaluated fundamental capabilities like user login, questionnaire presentation, rule-based inference, Bayesian suggestions, and result exporting. These tests were conducted on several browsers and devices to ensure everything operated as it should. The summary of the black-box testing results is presented in Table 2 (Section 3.3.1).

2.9.4. Whitebox Testing

White-box testing was conducted to verify the system's internal logic and algorithmic correctness, particularly in implementing the Dempster–Shafer theory and Bayesian Network. Key functions tested include the combination of belief masses (combineDS()), conflict resolution and normalization, and the inference process (inferBN()). Each decision branch and iteration was examined to ensure the logic follows theoretical principles and produces expected outcomes based on simulated inputs.

2.9.5. Accuracy Testing

We asked thirty students to finish the VAK learning style indicator using the method in order to evaluate accuracy. Dempster–Shafer theory was used to process their responses; then, Bayesian analysis produced individualised learning style recommendations. We next matched the results of the system with expert manual evaluations. Using a conventional formula, the accuracy was computed by matching the system's output with the expert judgments.

$$\text{Accuracy}\ (\%) = \frac{\text{Number of Correct Diagnoses}}{\text{Total Test Cases}} \times 100\% \quad (3)$$

3. RESULT AND DISCUSSION

3.1. Web-Based System Development

This study's expert system was made into a web-based app to be used on many different devices without needing to install any more software. The backend was made with PHP, the database was managed with MySQL, and the user interface was made with HTML, CSS, and JavaScript to be responsive. This architecture makes it possible to handle data in one place, ensuring user data and diagnostic results are always the same. The system has a form diagnosis interface with 30 VAK signs that students use to engage with it. The Dempster–Shafer inference engine processes the responses, and then Bayesian Network reasoning makes individualized learning suggestions.

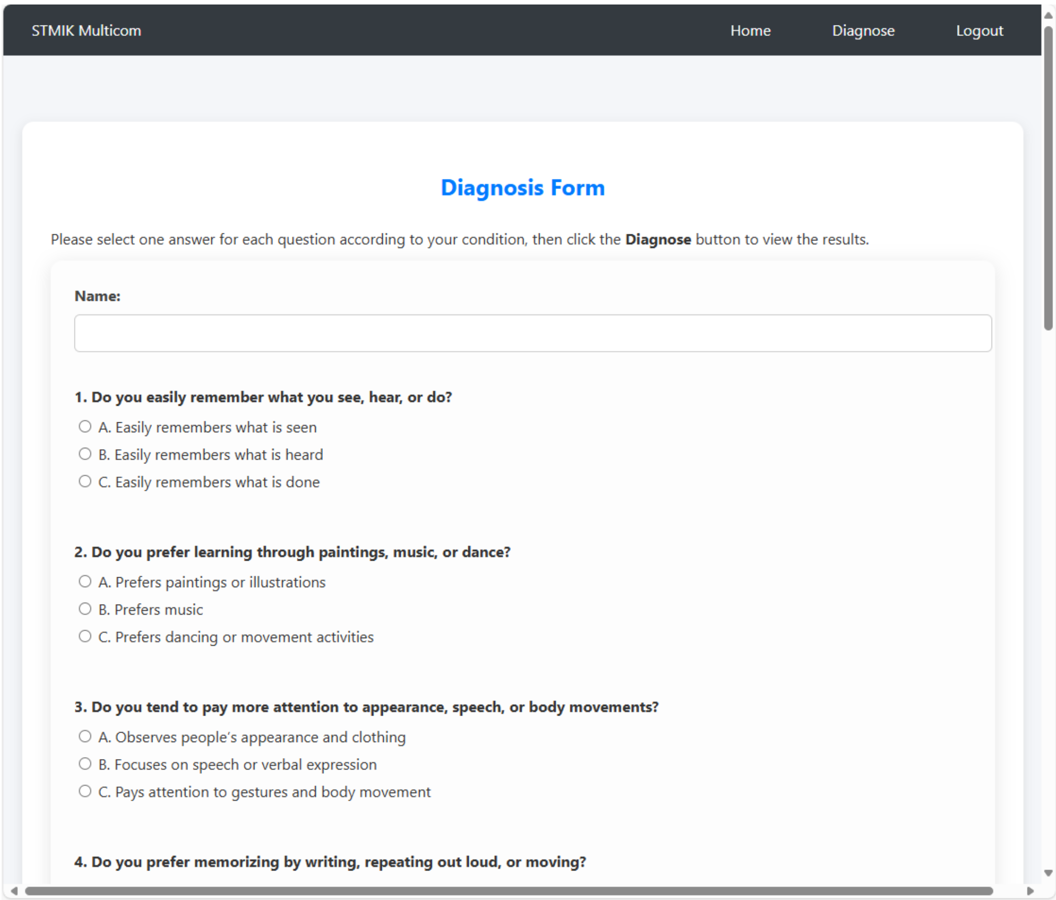
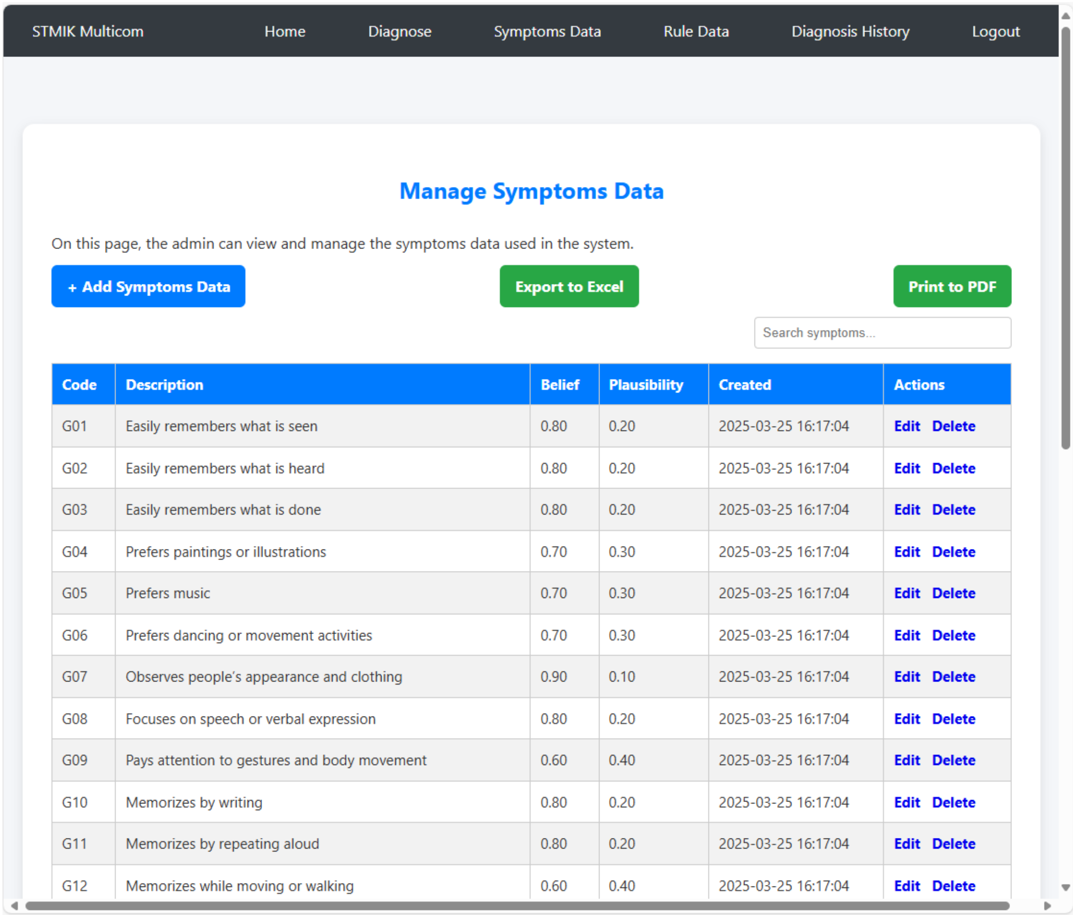


Figure 5. Student Web Interface For Learning Style - shows part of the student interface for learning style diagnosis (full questionnaire contains 30 items)

On the administrative side, the system includes a dashboard for lecturers or system managers. This dashboard enables authorized users to manage the knowledge base—such as editing indicators, adjusting rule weights, or modifying belief values—and to review and export diagnostic results. Figure 6 shows the administrative interface, where new rules and indicators can be configured to reflect updates in pedagogical knowledge or institutional policies.



Code	Description	Belief	Plausibility	Created	Actions
G01	Easily remembers what is seen	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G02	Easily remembers what is heard	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G03	Easily remembers what is done	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G04	Prefers paintings or illustrations	0.70	0.30	2025-03-25 16:17:04	Edit Delete
G05	Prefers music	0.70	0.30	2025-03-25 16:17:04	Edit Delete
G06	Prefers dancing or movement activities	0.70	0.30	2025-03-25 16:17:04	Edit Delete
G07	Observes people's appearance and clothing	0.90	0.10	2025-03-25 16:17:04	Edit Delete
G08	Focuses on speech or verbal expression	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G09	Pays attention to gestures and body movement	0.60	0.40	2025-03-25 16:17:04	Edit Delete
G10	Memorizes by writing	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G11	Memorizes by repeating aloud	0.80	0.20	2025-03-25 16:17:04	Edit Delete
G12	Memorizes while moving or walking	0.60	0.40	2025-03-25 16:17:04	Edit Delete

Figure 6. Administrator Dashboard for Knowledge

The approach of developing also focused on making things modular and easy to add to. We put each functional module (input interface, inference engine, recommendation module, and data output) in its own box so that we could add new features later, including mobile versions or interaction with current learning management systems (LMS). Also, basic security measures like login authentication, hashed passwords, and limited access restrictions were implemented to keep user data safe and the system running smoothly.

The developed web-based expert system met all functional and non-functional requirements defined during the planning phase. The fact that it works shows that you can make and use smart diagnostic tools for learning styles in schools using basic web technologies. This helps with adaptive and student-centered learning.

3.2. User Interface and Interaction

Users may get to the system through a responsive online interface that shows them a structured questionnaire with 30 questions about Visual, Auditory, and Kinesthetic learning styles. After you submit your choices, the inference engine processes belief and plausibility values from the knowledge base. The Dempster–Shafer theory takes these values and combines them to make a confidence mass for each learning style. Then, Bayesian Network inference is used to make individualized learning strategy suggestions.

In terms of interface design, the system provides a clean and minimal layout to accommodate users with varying levels of digital literacy. Students interact through a dedicated page that shows one indicator per row, with options to select based on their preferences. Once the learning style indicator is completed, the system displays the dominant learning style along with probabilistic scores and a recommendation explanation, as shown in Figure 7.

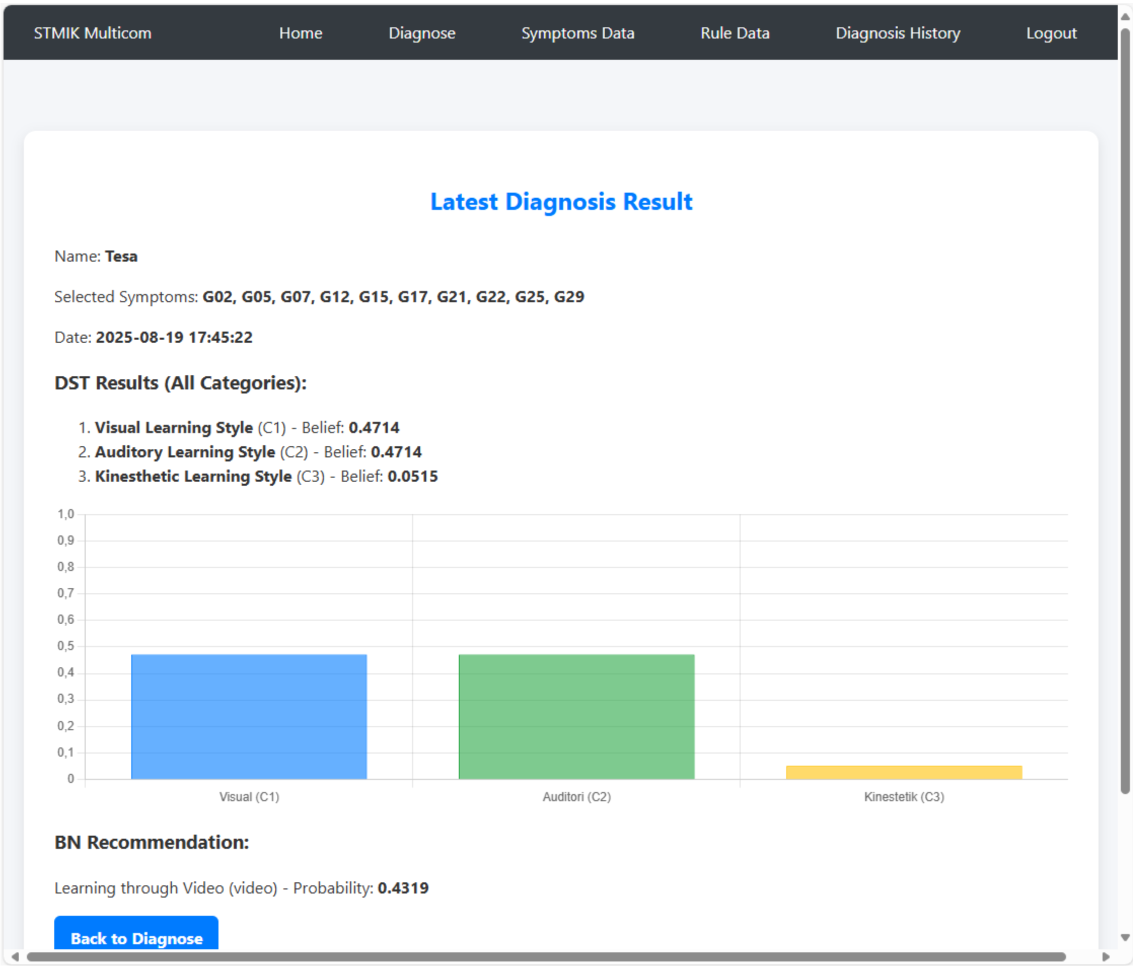


Figure 7. Result and Recommendation User Interface

3.3. *Testing Result*

Functional testing and accuracy testing were done to see how well the web-based expert system worked and how reliable it was.

3.3.1. *Blackbox Testing Result*

The black-box testing method was used for functional testing, which means validating the result based on specified inputs without looking at the code within, as shown in Table 2. This testing looked at important things like logging in as a user, showing a learning style indicator, making suggestions based on rules, making Bayesian suggestions, and exporting diagnostic data.

Table 2. Blackbox Testing Results

Test Case ID	Feature Tested	Input	Expected Output	Result
TC01	User Registration	Valid name input	Redirect to the questions page	Pass
TC02	Indicator Selection	Choose 10 indicators	Submit enabled	Pass
TC03	Inference Output	Complete answers	Diagnosis and BN recommendation displayed	Pass
TC04	Export Function	Click “Export to PDF”	Downloaded a PDF file containing the diagnosis result	Pass

3.3.2. *Whitebox Testing Result*

To confirm the internal logic and accuracy of the implemented algorithms used in the expert system's inference mechanism, white-box testing was carried out. This testing focused on looking at the source code and logical flow of key functions like inferBN() for Bayesian Network-based probabilistic reasoning and combineDS() for belief combination based on Dempster-Shafer theory.

To determine whether the theoretical expectations were consistently fulfilled in practice, synthetic input data were used to test each path, condition, and calculation branch within these functions.

Goals of the Test:

- Verify the proper handling of conflicting evidence (normalisation and conflict mass).
- Make sure the intersection rules are correct (for example, C1 ∩ U = C1, C1 ∩ C2 = Ø).
- Verify that the normalised outputs stay within the acceptable range of 0 to 1.
- Make sure BN correctly ranks and aggregates learning method probabilities.

Table 3. Whitebox Testing Results

Test Case	Function	Description	Input Example	Expected Output	Result
TC1	combineDS()	Combine two mass functions with partial overlap	m1 = {C1:0.6,U:0.4}, m2 = {C1:0.5,U:0.5}	Combined C1 > 0.6	Passed
TC2	combineDS()	Combine mass functions with full conflict (K = 0)	m1 = {C1:1.0}, m2 = {C2:1.0}	Output = {U:1}	Passed
TC3	intersect()	Evaluate intersections between sets	A = "C1", B = "U"	Output = "C1"	Passed
TC4	inferBN()	BN inference using belief values from DST	dsResult = {C1:0.7, C2:0.2, C3:0.1}	Recommendation = "video"	Passed
TC5	inferBN()	Normalization of the zero-sum condition	dsResult = {C1:0, C2:0, C3:0}	All output = 0, handled gracefully	Passed
TC6	inferBN()	Tie-breaking in BN when two methods are equal	Equal probabilities for "audio" and "video"	Picks one based on order or fallback	Passed

To ensure full logical coverage, white-box testing traced all control paths within the combineDS() and inferBN() functions. This includes evaluating the conflict calculation condition (K = 0), handling empty set intersections (Ø), and normalizing mass values. Various simulated input sets were tested to confirm that each rule path executed as expected and yielded accurate belief outputs. For instance, an input where all evidence led to full conflict (K = 0) correctly produced total uncertainty, while other input combinations successfully distributed belief across the expected categories (C1, C2, C3). The logic determining the dominant learning method in inferBN() was also verified to prioritize the highest weighted probability among visual, auditory, and kinesthetic options. These tests validate that the system's reasoning engine behaves in accordance with the theoretical models described in Section 2.6.

The white-box and accuracy testing procedures specifically highlight the logical correctness and reasoning accuracy of the Dempster–Shafer and Bayesian Network algorithms, as the evaluation of the inference mechanisms is the main objective of this study. This involves confirming normalisation, recommendation probability logic, and belief conflict resolution.

3.3.3. Accuracy Testing Result

The system was tested by thirty randomly chosen students from STMIK Multicom Bolaang Mongondow's Informatics Engineering program's second through fourth semesters. Following their completion of the system's learning style questionnaire, Dempster-Shafer and Bayesian inference were used to process their answers. To determine accuracy, the final diagnoses were contrasted with professional assessments.

The system's dependability in user registration, indicator selection, automated diagnosis, and exporting results in PDF and Excel formats was validated through functional testing across a variety of browsers and devices, proving compliance with predetermined functional requirements.

Out of 30 test cases, 26 diagnoses produced by the system matched the expert's judgment, resulting in an overall accuracy of:

$$\text{Accuracy (\%)} = \frac{\text{Number of Correct Diagnoses}}{\text{Total Test Cases}} \times 100\% = \frac{26}{30} \times 100\% = 86.67\% \quad (4)$$

Table 4 summarizes the results of the accuracy testing for each student participant.

Table 4. Accuracy Testing Result

Student ID	System Diagnosis	Expert Diagnosis	Match
S01	Visual	Visual	Yes
S02	Auditory	Auditory	Yes
S03	Kinesthetic	Kinesthetic	Yes
S04	Auditory	Auditory	Yes
S05	Visual	Visual	Yes
S06	Visual	Auditory	No
S07	Kinesthetic	Kinesthetic	Yes
S08	Kinesthetic	Kinesthetic	Yes
S09	Visual	Visual	Yes
S10	Visual	Visual	Yes
S11	Auditory	Auditory	Yes
S12	Kinesthetic	Visual	No
S13	Auditory	Auditory	Yes
S14	Visual	Visual	Yes
S15	Kinesthetic	Kinesthetic	Yes
S16	Auditory	Auditory	Yes
S17	Visual	Visual	Yes
S18	Kinesthetic	Kinesthetic	Yes
S19	Kinesthetic	Kinesthetic	Yes
S20	Visual	Auditory	No
S21	Kinesthetic	Kinesthetic	Yes
S22	Auditory	Auditory	Yes
S23	Kinesthetic	Kinesthetic	Yes
S24	Visual	Visual	Yes
S25	Auditory	Auditory	Yes
S26	Kinesthetic	Kinesthetic	Yes
S27	Visual	Visual	Yes
S28	Visual	Visual	Yes
S29	Auditory	Auditory	Yes
S30	Kinesthetic	Kinesthetic	Yes

These results show that the new expert system fixes the problems that handling uncertainty and gives personalized learning suggestions. In unclear circumstances, analogous methodologies employing Dempster–Shafer theory have proven to be highly effective in diagnosis [1]. Bayesian Network models have been demonstrated to effectively personalize learning through probabilistic reasoning [13]. By applying both strategies combined, this study was able to attain an accuracy of 86.67%. This demonstrates that integrating rule-based reasoning with probabilistic inference might enhance personalized learning tactics in higher education.

These results show that the suggested system does a decent job of filling the gap noted in Section 1. It achieves this by leveraging the Dempster–Shafer Theory (DST) and the Bayesian Network (BN) to make adaptive learning proposals better. DST can handle uncertainty, and BN is adept at probabilistic reasoning; thus, the system can provide you with accurate and individualized results. The method demonstrates its potential to enhance tailored learning tactics at colleges and universities where conventional diagnostic tools have proven ineffective. It has an 86.67% functional success rate and works well with all of its features.

The effectiveness of Bayesian Networks in educational environments has also been demonstrated by Putra et al. [19] used it effectively in an adaptive e-learning system to find out how students learn best and change the way information is delivered to fit those patterns. Their results show that BN is a strong aspect of intelligent tutoring systems, especially when it comes to giving individualized suggestions based on probabilistic inference.

3.4. Discussion

The results of this study are consistent with findings by Desri and Van Graha [20], who concluded that the majority of students preferred visual learning styles and that learning outcomes could be improved by aligning instructional strategies with students' preferred modalities. Their study emphasized the need for flexible and varied teaching methods to accommodate diverse learning preferences.

The system's diagnostic accuracy of 86.67% is in line with what Garonga et al. [8] found, which was that probabilistic classifiers like Naive Bayes do a better job of categorizing student learning styles using the VAK model than other algorithms like Decision Tree and Random Forest. Their survey also indicated that kinesthetic learning was the most popular approach among college students, which aligns with our study's findings.

Rahman et al. [17] did research before that showed that a fuzzy logic-based expert system could accurately identify the most common learning styles, with an efficacy score of 89% based on student assessments. But their system did not address uncertainty and had no mechanism to provide probabilistic recommendations. This study, on the other hand, combines Dempster–Shafer Theory with Bayesian Network to make diagnoses more reliable and tailored to each person.

Similar efforts to develop expert systems for learning modality classification have been conducted using the forward chaining and certainty factor approach. For instance, Hardiansyah et al. [18] built a web-based system with 100% matching accuracy using rule-based inference and CF weighting. But their model didn't deal with uncertainty propagation or probabilistic recommendation. Our method deals with these issues utilizing Dempster–Shafer Theory and Bayesian Network.

4. CONCLUSION

This study successfully integrated the Dempster–Shafer Theory and Bayesian Network into an online expert system to diagnose students' learning styles. The hybrid inference approach effectively handled uncertainty and produced reliable recommendations, achieving an overall diagnostic accuracy of 86.67%. These findings demonstrate that DST and BN can be applied as a feasible and efficient framework for personalized learning. In the future, the system may be extended for wider educational applications through expansion of the rule base and refinement of probabilistic mappings.

5. ACKNOWLEDGMENTS

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APPENDIX

A. Rule-Based Reasoning and Indicator

Table A1. Learning Style Categories

Code	Learning Style Type	Description
C01	Visual Learning Style	Learners who prefer visual input, such as images, diagrams, charts, and written materials.
C02	Auditory Learning Style	Learners who process information better through listening, discussions, or oral explanations.
C03	Kinesthetic Learning Style	Learners who learn more effectively through hands-on experience and physical interaction.

Table A2. Belief and Plausibility Values for Learning Style Indicators

Indicator Code	Deskripsi	Visual (C1)	Auditory (C2)	Kinesthetic (C3)	Belief	Plausibility
G01	Easily remembers what is seen	√			0.8	0.2
G02	Easily remembers what is heard		√		0.8	0.2
G03	Easily remembers what is done			√	0.8	0.2
G04	Prefers paintings or illustrations	√			0.7	0.3
G05	Prefers music		√		0.7	0.3
G06	Prefers dancing or movement activities			√	0.7	0.3
G07	Observes people's appearance and clothing	√			0.9	0.1
G08	Focuses on speech or verbal expression		√		0.8	0.2
G09	Pays attention to gestures and body movement			√	0.6	0.4
G10	Memorizes by writing	√			0.8	0.2
G11	Memorizes by repeating aloud		√		0.8	0.2
G12	Memorizes while moving or walking			√	0.6	0.4
G13	Doodles while speaking or presenting	√			0.8	0.2
G14	Prefers oral communication in presentations		√		0.8	0.2
G15	Uses hand gestures while speaking			√	0.5	0.5
G16	Easily distracted by cluttered visuals	√			0.4	0.6
G17	Easily distracted by noise		√		0.5	0.5
G18	Easily distracted by movement			√	0.4	0.6
G19	Interested in color	√			0.6	0.4
G20	Interested in sound		√		0.5	0.5
G21	Interested in body movement			√	0.5	0.5
G22	Struggles with messy textual content	√			0.6	0.4
G23	Has difficulty concentrating in noisy environments		√		0.8	0.2
G24	Has trouble sitting still for long periods			√	0.6	0.4
G25	Likes to be taught with drawings on the board	√			0.7	0.3
G26	Likes to be taught with clear verbal explanations		√		0.8	0.2
G27	Likes to be taught with practice and touching objects			√	0.7	0.3
G28	Speaks in a fast tempo	√			0.8	0.2
G29	Speaks in a moderate tempo		√		0.6	0.4
G30	Speaks in a slow tempo			√	0.6	0.4

Table A3. Rules Learning Style Categories

Rule	Production Rule (IF-THEN)
R1	IF G01 AND G04 AND G07 AND G10 AND G13 AND G16 AND G19 AND G22 AND G25 AND G28 THEN Visual (C1)
R2	IF G02 AND G05 AND G08 AND G11 AND G14 AND G17 AND G20 AND G24 AND G26 AND G29 THEN Auditory (C2)
R3	IF G03 AND G06 AND G09 AND G12 AND G15 AND G18 AND G21 AND G25 AND G27 AND G30 THEN Kinesthetic (C3)