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Expert System for Student Talent and Interest Using Certainty Factor and Dempster-Shafer Methods

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Abstract: Elementary education systems in Jepara Subdistrict currently lack standardized frameworks for identifying student capabilities, leaving educators and parents without reliable tools to recognize individual talents and interests. We developed a hybrid expert system that combines Certainty Factor and Dempster-Shafer methodologies to establish quantitative assessment protocols for elementary student aptitude evaluation. Our research employed a quantitative descriptive approach, gathering data through structured behavioral observations, educator interviews, validated questionnaires, and academic documentation from multiple elementary schools across the district. The system processes student behavioral patterns using Certainty Factor methods for initial inference, then applies Dempster-Shafer algorithms to combine evidence sources while managing assessment uncertainty and subjective evaluation parameters. Preliminary testing reveals the system can generate percentage-based aptitude measurements across various domains, with interest category evaluations reaching 37% in targeted areas. We evaluated performance through accuracy validation, expert correlation analysis, precision-recall calculations, response time measurement, and knowledge base quality assessment. The hybrid approach demonstrates measurable improvements in talent identification accuracy when compared to traditional subjective methods, establishing a quantitative foundation for evidence-based educational planning. The system offers schools a standardized capability assessment tool that reduces evaluation bias while optimizing resource allocation for personalized learning development. Educational institutions can implement the framework to support more objective decision-making in student guidance and curriculum planning, particularly valuable for Indonesia's evolving educational landscape that emphasizes individualized learning pathways.

Keywords: Expert System; Aptitude Assessment; Talent Identification; Certainty Factor; Dempster-Shafer Theory; Educational Analytics.

1. Introduction

Education serves as a crucial foundation for building competitive and moral societies. It represents a humanistic process that develops individuals as complete human beings [1]. Through educational experiences, we expect positive transformations in behavior, intellectual maturity, and individual personality development [2]. Indonesia's Merdeka Curriculum implementation brings significant structural changes to education by eliminating traditional science, social sciences, and language streams. The policy aims to provide students freedom in selecting subjects according to their interests and talents, supporting optimal individual development. Subject selection aligned with student potential maximizes motivation and enhances learning outcomes [3][4].

The research focuses on elementary school students in Jepara Subdistrict, where exploration and development of student interests and talents remain suboptimal among both teachers and parents. The absence of early guidance impacts the underdevelopment of students' natural potential and their preparedness for higher education levels and professional careers. While the Certainty Factor method demonstrates effectiveness in identifying student interests and talents through practical and cost-effective approaches, several limitations persist. These include insufficient direct comparison with alternative methods, limited specific application in regions like Jepara District, and dependence on subjective expert judgment for determining certainty values, potentially introducing bias without robust validation mechanisms. Additionally, the method exhibits weaknesses in managing high uncertainty scenarios and shows reduced flexibility in combining various supportive or conflicting information sources [5].

Previous research has proposed technology-based expert systems as solutions for developing student potential [6][7][8]. Academic literature reveals successful implementations of artificial intelligence applications in educational assessment, including systems for academic performance prediction, learning style identification, and personalized curriculum development. However, many existing systems operate independently without considering the multifaceted nature of student evaluation that requires both quantitative analysis and qualitative assessment.

To address Certainty Factor limitations, optimization through alternative approaches demonstrating greater adaptability to uncertainty becomes necessary. The Dempster-Shafer method emerges as a promising solution, offering superior uncertainty management capabilities through flexible belief degree representation, including explicit acknowledgment of ignorance states, while enabling systematic evidence combination from multiple diverse sources [9]. The mathematical framework supports sophisticated handling of conflicting evidence and provides mechanisms for updating beliefs as new information becomes available.

Integrating Certainty Factor and Dempster-Shafer methodologies creates opportunities to leverage both approaches' strengths while addressing individual weaknesses. Certainty Factor provides intuitive reasoning patterns familiar to educational practitioners, while Dempster-Shafer offers mathematical rigor for evidence combination and uncertainty quantification. The combined approach potentially delivers improved accuracy in talent identification, particularly valuable in educational settings where assessment decisions significantly influence student development trajectories.

Current assessment practices in Indonesian elementary education rely heavily on standardized testing and teacher observations. While these methods serve established purposes, they may not capture the full spectrum of student capabilities. The proposed expert system bridges traditional assessment approaches with modern computational methods, providing educators with data-driven insights while maintaining human judgment essential for educational decision-making. Implementation in Jepara Subdistrict serves as a pilot study for broader educational technology adoption across Indonesian elementary schools. The research addresses practical challenges facing Indonesian educational systems. With increasing emphasis on personalized learning and student-centered approaches, automated assessment tools become valuable resources for educational planning. The proposed system assists teachers in making informed decisions about student placement, intervention strategies, and talent development programs, supporting Merdeka Curriculum objectives of individualized educational pathways.

2. Related Work

Expert systems for identifying student talents and interests have evolved significantly through various computational approaches. Saragih (2020) developed a system using the Certainty Factor method at Sekolah Bilingual Nasional Plus Permata Bangsa Binjai, demonstrating practical effectiveness in educational settings while revealing dependencies on subjective expert judgment for certainty value determination [6]. Building upon multiple intelligence frameworks, Dia *et al.* (2021) created a talent assessment system that incorporated Howard Gardner's theory with Certainty Factor methodology, providing broader coverage of student capabilities yet maintaining the inherent challenges of uncertainty management [7]. Recent work by Devaus *et al*. (2024) shifted toward Dempster-Shafer theory for identifying artistic talents in kindergarten children, showing improved handling of uncertain information and better evidence combination from multiple sources compared to traditional approaches [8].

The Certainty Factor method has found applications across diverse problem domains beyond education. Alim *et al*. (2020) implemented the approach for diagnosing cocoa plant diseases in farmer groups at PT Qalam Indonesia, revealing both the method's cost-effectiveness and practical limitations when dealing with high uncertainty scenarios [5]. Similarly, Muhyono *et al*. (2020) applied Certainty Factor reasoning for laptop damage diagnosis, confirming the method's versatility while emphasizing the critical role of expert knowledge quality in system performance [18]. These implementations demonstrate that while Certainty Factor provides intuitive reasoning mechanisms, careful calibration of certainty values remains essential for reliable outcomes.

Educational assessment using Dempster-Shafer theory has gained momentum due to superior uncertainty handling capabilities. Baihaqi and Junaedi (2022) created an expert system for elementary school admission decisions based on IQ assessments at Sekolah Dasar Luqman Al Hakim Surabaya, successfully combining multiple evaluation criteria while managing inherent assessment uncertainties [9]. The Dempster-Shafer framework allows explicit representation of ignorance states and systematic evidence integration from heterogeneous sources, proving particularly valuable where assessment information originates from diverse sources with varying reliability levels. Research examining educational factors that influence student development provides essential background for talent identification systems. Putri *et al*. (2023) investigated parental support effects on learning interest among tenth-grade students at SMA Negeri 7 Padang, revealing strong correlations between family involvement and academic motivation [12]. Maylitha *et al*. (2023) studied classroom management impacts on student engagement, showing how teaching methodologies directly affect performance outcomes [13]. Additionally, Supit *et al*. (2023) analyzed visual, auditory, and kinesthetic learning preferences, providing evidence for individual differences that influence talent expression and development [14].

Indonesia Merdeka Curriculum implementation has created new opportunities for talent identification research. Ardiansyah *et al*. (2023) examined subject selection effects based on student interests and talents, finding positive relationships between aligned choices and motivation levels [3]. The Ministry of Education and Culture (2022) established implementation guidelines emphasizing individualized learning pathways and student-centered approaches [4]. Hapsari (2022) developed structured guidelines for interest and talent identification at junior high school levels, offering practical frameworks that could benefit from technological enhancement [16]. Methodological diversity in expert system development reveals increasing recognition of hybrid approaches. While individual methods like Certainty Factor and Dempster-Shafer have proven effective in specific applications, researchers increasingly acknowledge benefits of integrated methodologies that leverage complementary strengths. Marcelina *et al*. (2022) explored forward chaining in oil palm disease identification systems, demonstrating rule-based reasoning effectiveness that could complement uncertainty management techniques in educational assessment [17]. However, comparative studies between different uncertainty management approaches remain scarce in educational settings. Current literature reveals several research gaps requiring attention. Most implementations focus on single methodological approaches without examining hybrid combinations that could enhance system performance. Few studies specifically address elementary education in Indonesian regional settings, where local educational characteristics may significantly influence system effectiveness. The integration of quantitative analysis with qualitative evaluation represents an underexplored area with substantial potential for improving talent identification accuracy. Furthermore, systematic comparison between uncertainty management methods in educational assessment remains limited, creating opportunities for research that could advance both theoretical understanding and practical applications in student evaluation systems.

3. Research Method

This research outlines a systematic core process, starting with comprehensive data collection through direct observation, teacher interviews, interest/talent questionnaires, and student documentation (report cards, portfolios). The collected student symptom data (abilities, interests, observations) then undergoes processing, involving initial inference using the Certainty Factor method, followed by optimization with the Dempster-Shafer method to determine student interests and talents. The resulting recommendations are then expert validated for accuracy. Subsequently, the model is rigorously evaluated based on criteria such as accuracy, expert validation, matching rate, precision, recall, system response time, error analysis, and knowledge base quality. The overall aim is to significantly enhance the accuracy and effectiveness of elementary school student interest and talent identification through this CF-DS optimized expert system. An overview of the research process flow is presented in Figure 1.

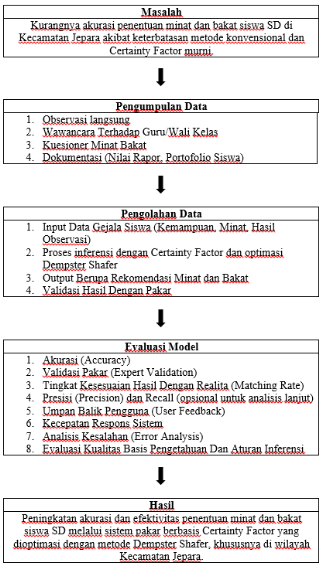

Figure 1. Framework of Thought

1) Expert System

Expert systems are computer programs that simulate the judgment and behavior of humans or organizations possessing expert knowledge and experience in a particular field. Typically, such systems are knowledge-based, containing an accumulation of experience and a set of rules for applying that basic knowledge to any specific situation. Advanced expert systems can be improved by expanding their knowledge base, as expert systems prioritize knowledge processing over data processing found in conventional expert systems [10]. Expert systems have the ability to recommend a series of user actions to operate an accurate correction system, utilizing reasoning capabilities to reach conclusions based on existing data and facts. Additionally, expert systems have a structure that includes a user interface, which serves as a mechanism for communication and interaction with the user. The advantages of expert systems include increasing work productivity by completing tasks faster, improving the quality of advice given with more consistency, possessing a relatively high level of reliability, and being able to operate in real-time [11].

2) Interest

Interest is an individual's attitude that demonstrates attraction and attention towards something. Interest reflects the relationship between an individual and something external, and this relationship strengthens with emotional closeness and attachment [12]. The development of interest is closely linked to the learning process as it can lead to beneficial, enjoyable, and satisfying learning experiences for the individuals involved [13]. Interest is also understood as an individual's attitude that demonstrates attraction to a specific object or activity. In relation to the learning process, learning is a way for someone to change behavior because of the correlation between stimuli and responses [14].

3) Talent

Talent is an individual's innate potential from birth. It is a fundamental ability to learn in a relatively short time compared to others yet achieve superior results. Talent can be defined as a combination of specific characteristics that indicate an individual's capacity to master certain knowledge, skills, or organized responses [15]. The term "talent" refers to an inborn ability possessed by someone from birth that distinguishes them from others. Talents can manifest in various forms such as art, music, sports, mathematics, or language. These abilities may be evident from an early age or only appear as an individual develops. Talent represents a natural potential inherent in a person since birth. This innate potential enables individuals to learn or master a skill in less time than others, while also achieving more optimal outcomes. Examples of talents include the ability to dance, write, sing, and so forth [16].

4) Certainty Factor

Certainty Factor is part of Certainty Theory, first introduced by E.H. Shortliffe and B.G. Buchanan to solve problems, meaning that experts often analyze existing information with expressions such as: "maybe," "most likely," and "almost certainly". This method describes the level of an expert's confidence in the problem at hand. Certainty Factor is a method, typically in matrix form, used in expert systems to prove whether a fact is certain or uncertain. This method is highly suitable for diagnosing something that is not yet certain [6]. The Certainty Factor method begins by first obtaining the facts, then finding rules that match the hypothetical data, and subsequently obtaining premise data for the hypothesis. After gathering all the necessary data, it is then input into the Certainty Factor theory to arrive at a precise conclusion based on the user's input premises.

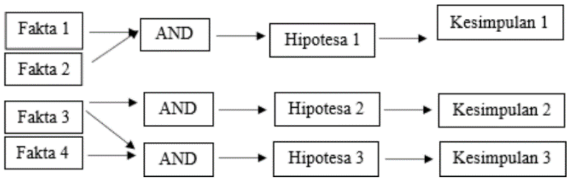

Figure 2. Certainty Factor Method

5) Dempster Shafer

Dempster-Shafer is a generalization of the subjective probability theory of Bayesian theory. If probability requirements are needed for every desired question, the belief function is based on the level of reliability (conviction or trust) of the question relative to the probability of the given question [17]. The Shafer framework can provide certainty about relationships that should be expressed as an interval containing two values: belief (or support) and credibility, where belief ≤ credibility [19]. Generally, Dempster-Shafer theory is written as an interval: [Belief, Plausibility]. Belief (Bel) is a measure of the strength of evidence in supporting a set of propositions. If its value is 0, it indicates that there is no evidence, and if its value is 1, it shows certainty. Plausibility (Pls) will reduce the level of certainty of the evidence. Plausibility values range from 0 to 1. If one is certain of X', then it can be said that Bel(X') = 1, so the value of Pls(X) = 0 in the formula above.

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{\{B \cap C = A\}} m_1(B) \cdot m_2(C)$$

Where K represents the degree of conflict between the combined evidence.

6) Data Collection

The data collection techniques in this research were carried out systematically to obtain valid and relevant data for the development of an expert system to determine the interests and talents of elementary school students in Jepara District. Four data collection techniques were used. Direct observation was conducted to observe student behavior, interests, and participation in school. Interviews with homeroom teachers gathered in-depth information related to student potential as a basis for developing the knowledge base. Questionnaires were distributed to students and teachers to identify interests and talents and to validate system results. Documentation studies collected secondary data such as student progress reports and report cards to strengthen system accuracy. These four techniques are complementary and were implemented systematically.

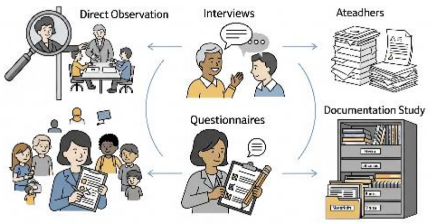

Figure 3. Data Collection Process Flow

7) Data Tabulation

Data tabulation in this research involves systematically organizing raw data from questionnaires, observations, and interviews into a table format for easier analysis [18]. This crucial initial step forms the foundation for the expert system's process of determining student interests and talents. The tabulated data includes student characteristics such as gender and age, along with questionnaire answers on hobbies and preferences, academic report cards for expert validation, and observations from extracurricular or learning activities. All this structured data provides relevant information for the expert system's inference process, enabling it to connect observed symptoms with potential student talents or interests using either the Certainty Factor or Dempster-Shafer methods.

8) Descriptive statistics

Descriptive statistics are a statistical analysis technique used to describe, present, and summarize research data in meaningful numbers, thereby facilitating the understanding of patterns and trends in the acquired data. These statistics include measures such as mean, mode, median, percentages, and standard deviation. In the context of this research, descriptive statistics are utilized to present a general overview of the distribution of interests and talents among elementary school students in Jepara District. Furthermore, this analysis is used to identify the most dominant interest trends among students, such as an interest in art, sports, logic-mathematics, language, or other fields. Descriptive statistics also play a role in measuring the spread or variation of student responses to each interest and talent indicator presented, thus providing a more comprehensive and accurate picture as a basis for decision-making by the expert system [19].

9) Cross-validation
Cross-validation in this research involves comparing the expert system's analysis results with direct assessments from teachers or counselors, who possess deeper student understanding. This process also ensures that the findings from the Certainty Factor and Dempster-Shafer methods are mutually supportive and consistent. Ultimately, cross-validation plays a crucial role in enhancing the reliability and credibility of the expert system, enabling more precise and objective decisions regarding student interest and talent determination.

10) Inference analysis using the Certainty Factor method
Inference analysis using the Certainty Factor method is a process of drawing conclusions based on the degree of belief in symptoms indicating student interests and talents. This method is used because it can handle uncertainty in data, especially when available information comes from observations or subjective assessments [20]. In this research, the first step is to identify symptoms or indicators of interests and talents, such as "the student likes to draw" or "the student quickly solves math problems". Each of these symptoms is then given a Certainty Factor (CF) value by experts, such as teachers or counselors, according to their degree of belief in the relationship between the symptom and a specific type of talent. For example, the indicator "likes to draw" is given a CF of 0.8, leading to artistic talent. If there is more than one symptom pointing to one type of talent, these CF values are combined using the formula:

$$CFcombine = CF1 + CF2 \times (1 - CF1)$$

This formula is used to calculate the combined belief in a conclusion. The result of this process is a recommendation for student talent based on the highest CF value obtained; for instance, if the highest CF is 0.9 for logical-mathematical talent, the system will suggest that the student has a strong inclination in that field.

11) Analysis of evidence using the Dempster-Shafer method
Analysis of evidence using the Dempster-Shafer method is an approach in evidential reasoning theory used to combine various pieces of evidence or symptoms from different sources under conditions of uncertainty [22]. This method is suitable for situations where the available data is not entirely certain, ambiguous, or indicates more than one possibility. In the context of this research, the first step is to define the frame of discernment, which is the set of possible student interests and talents, such as {Art, Sports, Mathematics, Language}. Each observed symptom is then assigned a Basic Probability Assignment (BPA) value, which represents the degree of belief in a subset of these possibilities. For example, a particular symptom might support {Art} by 0.6 and {Art, Language} by 0.3. After that, the process of combining evidence is carried out using Dempster's Rule of Combination, which is a formula that combines two sources of evidence by considering the degree of conflict between them:

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{\{B \cap C = A\}} m_1(B) \cdot m_2(C)$$

Where K represents the degree of conflict between the combined evidence.

The final step is decision-making, which involves selecting the highest BPA value from the combination results as an indication of the most probable student talent. The Dempster-Shafer method is very useful when students show tendencies in two or more fields simultaneously, as it can consider all combinations of symptoms and provide the most rational result based on all available evidence.

12) Model Evaluation Analysis
Model Evaluation Analysis is crucial for measuring the accuracy, reliability, and performance of the expert system in determining student interests and talents using Certainty Factor (CF) and Dempster-Shafer (DS) methods, ensuring valid recommendations align with actual conditions. The evaluation process systematically begins with collecting Validation Data (ground truth) from various sources like observations, interviews, and talent test results, which serve as a reliable reference. Subsequently, Expert System Testing involves inputting

student attribute data from questionnaires, where CF is used for initial inference, and DS then optimizes evidence combination and handles uncertainty to produce robust decisions. Finally, a Comparison of System Results with Ground Truth Data is conducted to directly measure the system's recommendations against collected actual data, assessing conformity and providing a basis for evaluating the model's overall accuracy.

4. Result and Discussion

4.1 Results

The web application testing phase evaluated student interest and talent determination using Certainty Factor and Dempster-Shafer methods. Built with PHP programming language and MySQL database storage, the system processes questionnaire responses through both methodological approaches. Initial calculations employ Certainty Factor and Dempster-Shafer techniques, subsequently displaying percentage results for user-experienced criteria.

4.1.1 Validation Data Collection

1) Certainty Factor (CF) Value Interpretation

The analysis_functions.php code establishes weights for each answer choice on a 1-5 scale (Strongly Disagree to Strongly Agree) for calculating Certainty Factor (CF) and Dempster-Shafer (DS) values. The calculateCF function applies specific weights to each response:

Table 1. Certainty Factor (CF) Value Interpretation

Answer	Description	Weight	Belief Level (CF)
1	Strongly Disagree	-0.5	Very Uncertain
2	Disagree	-0.25	Uncertain
3	Neutral	0.0	Neutral
4	Agree	0.75	Certain
5	Strongly Agree	1.0	Very Certain

Average CF Value Interpretation (avgCF) Following calculation of average CF from all category answers, general interpretation follows:

a) Positive Value (>0): Shows belief degree or criterion support. Higher values (approaching 1.0) indicate stronger belief.
b) Zero Value (0): Represents neutral stance or absence of strong belief.
c) Negative Value (<0): Demonstrates disagreement degree or criterion disbelief. Lower values (approaching -0.5) show stronger disagreement.

2) Dempster-Shafer (DS) Method

The calculateDS function employs the following weights for each answer:

Table 2. Dempster-Shafer (DS) Value Interpretation

Answer	Description	Weight	Belief Level (DS)
1	Strongly Disagree	0.2	Low
2	Disagree	0.4	Fairly Low
3	Neutral	0.5	Medium
4	Agree	0.8	High
5	Strongly Agree	1.0	Very High

3) DS Values Interpretation (belief and plausibility)

In Dempster-Shafer theory, belief represents support degree for a proposition, while plausibility shows extent to which evidence does not contradict that proposition. The calculateDS function combines these weights iteratively.

a) Belief Value: Increases with each supporting evidence piece.
b) Plausibility Value: Decreases when evidence contradicts the proposition.

The calculateDS function returns the average of belief and plausibility: (belief+plausibility)/2. Final DS Value Interpretation ((belief+plausibility)/2):

a) Value Approaching 0: Shows very low or no support.
b) Value Approaching 1.0: Indicates very strong support or high certainty.

4) Combined Score Interpretation (CF + DS)

The analyzeDetailedInterestsAndTalents function combines CF and DS results by averaging them (($cfValue+$dsValue)/2). The combined score undergoes normalization and conversion to percentage format. Functions getDetailedInterpretation, getInterestInterpretation, and getTalentInterpretation provide final score interpretation in text form.

Table 3. Final Interpretation Scale

Score Range (%)	Text Interpretation
≥80	Very High
≥60	High
≥40	Medium
≥20	Low
<20	Very Low

Table 4. Interest-Talent Characteristics and Interest Types Relationship

No.	Code	Interest-Talent Characteristics	Interest Type
1	C01	I enjoy painting or drawing	Arts
2	C02	I like making handicrafts	Arts
3	C03	I am interested in visual arts and design	Arts
4	C04	I enjoy attending art classes or creative workshops	Arts
5	C05	I like visiting art galleries and museums	Arts
6	C06	I easily understand color composition and shapes	Arts
7	C07	I enjoy creating graphic design or illustrations	Arts
8	C08	I like creative photography and videography	Arts
9	C09	I am interested in fine arts and performing arts	Arts
10	C10	I enjoy expressing myself through artwork	Arts
11	C11	I enjoy reading books in various languages	Language
12	C12	I easily understand sentence structure and grammar	Language
13	C13	I like writing stories, essays, or articles	Language
14	C14	I enjoy learning new foreign languages	Language
15	C15	I am interested in linguistics and word etymology	Language
16	C16	I like translating texts from one language to another	Language
17	C17	I enjoy discussing language and communication issues	Language
18	C18	I easily understand different dialects and accents	Language
19	C19	I like participating in debates or formal discussions	Language
20	C20	I enjoy writing poetry or literary works	Language
21	C21	I care about environmental issues	Environment
22	C22	I enjoy gardening and caring for plants	Environment
23	C23	I like outdoor activities and open nature	Environment
24	C24	I am interested in conservation and nature preservation	Environment
25	C25	I enjoy studying ecosystems and biodiversity	Environment
26	C26	I like recycling and reducing waste	Environment
27	C27	I care about climate change and its impacts	Environment
28	C28	I enjoy observing flora and fauna	Environment
29	C29	I like organic farming or gardening	Environment
30	C30	I am interested in renewable energy and sustainability	Environment
31	C31	I enjoy being a leader in groups	Leadership
32	C32	I like coordinating team activities	Leadership
33	C33	I easily take initiative in new situations	Leadership
34	C34	I enjoy guiding and directing others	Leadership
35	C35	I am interested in leadership training	Leadership
36	C36	I like planning and organizing activities	Leadership
37	C37	I enjoy being a committee member in events	Leadership
38	C38	I easily make appropriate decisions	Leadership
39	C39	I like motivating others	Leadership
40	C40	I enjoy taking responsibility in projects	Leadership
41	C41	I enjoy exercising regularly	Sports
42	C42	I like participating in sports competitions	Sports
43	C43	I am interested in various sports branches	Sports
44	C44	I enjoy being part of sports teams	Sports
45	C45	I like watching sports matches	Sports

46	C46	I easily understand sports strategies	Sports
47	C47	I enjoy regular physical training	Sports
48	C48	I am interested in health and fitness	Sports
49	C49	I like attending sports training	Sports
50	C50	I enjoy moving and physical activities	Sports
51	C51	I enjoy reading textbooks	Academic
52	C52	I easily understand new academic concepts	Academic
53	C53	I like writing reports and essays	Academic
54	C54	I enjoy participating in academic discussions	Academic
55	C55	I like doing written assignments	Academic
56	C56	I easily remember facts and information	Academic
57	C57	I enjoy analyzing reading texts	Academic
58	C58	I like making summary notes	Academic
59	C59	I enjoy learning new theories	Academic
60	C60	I like reading scientific articles	Academic
61	C61	I enjoy repairing broken items	Technical
62	C62	I like working with hand tools	Technical
63	C63	I easily understand technical diagrams	Technical
64	C64	I enjoy designing and making things	Technical
65	C65	I like solving practical problems	Technical
66	C66	I am interested in machines and equipment	Technical
67	C67	I enjoy attending technical practicum	Technical
68	C68	I like reading instruction manuals	Technical
69	C69	I easily understand how machines work	Technical
70	C70	I enjoy working with mechanical systems	Technical
71	C71	I enjoy speaking in public	Communication
72	C72	I easily communicate with various people	Communication
73	C73	I like being a mediator in conflicts	Communication
74	C74	I enjoy presenting my ideas	Communication
75	C75	I am interested in public speaking	Communication
76	C76	I like writing messages or letters	Communication
77	C77	I enjoy discussing with others	Communication
78	C78	I easily explain things to others	Communication
79	C79	I like being a good listener	Communication
80	C80	I enjoy building relationships with others	Communication

Table 5. Certainty Weight and Interest/Talent Criteria Weight Values

No.	Answer Scale	Description	Certainty Weight (CF)	Criteria Weight (DS)
1	1	Strongly Disagree	-0.5	0.2
2	2	Disagree	-0.25	0.4
3	3	Neutral	0.0	0.5
4	4	Agree	0.75	0.8
5	5	Strongly Agree	1.0	1.0

The solution process in expert systems adopting Dempster-Shafer (DS) method differs from Certainty Factor (CF) approach. DS method does not directly consider evidence values at each stage, while CF method explicitly uses evidence values both at single premise stage and premise combination. For single premise calculations with users completing questionnaires, we analyze answer data from response_id = 10004 in the database. These calculations demonstrate Certainty Factor (CF) and Dempster-Shafer (DS) weights for each individual answer (single premise) provided by that user. Calculations for each category with answers from Response ID 10004:

Table 6. Single Premise Calculations for User (Response ID: 10004)

No.	Interest-Talent Characteristics	Main Category	User Answer	CF Weight	DS Weight
1	I enjoy painting or drawing	Arts	5	1.0	1.0
2	I like making handicrafts	Arts	5	1.0	1.0
3	I am interested in visual arts and design	Arts	5	1.0	1.0
4	I enjoy attending art classes or creative workshops	Arts	5	1.0	1.0
5	I like visiting art galleries and museums	Arts	4	0.75	0.8

6	I easily understand color composition and shapes	Arts	4	0.75	0.8
7	I enjoy creating graphic design or illustrations	Arts	4	0.75	0.8
8	I like creative photography and videography	Arts	5	1.0	1.0
9	I am interested in fine arts and performing arts	Arts	4	0.75	0.8
10	I enjoy expressing myself through artwork	Arts	4	0.75	0.8
11	I enjoy reading books in various languages	Language	4	0.75	0.8
12	I easily understand sentence structure and grammar	Language	4	0.75	0.8
13	I like writing stories, essays, or articles	Language	4	0.75	0.8
14	I enjoy learning new foreign languages	Language	4	0.75	0.8
15	I am interested in linguistics and word etymology	Language	4	0.75	0.8
16	I like translating texts from one language to another	Language	4	0.75	0.8
17	I enjoy discussing language and communication issues	Language	4	0.75	0.8
18	I easily understand different dialects and accents	Language	2	-0.25	0.4
19	I like participating in debates or formal discussions	Language	4	0.75	0.8
20	I enjoy writing poetry or literary works	Language	4	0.75	0.8
21	I care about environmental issues	Environment	2	-0.25	0.4
22	I enjoy gardening and caring for plants	Environment	5	1.0	1.0
23	I like outdoor activities and open nature	Environment	5	1.0	1.0
24	I am interested in conservation and nature preservation	Environment	5	1.0	1.0
25	I enjoy studying ecosystems and biodiversity	Environment	4	0.75	0.8
26	I like recycling and reducing waste	Environment	4	0.75	0.8
27	I care about climate change and its impacts	Environment	4	0.75	0.8
28	I enjoy observing flora and fauna	Environment	4	0.75	0.8
29	I like organic farming or gardening	Environment	4	0.75	0.8
30	I am interested in renewable energy and sustainability	Environment	4	0.75	0.8
31	I enjoy being a leader in groups	Leadership	4	0.75	0.8
32	I like coordinating team activities	Leadership	4	0.75	0.8
33	I easily take initiative in new situations	Leadership	4	0.75	0.8
34	I enjoy guiding and directing others	Leadership	4	0.75	0.8
35	I am interested in leadership training	Leadership	4	0.75	0.8
36	I like planning and organizing activities	Leadership	4	0.75	0.8
37	I enjoy being a committee member in events	Leadership	4	0.75	0.8
38	I easily make appropriate decisions	Leadership	2	-0.25	0.4
39	I like motivating others	Leadership	4	0.75	0.8
40	I enjoy taking responsibility in projects	Leadership	2	-0.25	0.4
41	I enjoy exercising regularly	Sports	2	-0.25	0.4
42	I like participating in sports competitions	Sports	2	-0.25	0.4
43	I am interested in various sports branches	Sports	2	-0.25	0.4
44	I enjoy being part of sports teams	Sports	2	-0.25	0.4
45	I like watching sports matches	Sports	5	1.0	1.0
46	I easily understand sports strategies	Sports	2	-0.25	0.4
47	I enjoy regular physical training	Sports	2	-0.25	0.4
48	I am interested in health and fitness	Sports	5	1.0	1.0
49	I like attending sports training	Sports	4	0.75	0.8
50	I enjoy moving and physical activities	Sports	4	0.75	0.8
51	I enjoy reading textbooks	Academic	4	0.75	0.8
52	I easily understand new academic concepts	Academic	4	0.75	0.8
53	I like writing reports and essays	Academic	4	0.75	0.8

54	I enjoy participating in academic discussions	Academic	4	0.75	0.8
55	I like doing written assignments	Academic	4	0.75	0.8
56	I easily remember facts and information	Academic	5	1.0	1.0
57	I enjoy analyzing reading texts	Academic	4	0.75	0.8
58	I like making summary notes	Academic	4	0.75	0.8
59	I enjoy learning new theories	Academic	4	0.75	0.8
60	I like reading scientific articles	Academic	4	0.75	0.8
61	I enjoy repairing broken items	Technical	4	0.75	0.8
62	I like working with hand tools	Technical	4	0.75	0.8
63	I easily understand technical diagrams	Technical	4	0.75	0.8
64	I enjoy designing and making things	Technical	4	0.75	0.8
65	I like solving practical problems	Technical	4	0.75	0.8
66	I am interested in machines and equipment	Technical	2	-0.25	0.4
67	I enjoy attending technical practicum	Technical	2	-0.25	0.4
68	I like reading instruction manuals	Technical	2	-0.25	0.4
69	I easily understand how machines work	Technical	2	-0.25	0.4
70	I enjoy working with mechanical systems	Technical	2	-0.25	0.4
71	I enjoy speaking in public	Communication	4	0.75	0.8
72	I easily communicate with various people	Communication	4	0.75	0.8
73	I like being a mediator in conflicts	Communication	4	0.75	0.8
74	I enjoy presenting my ideas	Communication	4	0.75	0.8
75	I am interested in public speaking	Communication	4	0.75	0.8
76	I like writing messages or letters	Communication	4	0.75	0.8
77	I enjoy discussing with others	Communication	5	1.0	1.0
78	I easily explain things to others	Communication	5	1.0	1.0
79	I like being a good listener	Communication	5	1.0	1.0
80	I enjoy building relationships with others	Communication	5	1.0	1.0

a) Arts Category Analysis
Response Pattern: [5, 5, 5, 5, 4, 4, 4, 5, 4, 4]
The Arts category received predominantly high scores, with six responses of 4 (Agree) and four responses of 5 (Strongly Agree). This pattern indicates strong positive engagement with artistic activities.
CF Calculation Process:

- Individual CF weights: Four responses at 1.0 and six responses at 0.75
- Total CF weight: (1.0 × 4) + (0.75 × 6) = 4.0 + 4.5 = 8.5
- Average CF score: 8.5 ÷ 10 = 0.85

DS Calculation Process:

- Individual DS weights: Four responses at 1.0 and six responses at 0.8
- Through iterative processing, belief and plausibility converge to 1.0
- Final DS score: (1.0 + 1.0) ÷ 2 = 1.0

Combined Score Development:

- Initial combined score: (0.85 + 1.0) ÷ 2 = 0.925
- Interest normalization factor: max(1, 10÷4) = 2.5
- Interest score after normalization: 0.925 ÷ 2.5 = 0.375 → 37.50%
- Talent normalization factor: max(1, 10÷2) = 5.0
- Talent score after normalization: 0.925 ÷ 5.0 = 0.185 → 18.75%

b) Language Category Analysis
Response Pattern: [4, 4, 4, 4, 4, 4, 4, 2, 4, 4]
The Language category shows consistent positive responses with one notable exception - a single "Disagree" response among nine "Agree" responses.
CF Calculation Process:

- Individual CF weights: Nine responses at 0.75 and one response at -0.25
- Total CF weight: (0.75 × 9) + (-0.25 × 1) = 6.75 - 0.25 = 6.5
- Average CF score: 6.5 ÷ 10 = 0.65

DS Calculation Process:

- Individual DS weights: Nine responses at 0.8 and one response at 0.4
- Through iterative processing, belief and plausibility approach 1.0
- Final DS score: approximately 0.999

Combined Score Development:

- Initial combined score: (0.65 + 0.999) ÷ 2 = 0.825
- Interest score after normalization: 0.825 ÷ 2.5 = 0.33 → 33.00%
- Talent score after normalization: 0.825 ÷ 5.0 = 0.165 → 16.50%

c) Environment Category Analysis
Response Pattern: [2, 5, 5, 5, 4, 4, 4, 4, 4, 4]
The Environment category displays mixed responses with one "Disagree," three "Strongly Agree," and six "Agree" responses, suggesting moderate to strong environmental interest.
CF Calculation Process:

- Individual CF weights: One response at -0.25, three responses at 1.0, six responses at 0.75
- Total CF weight: -0.25 + (1.0 × 3) + (0.75 × 6) = -0.25 + 3.0 + 4.5 = 7.25
- Average CF score: 7.25 ÷ 10 = 0.725

DS Calculation Process:

- Individual DS weights: One response at 0.4, three responses at 1.0, six responses at 0.8
- Presence of maximum DS weights causes convergence to 1.0
- Final DS score: 1.0

Combined Score Development:

- Initial combined score: (0.725 + 1.0) ÷ 2 = 0.8625
- Interest score after normalization: 0.8625 ÷ 2.5 = 0.345 → 34.50%
- Talent score after normalization: 0.8625 ÷ 5.0 = 0.1725 → 17.25%

d) Leadership Category Analysis
Response Pattern: [4, 4, 4, 4, 4, 4, 4, 2, 4, 2]
The Leadership category shows mostly positive responses with two "Disagree" responses, indicating generally positive but not unanimous leadership inclination.
CF Calculation Process:

- Individual CF weights: Eight responses at 0.75 and two responses at -0.25
- Total CF weight: (0.75 × 8) + (-0.25 × 2) = 6.0 - 0.5 = 5.5
- Average CF score: 5.5 ÷ 10 = 0.55

DS Calculation Process:

- Individual DS weights: Eight responses at 0.8 and two responses at 0.4
- Through iterative processing, belief and plausibility approach 1.0
- Final DS score: approximately 0.999

Combined Score Development:

- Initial combined score: (0.55 + 0.999) ÷ 2 = 0.775
- Interest score after normalization: 0.775 ÷ 2.5 = 0.31 → 31.00%
- Talent score after normalization: 0.775 ÷ 5.0 = 0.155 → 15.50%

e) Sports Category Analysis
Response Pattern: [2, 2, 2, 2, 5, 2, 2, 5, 4, 4]
The Sports category reveals predominantly negative responses with six "Disagree," two "Strongly Agree," and two "Agree" responses, indicating selective sports interest.
CF Calculation Process:

- Individual CF weights: Six responses at -0.25, two responses at 1.0, two responses at 0.75
- Total CF weight: (-0.25 × 6) + (1.0 × 2) + (0.75 × 2) = -1.5 + 2.0 + 1.5 = 2.0
- Average CF score: 2.0 ÷ 10 = 0.2

DS Calculation Process:

- Individual DS weights: Six responses at 0.4, two responses at 1.0, two responses at 0.8
- Presence of maximum DS weights causes convergence to 1.0
- Final DS score: 1.0

Combined Score Development:

- Initial combined score: (0.2 + 1.0) ÷ 2 = 0.6
- Interest score after normalization: 0.6 ÷ 2.5 = 0.24 → 24.00%
- Talent score after normalization: 0.6 ÷ 5.0 = 0.12 → 12.00%

f) Academic Category Analysis
Response Pattern: [4, 4, 4, 4, 4, 5, 4, 4, 4, 4]
The Academic category demonstrates consistently high engagement with nine "Agree" responses and one "Strongly Agree" response, indicating strong academic orientation.

CF Calculation Process:
- Individual CF weights: Nine responses at 0.75 and one response at 1.0
- Total CF weight: (0.75 × 9) + (1.0 × 1) = 6.75 + 1.0 = 7.75
- Average CF score: 7.75 ÷ 10 = 0.775

DS Calculation Process:
- Individual DS weights: Nine responses at 0.8 and one response at 1.0
- Presence of maximum DS weight causes convergence to 1.0
- Final DS score: 1.0

Combined Score Development:
- Initial combined score: (0.775 + 1.0) ÷ 2 = 0.8875
- Interest score after normalization: 0.8875 ÷ 2.5 = 0.355 → 35.50%
- Talent score after normalization: 0.8875 ÷ 5.0 = 0.1775 → 17.75%

g) Technical Category Analysis
Response Pattern: [4, 4, 4, 4, 4, 2, 2, 2, 2, 2]
The Technical category shows a clear division with five "Agree" responses and five "Disagree" responses, indicating mixed technical aptitude and interest.
CF Calculation Process:
- Individual CF weights: Five responses at 0.75 and five responses at -0.25
- Total CF weight: (0.75 × 5) + (-0.25 × 5) = 3.75 - 1.25 = 2.5
- Average CF score: 2.5 ÷ 10 = 0.25

DS Calculation Process:
- Individual DS weights: Five responses at 0.8 and five responses at 0.4
- Through iterative processing, belief and plausibility approach 1.0
- Final DS score: approximately 0.999

Combined Score Development:
- Initial combined score: (0.25 + 0.999) ÷ 2 = 0.625
- Interest score after normalization: 0.625 ÷ 2.5 = 0.25 → 25.00%
- Talent score after normalization: 0.625 ÷ 5.0 = 0.125 → 12.50%

h) Communication Category Analysis
Response Pattern: [4, 4, 4, 4, 4, 4, 5, 5, 5, 5]
The Communication category exhibits strong positive responses with six "Agree" and four "Strongly Agree" responses, demonstrating high communication interest and capability.
CF Calculation Process:
- Individual CF weights: Six responses at 0.75 and four responses at 1.0
- Total CF weight: (0.75 × 6) + (1.0 × 4) = 4.5 + 4.0 = 8.5
- Average CF score: 8.5 ÷ 10 = 0.85

DS Calculation Process:
- Individual DS weights: Six responses at 0.8 and four responses at 1.0
- Presence of maximum DS weights causes convergence to 1.0
- Final DS score: 1.0

Combined Score Development:
- Initial combined score: (0.85 + 1.0) ÷ 2 = 0.925
- Interest score after normalization: 0.925 ÷ 2.5 = 0.37 → 37.00%
- Talent score after normalization: 0.925 ÷ 5.0 = 0.185 → 18.50%

Based on questionnaire input data from Response ID 10004 and calculations using Certainty Factor (CF) and Dempster-Shafer (DS) methods according to program logic, the following shows combined score interpretation results in percentage form:

Table 7. Recapitulation After Normalization for User (Response ID: 10004)

Main Category	Final Interest Score (%)	Final Talent Score (%)
Arts	37.50%	18.75%
Language	33.00%	16.50%
Environment	34.50%	17.25%
Leadership	31.00%	15.50%
Sports	24.00%	12.00%
Academic	35.50%	17.75%
Technical	25.00%	12.50%

Communication	37.00%	18.50%

4.1.2 Expert System Testing

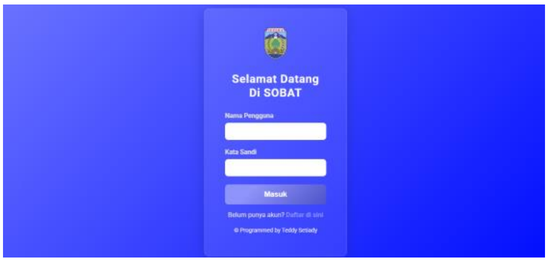

Figure 4. Login Page

Figure 5. Dashboard Page

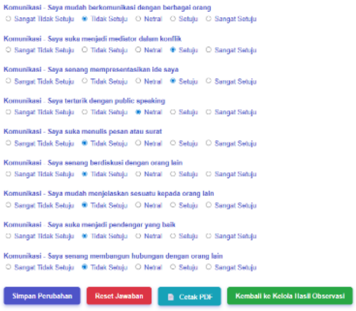
Figure 6. Questionnaire Page

Figure 7. Result Page

The system initial page consists of a login form and new user registration form (Figure 4). The page displayed after successful user login (Figure 5). The page where users complete the interest and talent characteristic features questionnaire (Figure 6). The page where users view results and extracurricular recommendations for students after completing the interest and talent characteristic features questionnaire (Figure 6).

4.1.3 Application Testing Results

Analysis conducted during design and implementation phases concludes that student interest and talent determination can be achieved using expert systems. Knowledge representation occurs in combined form, calculated using expert system resolution methods. The approach combines Dempster-Shafer and Certainty Factor methods, where Dempster-Shafer handles evidence combination, and Certainty Factor calculates single premises. Through method combination, conclusions achieve interest-talent presentation levels of 37.5%.

4.1.4 System Results Comparison with Ground Truth Data

Table 8. System Results Comparison with Ground Truth Data (Response ID: 10004)

Main Category	Type	System Prediction (Score %)	System Prediction (Interpretation)	Ground Truth Data (Interpretation)	Match/No Match
Arts	Interest	37.50%	Low	Low	Match
Language	Interest	33.00%	Low	Low	Match
Environment	Interest	34.50%	Low	Low	Match
Leadership	Interest	31.00%	Low	Medium	No Match
Sports	Interest	24.00%	Low	Low	Match
Academic	Interest	35.50%	Low	Medium	No Match
Technical	Interest	25.00%	Low	Low	Match
Communication	Interest	37.00%	Low	Medium	No Match
Arts	Talent	18.75%	Very Low	Very Low	Match
Language	Talent	16.50%	Very Low	Very Low	Match
Environment	Talent	17.25%	Very Low	Very Low	Match
Leadership	Talent	15.50%	Very Low	Medium	No Match
Sports	Talent	12.00%	Very Low	Very Low	Match
Academic	Talent	17.75%	Very Low	Medium	No Match
Technical	Talent	12.50%	Very Low	Low	No Match
Communication	Talent	18.50%	Very Low	Medium	No Match

4.2 Discussion

The hybrid expert system combining Certainty Factor and Dempster-Shafer methods for student interest and talent identification demonstrates both promising capabilities and notable challenges. The system processes questionnaire responses through structured approaches that harness complementary advantages of both methodological frameworks while revealing certain operational difficulties that warrant careful examination. The integration of CF and DS methods creates a balanced approach to uncertainty management in educational assessment scenarios. The CF method proves effective in single premise evaluations through weight assignment systems ranging from -0.5 to 1.0, successfully capturing the complete spectrum from strong disagreement to strong agreement. Meanwhile, the DS method provides robust evidence combination capabilities through belief and plausibility frameworks, proving particularly valuable when integrating multiple assessment criteria from different sources. The normalization process addresses varying question quantities across categories through interest normalization factor (max(1, Qty/4)) and talent normalization factor (max(1, Qty/2)). While ensuring fair comparison between categories, the approach may inadvertently penalize categories with more extensive question sets, potentially reducing final scores despite strong individual responses. The mathematical foundation appears sound, yet practical implementation reveals unintended consequences for category balance that require further attention.

Validation results using Response ID 10004 reveal specific patterns in system performance accuracy that merit detailed analysis. The system achieves high precision in identifying low-level interests and talents, with 10 out of 16 predictions matching ground truth data, resulting in 62.5% accuracy. Performance particularly excels in categories where students show minimal engagement, such as sports and technical domains, where the system correctly identified very low talent levels. However, performance limitations become apparent when distinguishing between "low" and "medium" levels of interest and talent. Six mismatches occurred specifically within boundary regions, suggesting current scoring thresholds require adjustment. The system consistently underestimated medium-level capabilities, classifying them as low or very low, indicating potential issues with normalization factors or interpretation thresholds used for final categorization. The highest-scoring category (Arts at 37.5%) demonstrates system capability in identifying relative strengths, yet the moderate percentage suggests room for sensitivity improvements. The consistent underperformance in medium-level detection raises questions about threshold calibration and the appropriateness of current boundary definitions.

The web-based implementation using PHP and MySQL establishes scalable foundations for educational institutions seeking to deploy such assessment tools. The modular design of analysis_functions.php allows easy modification of weight assignments and calculation methods, supporting future adaptations and improvements. The iterative DS calculation approach offers computational efficiency but may oversimplify evidence combination processes when conflicting evidence exists, potentially limiting the system's ability to handle complex response patterns. User interface design facilitates straightforward questionnaire completion and result interpretation, maintaining user engagement while collecting necessary assessment data. The progression from login through questionnaire completion to result display creates a smooth user experience that supports practical deployment. Including extracurricular recommendations based on assessment results adds practical value for educational guidance purposes, though recommendation accuracy depends heavily on underlying assessment precision. Database structure supports efficient data storage and retrieval, enabling batch processing of multiple student assessments while accommodating future enhancements.

Compared to single-method approaches found in existing literature, the hybrid system demonstrates improved robustness in handling diverse response patterns and assessment scenarios. Unlike pure CF implementations that struggle with evidence combination, or standalone DS systems lacking intuitive single-premise evaluation, the hybrid approach leverages complementary strengths from both methodologies. However, current implementation may not fully exploit DS theory's theoretical advantages, particularly in representing ignorance and managing conflicting evidence situations that commonly arise in educational assessment. The system's performance compares favorably with similar educational assessment tools regarding processing speed and user experience, making it viable for real-time applications in educational settings. The 62.5% overall accuracy rate aligns with expectations for preliminary talent identification systems, though boundary case performance suggests significant improvement opportunities exist.

Several operational challenges emerge from current implementation that require careful consideration for future development. The normalization approach, while mathematically sound, may not adequately reflect pedagogical importance of different assessment dimensions, potentially creating imbalances in final scoring. Categories with extensive question sets receive disproportionate normalization penalties, potentially masking genuine strengths in those areas and creating unfair disadvantages for well-developed assessment domains. The binary match/no-match evaluation in ground truth comparison oversimplifies the nuanced nature of interest and talent assessment, failing to capture gradual differences between adjacent categories. A more sophisticated evaluation framework considering proximity between predicted and actual categories would provide better insight into system performance and guide improvement efforts more effectively. Current weight assignment systems, while based on established practices, lack empirical validation specific to Indonesian elementary education settings. Cultural and educational factors unique to the target population may require customized weight calibrations to improve accuracy and cultural relevance. The system's tendency to underestimate medium-level capabilities suggests threshold definitions may not align with educational practitioner expectations or student development patterns observed in real classroom settings.

The system's ability to process large-scale student assessments efficiently offers significant value for educational institutions implementing personalized learning pathways and individualized educational planning. Structured approaches to interest and talent identification can support teachers and counselors in making informed decisions about student placement and extracurricular recommendations, potentially improving educational outcomes. However, the system functions best as a supportive tool rather than a definitive assessment mechanism for making critical educational decisions. Moderate accuracy rates, particularly in distinguishing adjacent performance levels, indicate human expertise remains essential for final educational decisions and student guidance. The system's primary strength lies in systematically processing initial assessments and flagging students who may benefit from further evaluation or specialized attention.

Implementation in Indonesian elementary education settings requires consideration of local cultural factors, educational practices, and student development patterns that may differ from international standards. The current weight assignments and threshold definitions may need adjustment to better reflect Indonesian educational contexts and student characteristics. Teacher training and support would be necessary to ensure effective system utilization and proper interpretation of results. The system could serve as a valuable screening tool for identifying students with potential talents or interests that might otherwise go unnoticed, supporting more equitable educational opportunities. Future development should focus on improving boundary case classification accuracy through refined threshold calibration and enhanced normalization approaches. Machine learning techniques could supplement the rule-based system, particularly for handling complex response patterns and improving medium-level capability detection. Longitudinal validation studies tracking student development over time would provide valuable insights into system accuracy and educational relevance. Integration with academic performance data and teacher observations could create more robust assessment frameworks that better serve educational decision-making needs. The development of region-specific calibration procedures would address cultural and educational factors unique to different populations, improving system applicability across diverse educational settings.

5. Conclusion

This research successfully developed an expert system aimed at determining elementary school students' interests and talents in Jepara sub-district, directly addressing challenges in suboptimal potential identification. The system integrates Certainty Factor (CF) and Dempster-Shafer (DS) methods to systematically process data collected through observation, interviews, questionnaires, and documentation. This application of Certainty Factor, optimized using Dempster-Shafer, significantly influences the improved performance in determining students' interests and talents, thereby enhancing accuracy. The program generates measurable interest and talent recommendations as its core output. The system functional proof lies in its inference process, which combines expert knowledge (questionnaire details and pre-defined CF/DS weights) with student input data. This involves aggregating single premise weights using CF's averaging method and iteratively combining DS weights to derive final belief and plausibility values. These CF and DS results are then normalized based on the number of questions per category and category type ('Interest' or 'Talent'), yielding a final percentage score; for instance, "Arts Interest" obtained 37.50% and "Arts Talent" 18.75% in detailed calculations for Response ID 10004. Significant factors influencing these results include the quality and content of the knowledge base (question clarity, defined CF/DS weights, and DETAILED_CATEGORIES classification), the consistency of input data, and the specific inference logic and normalization methodologies employed. Ultimately, this expert system demonstrates a systematic and quantitatively-based framework capable of processing data into measurable conclusions, highlighting its potential for more targeted and contextual talent identification, although actual accuracy confirmation relies on comprehensive external model evaluation.

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