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Expert System for Early Childhood Talent Detection Using Certainty Factor and Dempster Shafer Algorithms

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Abstract

Early life is a crucial window for recognizing children's interests and talents that shape later development. This study implements and compares two reasoning algorithms—Certainty Factor (CF) and Dempster–Shafer Theory (DST)—within a rule-based expert system designed to determine early-childhood interests and talents. Observable "symptoms" (behavior, preferences, and responses to stimuli) are mapped to potential talents, including linguistic, musical, logical-mathematical, and kinesthetic intelligences. The CF module computes confidence values from expert-assigned belief weights, yielding a single interpretable score per talent; the DST module aggregates evidence while explicitly representing uncertainty through basic probability assignments over the frame of discernment. We evaluate both methods in the deployed application with respect to accuracy, decision consistency, and response speed. Results show that, for the representative trait set aligning with linguistic indicators, CF produced the highest agreement with expert judgment 84% confidence while DST assigned 65% mass to the same singleton hypothesis, reserving the remainder for competing hypotheses and ignorance. These findings indicate that CF offers a more decisive signal under congruent evidence, whereas DST contributes caution by quantifying residual uncertainty. Together, the dual approach supports transparent and scalable screening of early talents, enabling caregivers and educators to act when support is strong and seek additional observations when uncertainty persists.

Keywords: Expert System; Certainty Factor; Dempster–Shafer Theory; Early Childhood Education; Talent Identification

1. INTRODUCTION

Interests and talents play a crucial role in shaping a child's overall development. These two aspects are not just complementary elements of growth—they are foundational in nurturing a child's identity, academic potential, and social capabilities. Particularly during the early years, between the ages of 4 and 6, the brain undergoes rapid development, forming connections that lay the groundwork for future learning and behavior. At this golden age, children begin to show preferences, abilities, and behaviors that can signal specific inclinations or talents.

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Identifying and directing these early can make a significant difference in maximizing a child's potential and ensuring their development follows a path aligned with their natural strengths [1].

However, recognizing a child's interests and talents is not always straightforward. Children at this stage often express themselves through behavior rather than words, making it difficult to interpret their true inclinations. This process requires a deep understanding of child psychology and behavior—something that not all parents or educators are equipped to navigate without support. Complicating matters further, many caregivers and teachers face constraints such as limited time, insufficient training, and a lack of structured tools for systematic observation and analysis [2], [3]. These challenges often lead to missed opportunities in identifying children's unique strengths at a time when timely intervention can have the greatest impact.

To address these challenges, technology—particularly expert systems—offers a promising solution. An expert system is essentially a computer-based application designed to simulate the decision-making abilities of a human expert, using a combination of data, rules, and inference engines to provide logical conclusions [4]. When applied to the realm of early childhood development, these systems can analyze behavioral patterns and other indicators to help identify interests and talents with a higher degree of accuracy. Such systems are not only consistent in their analysis but also scalable, making them an ideal tool for educators and parents alike who need guidance in interpreting complex child behavior [5].

Two algorithms commonly integrated into expert systems for this purpose are the Certainty Factor (CF) and the Dempster-Shafer (DS) theory. The Certainty Factor method is particularly known for its simplicity and speed, offering a structured approach to measuring the confidence level of specific observations or symptoms, based on expert-defined knowledge [6]. On the other hand, the Dempster-Shafer theory provides a more nuanced and flexible method of handling uncertainty. It allows the system to weigh multiple pieces of evidence before arriving at a decision, which is especially useful when dealing with incomplete or ambiguous data sets, a frequent occurrence in early childhood behavioral analysis [7].

Numerous studies have explored the use of these algorithms in expert systems for identifying children's interests and talents. Research studies [8], [9], [10] have shown how both algorithms can be effectively implemented in different contexts, each offering unique strengths. Further, investigations like [11], [12], and [13] have successfully employed the Certainty Factor to detect children's talents in structured environments. Conversely, the study [14] highlights the advantages of the Dempster-Shafer approach in scenarios involving high levels of uncertainty, such as developmental delays or atypical behavior. Building on this foundation, the

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current research aims to develop an expert system capable of identifying interests and talents in early childhood using both algorithms. The core questions guiding this study are: 1) How can an expert system be implemented to detect early childhood talents using Certainty Factor and Dempster-Shafer algorithms? and 2) Which of these algorithms proves to be more effective and efficient in supporting expert-based talent identification systems for young children?

2. METHODS

This study focuses on developing an expert system for detecting early childhood talents by implementing two well-known reasoning algorithms: Certainty Factor (CF) and Dempster-Shafer (DS). The research design follows a quantitative experimental method with a comparative approach, allowing for the analysis and evaluation of both algorithms in identifying and classifying children's talents based on behavioral characteristics. The research flow, illustrated in Figure 1, outlines the systematic stages followed in the development of the expert system for early childhood talent detection.

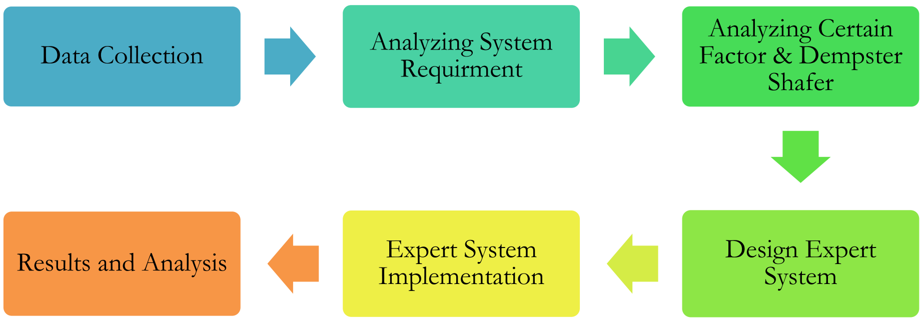

Figure 1. Research Flow Diagram

Based on Figure 1, the overall process begins with data collection and knowledge base formulation, followed by requirement analysis, algorithm implementation, system design, system development, and finally, system testing and evaluation. Each step contributes to building an accurate and efficient system tailored for use by both teachers and parents.

2.1 Data Collection and Knowledge Base Formation

At the initial stage, data were collected through interviews with expert teachers specializing in early childhood education. The goal was to identify key talents and the behavioural indicators (characteristics) that suggest those talents in children aged 4 to 6 years. Based on the interview results, eight core talents were identified,

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along with 56 corresponding characteristics. These talents and their respective codes are shown in Table 1.

Table 1. CF Talent Data

Code	Talent
B-001	Linguistics (Language)
B-002	Logic
B-003	Spatial Visuals (Imagination)
B-004	Kinestik (Body Smart)
B-005	Musical (Music)
B-006	Interpersonal
B-007	Intrapersonal Introspection
B-008	Naturalist (Nature Smart)

Each talent is supported by a detailed set of behavioral indicators, which form the knowledge base. These indicators are outlined in Table 2 and are used to form logical relationships with talents.

Table 2. Knowledge Base Characteristics of CF

Code	Features
C-001	Hobbies of reading books
C-002	Loves to tell stories, including fairy tales and funny stories
C-003	If you are upset or angry, you can say it fluently
C-004	Love to make up stories
C-005	Enjoy the discussion
C-006	Finding it easy to talk to new people
C-007	Likes to write a diary
C-008	It's fun to figure out how each thing works
C-009	Can solve counting problems
C-010	Really enjoyed math lessons
C-011	Likes to play chess, checkers, or monopoi
C-012	If the toy is broken and not working, find out how to fix it
C-013	Enjoy crossword puzzles, word searches or word puzzles
C-014	Often have unique ideas when playing with friends
C-015	Fun to draw
C-016	Often daydreaming
C-017	Happy to make doodles on paper whenever you can
C-018	When reading magazines, I prefer to look at the pictures rather than read the writing.
C-019	Be able to visualize images clearly when closing your eyes
C-020	Love to see exhibitions such as photo exhibitions, cars or motorcycles or other products
C-021	Likes to stick or make pictures or photos in the room
C-022	Since I love sports, gymnastics has been my favorite sport.

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Code	Features
C-023	When looking at things, it's nice to touch them and it's not enough to just look at them
C-024	Use a lot of body movements when speaking.
C-025	If I have to remember something, I write it down many times until I understand it
C-026	Tends to tap fingers or play with pens/pencils during class hours
C-027	If the toy is damaged, try to repair it by disassembling it and then assembling it again
C-028	I tend to tap my fingers or play with a pen or pencil during lessons
C-029	Can play one of the musical instruments well.
C-030	Loves to sing.
C-031	I love listening to music and radio.
C-032	Can memorize the notes of many songs.
C-033	Likes to listen to music while studying or while reading a book.
C-034	In school one of my favorite subjects is Music Arts.
C-035	Always dreamed of becoming a musician or singer.
C-036	I enjoy working together in a group.
C-037	I like to organize task breakdowns during group work
C-038	I enjoy meeting new people
C-039	Friends often ask me for advice.
C-040	If I want a test, I ask someone to test me to see if I already understand it
C-041	I have a few close friends.
C-042	I am able to get along well with others.
C-043	I like to work alone without any distractions from others.
C-044	I prefer to play alone.
C-045	I often daydream.
C-046	I have a sense of confidence.
C-047	I know my strengths and weaknesses.
C-048	I have a strong determination, independence and strong stance (not easy to follow others)
C-049	I can be held accountable for the actions I take.
C-050	I love watching shows about nature.
C-051	I love walking in the woods (or parks) and looking at trees and flowers.
C-052	I love gardening or taking care of plants.
C-053	I like to collect things like rocks, and the like.
C-054	I enjoy learning the names of living things in the environment I live in, such as flowers and trees.
C-055	I love keeping fish.
C-056	If my toy breaks down and doesn't work, I pay attention to my surroundings to see what I can find to fix it

These features are then used to construct rules that link specific behaviours to corresponding talents, as shown in Table 3, where numeric values represent the confidence levels assigned by experts. These confidence values range from 0 (no

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belief) to 1 (full belief), as referenced in [7]. The higher the value, the stronger the correlation between the trait and the talent.

Table 3. Talent Relations and Characteristics

Features	Talent							
	B-001	B-002	B-003	B-004	B-005	B-006	B-007	B-008
C-001	0,6							
C-002	0,6							
C-003	0,4							
C-004	0,2							
C-005	0,4							
C-006	0,6							
C-007	0,2							
C-008		0,6						
C-009		0,4						
C-010		0,4						
C-011		0,4						
C-012		0,6						
C-013		0,6						
C-014		0,4						
C-015			0,4					
C-016			0,4					
C-017			0,6					
C-018			0,6					
C-019			0,4					
C-020			0,6					
C-021			0,4					
C-022				0,4				
C-023				0,4				
C-024				0,6				
C-025				0,6				
C-026				0,6				
C-027				0,6				
C-028				0,4				
C-029					0,2			
C-030					0,4			
C-031					0,6			
C-032					0,4			
C-033					0,6			
C-034					0,4			
C-035					0,4			
C-036						0,6		
C-037						0,6		
C-038						0,4		
C-039						0,6		
C-040						0,4		
C-041						0,6		

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Features	Talent							
	B-001	**B-002**	**B-003**	**B-004**	**B-005**	**B-006**	**B-007**	**B-008**
C-042						0,4		
C-043							0,6	
C-044							0,6	
C-045							0,4	
C-046							0,4	
C-047							0,6	
C-048							0,6	
C-049							0,6	
C-050								0,6
C-051								0,6
C-052								0,4
C-053								0,4
C-054								0,4
C-055								0,4
C-056								0,6

The value of trust is obtained from the statement of an expert, which is measured by how much the value of the expert's belief in the characteristics of early childhood talent. The magnitude of the trust value can be measured from the value range from 0 to 1. The more the belief value of a phenomenon reaches 1, the greater the value of the belief. The greater the trust value of a symptom for one type of disorder, the greater the symptom can affect the type of disorder[7].

2.2 System Requirements Analysis

This study develops an expert system to detect early childhood talents by codifying domain expertise and applying evidence-based inference. The development process encompasses:

1) Expert knowledge acquisition: eliciting traits, indicators (symptoms), and talent categories from child development specialists and teachers.
2) Data artifacts: curated trait–talent mappings, rule bases (for Certainty Factor, CF), and basic probability assignments (for Dempster–Shafer, DS).
3) Technology stack: web and mobile clients, an application server implementing CF and DS inference, and a relational database for persistent storage.
4) Design & development: requirements modeling with UML, iterative prototyping, verification with synthetic and real classroom data.
5) Deployment: role-based access (parents, teachers), secure authentication, and responsive UIs enabling use on laptops and smartphones.

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The target users are parents (screening and receiving recommendations) and teachers (managing data, rules/weights, and reviewing results).

2.3. Inference Methods

This study combines two complementary evidential reasoning approaches:

1) Certainty Factor (CF): encodes an expert's belief and disbelief linking observed traits (symptoms) to hypothesized talents.
2) Dempster–Shafer (DS) theory of evidence: fuses multiple independent pieces of evidence as basic probability assignments over a frame of discernment.

Using both allows us to (i) mirror rule-of-thumb expert reasoning (CF) and (ii) explicitly account for ignorance/uncertainty (DS), then compare or ensemble the outcomes.

2.4. Certainty Factor (CF)

1) Definition

For a hypothesis H (e.g., a talent) given evidence E (e.g., a selected trait), the Certainty Factor is as shown in Equation 1.

$$CF(H/E) = MB(H,E) - MD(H,E) \quad (1)$$

where:

$\mathrm{MB}(H,E) \in [0,1]$ is the measure of belief (degree of confidence in H),
$\mathrm{MD}(H,E) \in [0,1]$ is the measure of disbelief (degree of doubt in H).

When experts provide a single weight $w \in [0,1]$ indicating support for H from trait E, we set $\mathrm{MB} = w$ and $\mathrm{MD} = 0$, so $\mathrm{CF} = w$.

2) Combining Multiple Supporting Traits

Given two pieces of **supporting** evidence for the same hypothesis with CFs CF_1 and CF_2 (both ≥ 0), the combined certainty is as shown in Equation 2.

$$CF_{new} = CF_{old} + (1-CF_{old})\, CF_{add} \quad (2)$$

Applied iteratively over a set of supporting traits $\{E_i\}$, this yields a monotonic increase up to 1 while preserving diminishing returns.

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3) CF Pseudocode

This routine aggregates supportive evidence for a single target talent using the standard Certainty Factor (CF) update. It takes the set of selected traits, a CF rule base that maps (trait, talent) pairs to expert weights in [0,1], and the target talent to evaluate. Starting from CF_total = 0, each matching trait contributes its weight via the progressive combination CF_total ← CF_total + (1 − CF_total) * CF_add, which ensures monotonic growth with diminishing returns and keeps the result within [0,1]. Traits without a rule for the target are ignored. The procedure is order-independent for non-negative supports, runs in O(n) over the selected traits, and returns the final CF score for that talent.

```
function CF_Aggregate(traits_selected, rules_CF, target_talent):
    CF_total ← 0.0
    for each trait in traits_selected:
        if (trait, target_talent) in rules_CF:
            CF_add ← rules_CF[(trait, target_talent)]      # expert
weight in [0,1]
            CF_total ← CF_total + (1 - CF_total) * CF_add  # combine
support
    return CF_total
```

2.5. Dempster–Shafer Evidence Theory (DS)

1) Core Concepts

Let the frame of discernment be $\Theta = \{$Linguistic (B),Logic (L),Musical (M)$\}$. Each piece of evidence (trait) provides a basic probability assignment (BPA) $m: 2^{\Theta} \rightarrow [0,1]$such that $\sum_{A \subseteq \Theta} \quad m(A) = 1$and $m(\emptyset) = 0$.

Key measures:

Belief: Bel(A)= $\sum_{B \subseteq A}$ m(B)— lower bound (committed support).
Plausibility: Pl(A)= $\sum_{B \cap A \neq \emptyset}$ m(B)— upper bound (not contradicted).

2) Dempster's Rule of Combination

For two independent BPAs $m_1$and m_2, their orthogonal sum $m = m_1 \oplus m_2$is

$$m(A) = \frac{\sum_{B \cap C = A} \quad m_1(B)\, m_2(C)}{1\text{-}K}, where K = \sum_{B \cap C = \emptyset} \quad m_1(B)\, m_2(C).$$

Kquantifies conflict; the denominator $1 - K$rescales non-conflicting mass.

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3) DS Pseudocode

```
function DS_Combine(m_list):
    # m_list: list of BPAs (each a map from subsets of Θ to mass)
    m_acc ← m_list[0]
    for i from 1 to len(m_list)-1:
        m_next ← empty map default 0
        K ← 0
        for each (A, massA) in m_acc:
            for each (B, massB) in m_list[i]:
                if A ∩ B = ∅:
                    K ← K + massA * massB
                else:
                    m_next[A ∩ B] ← m_next[A ∩ B] + massA * massB
        for each (C, massC) in m_next:
            m_next[C] ← massC / (1 - K)
        m_acc ← m_next
    return m_acc
```

2.6. Designing Expert Systems

The system design describes the description of the system to be built. The system design is carried out using the Unified Modeling Language (UML). The design form of the system to be built can be seen in Figure 4, Figure 5, and Figure 6.

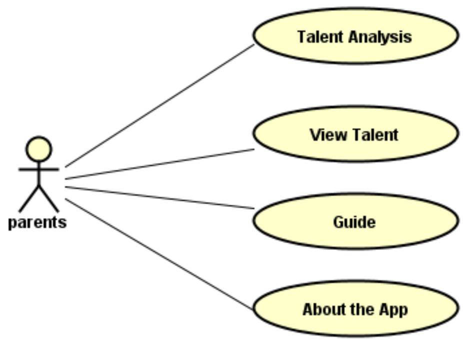

Figure 4. Use case Diagram of Parents

Figure 4 explains where parents can analyze their children's talents by selecting characteristics using an expert system application that has been built. The system detects early childhood talent based on the characteristics that have been selected using the Dempster Shafer algorithm and the Certainty Factor so that the detection results occur for the recommendation of children's talents. Figure 5 explains teachers in interacting with the expert system that has been built, where all data management in the system is managed by teachers, starting from logins, teacher data, talent data, trait data, DS management, and CF management. Figure 6 describes the relationship to a database that can be built for a child talent detection expert system using the Dempster Shafer and Certainty Factor algorithms, where

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there are seven tables consisting of tables of aturan_cf, aturan_ds, bobot_cf, bobot_ds, talent, traits, and teachers.

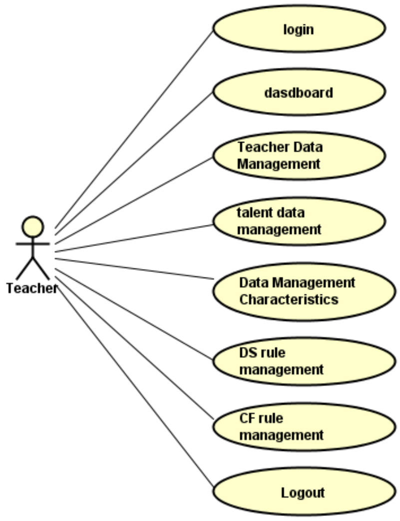

Figure 5. Teacher Use Case Diagram

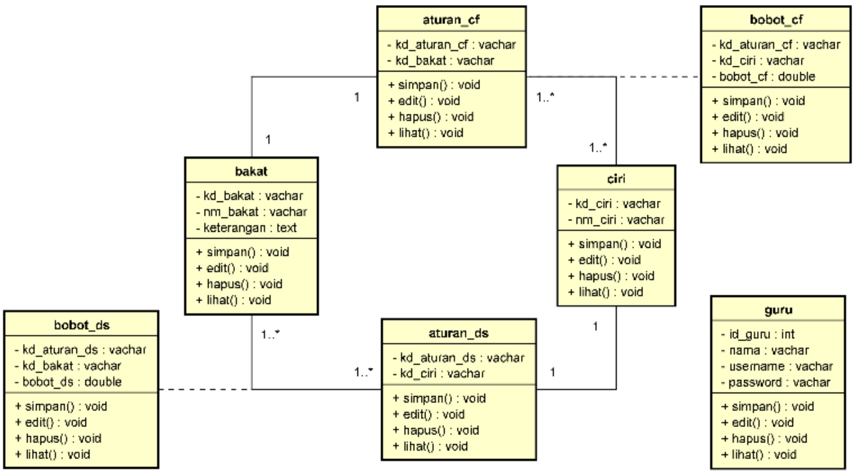

Figure 6. Class Diagram

The expert system is implemented as a web and mobile application to ensure ubiquitous access:

1) Frontend: responsive UI for browsers and hybrid mobile (e.g., React/Flutter), with parent and teacher dashboards.

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2) Backend: RESTful API implementing CF and DS engines, input validation, and result formatting.
3) Database: relational storage for users, traits, talents, and rule weights/masses.
4) Security & privacy: role-based access, TLS, and minimal collection of child data (traits only) per ethical guidelines.

2.7. Certainty Factor (CF) Calculation

The discussion in this study is to test the Certainty Factor and Dempster Shafer algorithms to detect children's talents with characteristics, so that they can be implemented into the expert system. The data of the characteristics to be tested can be seen in Table 4.

Table 4. CF Algorithm Calculation

No.	Selected Features	Talent	CF
1.	Hobby of reading books	Linguistics (Language)	0,6
3.	Really enjoy math lessons	Logic	0,4
4.	Loves to sing	Musical	0,4

In this example, the Linguistic talent is supported by **two** linguistic indicators of equal weight (e.g., codes C-001 and C-002, each 0.60). Combining two supporting CFs:

$$\begin{aligned} CF_B &= 0.60 + (1\text{-}0.60)\times 0.60 \\ &= 0.60 + 0.40\times 0.60 \\ &= 0.60 + 0.24 \\ &= 0.84 \Rightarrow 84\%. \end{aligned}$$

For the other talents (each supported by one trait):

$$CF_L = 0.40 \Rightarrow 40\%, CF_M = 0.40 \Rightarrow 40\%.$$

CF Conclusion. The highest CF score is Linguistic (B) at 84%, indicating the strongest support among the three talents under CF reasoning.

2.8. Dempster–Shafer (DS) Calculation

1) Define the Frame and BPAs

Frame of discernment: $\Theta=\{B,L,M\}$

Trait 1 — Hobby of reading books
Assign specific support to Linguistic and the remainder to ignorance:

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$$m_1(\{B\})=0.30,\ m_1(\Theta)=1\text{-}0.30=0.70.$$

Trait 2 — Really enjoys mathematics lessons

$$m_2(\{L\})=0.40,\ m_2(\Theta)=1\text{-}0.40=0.60.$$

Trait 3 — Loves to sing

$$m_4(\{M\})=0.70,\ m_4(\Theta)=1\text{-}0.70=0.30.$$

2) Combine Trait 1 and Trait 2: $m_3=m_1 \oplus m_2$

Conflict:

$$K=m_1(\{B\})\, m_2(\{L\})=0.30\times0.40=0.12.$$

Non-conflicting numerators:

$$\begin{aligned}
&\text{for } \{B\}: && m_1(\{B\})\, m_2(\Theta)=0.30\times0.60=0.18,\\
&\text{for } \{L\}: && m_1(\Theta)\, m_2(\{L\})=0.70\times0.40=0.28,\\
&\text{for } \Theta: && m_1(\Theta)\, m_2(\Theta)=0.70\times0.60=0.42.
\end{aligned}$$

Normalize by $1-K=0.88$:

$$m_3(\{B\})=\frac{0.18}{0.88}\approx0.205, m_3(\{L\})=\frac{0.28}{0.88}\approx0.318, m_3(\Theta)=\frac{0.42}{0.88}\approx0.477.$$

3) Combine With Trait 3: $m_5 = m_3 \oplus m_4$

Conflict:

$$K = m_3(\{B\})\, m_4(\{M\}) + m_3(\{L\})\, m_4(\{M\}) \approx 0.205\times0.70 + 0.318\times0.70 \approx 0.364.$$

Non-conflicting numerators:

$$\begin{aligned}
&\text{for } \{M\}: && m_3(\Theta)\, m_4(\{M\})\approx0.477\times0.70=0.334,\\
&\text{for } \{L\}: && m_3(\{L\})\, m_4(\Theta)\approx0.318\times0.30=0.095,\\
&\text{for } \{B\}: && m_3(\{B\})\, m_4(\Theta)\approx0.205\times0.30=0.061,\\
&\text{for } \Theta: && m_3(\Theta)\, m_4(\Theta)\approx0.477\times0.30=0.143.
\end{aligned}$$

Normalize by $1\text{-}K\approx0.636–0.642$ (depending on rounding). Using precise intermediate values:

$$m_5(\{M\}) \approx \frac{0.334}{1\text{-}0.364} \approx 0.520 (\approx 52.0\%),$$
$$m_5(\{L\}) \approx \frac{0.095}{1\text{-}0.364} \approx 0.149 (\approx 14.9\%),$$
$$m_5(\{B\}) \approx \frac{0.061}{1\text{-}0.364} \approx 0.096 (\approx 9.6\%),$$
$$m_5(\Theta) \approx \frac{0.143}{1\text{-}0.364} \approx 0.223 (\approx 22.3\%).$$

Rounded to two/three decimals (as in the original notes), this corresponds closely to:$m_5(\{M\})\approx 0.528, m_5(\{L\})\approx 0.151, m_5(\{B\})\approx 0.094, m_5(\Theta)\approx 0.226$.

3. RESULTS AND DISCUSSION

3.1. Expert System for Early Childhood Talent Detection

The expert system translates the methodological framework into a cohesive, end-to-end workflow that parents and teachers can complete with minimal training, while preserving methodological rigor and auditability. After secure authentication, users arrive at the Main Menu (Figure 7), whose information architecture is intentionally minimalist—"Start New Analysis," "Results History," and a role-gated "Administration" area for teachers—so non-technical users can begin screening with one or two taps. A brief, optional onboarding tip clarifies that the system is a decision-support tool rather than a diagnostic instrument. From there, the Talent Analysis screen (Figure 8) presents observable child characteristics written in concise, parent-friendly language and grouped by domain (e.g., language/literacy, numeracy/logic, music/rhythm). To reduce bias and duplicate counting, near-synonymous traits are softly grouped and visually de-duplicated; selection caps and gentle prompts encourage breadth over redundancy (e.g., "Try adding 1–2 traits from another domain"). Client-side checks nudge users to supply sufficient evidence (minimum trait count per session), while server-side validation ensures that every selected characteristic maps to a live rule or mass assignment in the knowledge base. If a trait lacks a mapping (for example, after a knowledge-base update), the interface offers a clear replacement suggestion rather than failing silently. Inputs are autosaved to prevent loss on mobile devices, and sensitive data entry fields are limited to observational traits only to minimize personal data handling. The submission step is explicit and reversible: a summary panel lists chosen traits and their domains, and users confirm before analysis runs.

Upon submission, the backend executes a dual inference pipeline designed for both decisiveness and transparency. The Certainty Factor (CF) engine aggregates supportive evidence for each talent using the progressive update described in the

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Methods, producing a single confidence value in [0,1] per hypothesis and ensuring diminishing returns as support accumulates. In parallel, the Dempster–Shafer (DS) engine constructs and combines basic probability assignments over the frame of discernment Θ = {Linguistic, Logic, Musical}, explicitly preserving residual uncertainty on Θ where evidence is broad, sparse, or conflicting. Performance-wise, both engines are implemented as stateless services sitting behind an API gateway; typical analyses complete within a few hundred milliseconds on mid-range mobile networks, and a retry-safe request ID guarantees idempotency if users resubmit due to connectivity hiccups. Each analysis is tagged with the active knowledge-base version, timestamps, and the user role (parent/teacher), enabling full reproducibility of past results even as rules evolve. Teachers maintain the knowledge base via role-restricted screens accessible from Figure 7, where they can add or revise characteristics, update CF weights or DS mass assignments, and publish semantic, versioned releases. Draft changes are previewed on sandbox cases before being promoted to production, and release notes are surfaced in-app so users understand when and why results may differ from prior sessions.

Figure 7. Main Menu Screen Display

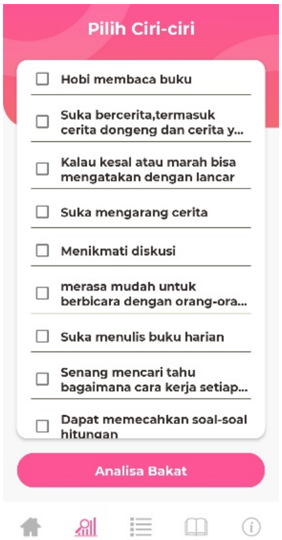

Figure 8. Talent Analysis Screen Display

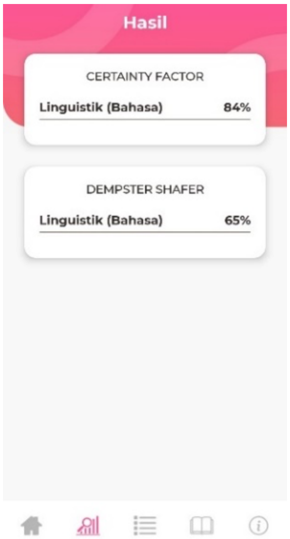

Figure 9. Analysis Results Display

The Analysis Results view (Figure 9) integrates both perspectives into a single, legible report: talents are ranked, CF percentages appear alongside DS masses, and an optional "Advanced" toggle reveals brief notes explaining why the top talent ranked first (e.g., "Reading preference" and "Vocabulary play" contributed most) and what residual uncertainty means operationally. When CF is high but DS leaves notable mass on Θ, a gentle banner explains the discrepancy ("Strong support with

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remaining uncertainty") and suggests practical next steps—collecting additional observations at home, repeating the screen after a set interval, or asking a teacher to confirm traits in the classroom. To support actionability, the results card also includes age-appropriate enrichment suggestions aligned to the leading talent and a quick link back to Figure 8 for iterative refinement. Accessibility and inclusivity are built in: the layout adapts to phones and tablets; touch targets meet mobile guidelines; text scales with system settings; and language can be switched where available. Privacy is preserved by design: the system stores only trait selections and non-identifying session metadata; no free-text notes about the child are required; and exports omit internal identifiers while retaining the analysis version for auditing. In short, Figures 7–9 illustrate how the system carries users from everyday observations to transparent, evidence-aware recommendations without exposing them to algorithmic complexity—yet still surfacing enough explanation for trust, reproducibility, and informed follow-up.

3.2. Expert System Testing

We conducted a formative usability evaluation to assess ease of use, clarity of outputs, and overall satisfaction when operating the expert system. The study involved 20 parent participants who completed a typical end-to-end session (sign-in → trait selection → results review) on their own devices, followed by a 10-item Likert questionnaire. Items probed core dimensions of human–computer interaction—navigation ("I can find what I need quickly"), input clarity ("Trait wording is easy to understand"), feedback and trust ("I understand what the percentages mean"), performance ("The app responds quickly"), readability/accessibility (mobile layout, font size, touch targets), and perceived usefulness (recommendations feel actionable). Responses used a five-point scale coded as STS (Strongly Disagree), TS (Disagree), N (Neutral), S (Agree), and SS (Strongly Agree). Scores were normalized to a 0–100 index by mapping STS=0, TS=25, N=50, S=75, SS=100 and averaging across items per participant, then across participants.

Results indicate high perceived usability. The overall mean score was 88%, suggesting the interface and dual-metric presentation (CF and DS) are both understandable and helpful for decision support. As summarized in Figure 10, response frequencies were heavily skewed toward positive endorsements: 48% of all item responses were Agree (S), 47% were Strongly Agree (SS), 5% were Neutral (N), and 0% registered disagreement (TS or STS). Narrative comments highlighted three strengths: (i) the Talent Analysis screen's concise, parent-friendly wording of traits (Figure 8); (ii) the Results view's side-by-side display of CF percentages and DS masses (Figure 9) with brief interpretive notes; and (iii) the overall speed and stability during submission on mobile networks. A minority of participants requested richer "why" explanations (e.g., showing the top contributing traits more

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explicitly) and more examples of age-appropriate enrichment activities linked to the leading talent—both have been added to the product backlog.

The test provides encouraging evidence that the expert system is usable and comprehensible for its intended audience; however, it is necessarily preliminary. The sample size is modest, the respondent pool consists solely of parents (teachers will be included next), and the study measured perceived usability rather than longitudinal learning outcomes. To strengthen external validity, we plan a multi-site evaluation with larger and more diverse cohorts, include teachers as primary users for knowledge-based maintenance, and introduce A/B experiments on explanation depth and wording. We will also track time-on-task, error rates (e.g., incomplete submissions), and retention of key concepts (e.g., the meaning of residual mass on Θ) to complement self-reported satisfaction. Together, these steps will help ensure the expert system remains both easy to use and methodologically transparent as it scales.

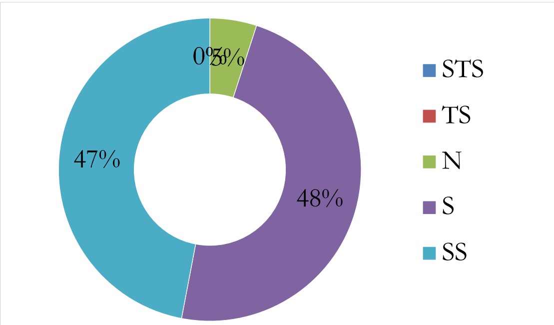

Figure 10. Usability testing distribution across Likert categories

3.3. Discussion

The findings demonstrate that an expert-system approach can translate everyday observations from parents and teachers into transparent, evidence-aware talent indications for young children. Placing the Certainty Factor (CF) and Dempster–Shafer (DS) engines side-by-side inside a single workflow (see Figures 7–9) proved useful in practice: CF delivered decisive, single-value confidences that aligned with expert intuition and were easy for non-technical users to interpret, while DS preserved residual uncertainty on Θ and made conflict explicit when traits pointed to more than one plausible talent. In the representative run shown in Figure 9, CF produced a leading confidence of 84% for the top talent, whereas DS assigned 65% mass to its leading singleton while reserving the remainder for competing hypotheses and Θ. This divergence is not a defect but a design feature: CF aggregates supportive evidence with diminishing returns, which tends to amplify consistent signals; DS, by contrast, distributes belief across hypotheses and uncertainty, tempering conclusions when evidence is sparse, overlapping, or weakly discriminative. Taken together, these complementary views help caregivers act where the signal is strong and pause where uncertainty warrants further observation, aligning with the study's intent to support—not replace—human judgment during a sensitive developmental window.

From a human–computer interaction perspective, the usability study (Figure 10) underscores that methodological rigor can be delivered in a form that is approachable to lay users. An average score of 88% and a response distribution concentrated in Agree (S) and Strongly Agree (SS) suggest that the interface communicates complex outputs without overwhelming users. Narrative feedback maps cleanly onto design decisions made earlier: the Talent Analysis screen (Figure 8) benefited from plain-language trait wording and gentle guardrails that prevent duplicate counting of near-synonymous traits; the Analysis Results view (Figure 9) gained trust by co-displaying CF percentages and DS masses, along with short interpretive notes that clarify why a talent ranked first and what residual uncertainty means operationally. Notably, participants requested more "why" details (e.g., top contributing traits per result) and richer, age-appropriate activity suggestions—signals that the system is already usable, and that the next increment of value will come from deeper explanation and action guidance rather than core inference changes.

Methodologically, the dual-engine design mitigates characteristic risks of each approach when used in isolation. CF's progressive update can overstate confidence if users select multiple highly correlated traits within one domain; the interface addresses this by softly grouping near-synonyms and encouraging breadth across domains, while DS further counterbalances over-aggregation by reserving mass on Θ when evidence lacks discriminatory power. Conversely, DS can appear conservative to end users unfamiliar with evidential reasoning; pairing it with CF's intuitive percentage and adding brief, context-sensitive notes reduced misinterpretation in the study. This pairing also creates productive avenues for triangulation in practice: for example, high CF with substantial DS mass on Θ triggers a recommendation to gather additional observations or seek classroom confirmation, whereas high agreement between CF and DS supports earlier enrichment activities tailored to the leading talent. In this way, the system operationalizes a prudent, iterative cycle of screening, guided enrichment, and follow-up review, which is consistent with best practices in early childhood assessment.

At the same time, several limitations should be acknowledged to contextualize the results. First, the usability evaluation involved 20 parents and did not yet include teachers as primary maintainers of the knowledge base; broader sampling across schools and communities is needed to ensure generalizability. Second, outcomes

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reported here are perceptual and procedural (usability, clarity, interpretability) rather than longitudinal, meaning we have not yet linked system recommendations to later developmental milestones or academic indicators. Third, the current knowledge base primarily encodes supportive traits; incorporating contradictory or inhibitory evidence—and weighting context (e.g., setting, frequency, or sustained duration of behaviors)—could improve calibration, especially in edge cases. Fourth, while Figures 7–9 illustrate strong performance on typical mobile connections, real-world deployments should continue to monitor latency, offline behavior, and accessibility accommodations (e.g., language localization, screen-reader support) as usage scales.

These limitations inform a future work agenda. On the methodological side, we plan to (i) extend the DS layer with explicit modeling of dependence among traits to reduce over-counting when evidence sources are not independent; (ii) enrich CF rules with negative evidence and context weights; and (iii) pilot lightweight ensembles (e.g., CF-guided priors for DS, or DS-adjusted CF penalties when Θ remains high) to harmonize outputs where appropriate. On the product side, we will (iv) add explainer modules that list the most influential traits per result, with concise rationales; (v) expand the library of actionable, age-appropriate activities linked to leading talents; (vi) integrate teacher workflows for knowledge-base review and publishing with clearer release notes; and (vii) run multi-site studies that include both parents and teachers, measuring not only usability but also decision quality (e.g., appropriateness of chosen activities) and medium-term outcomes (e.g., engagement, persistence in enrichment tasks). Finally, we will explore optional privacy-preserving analytics to learn from aggregate, de-identified usage patterns while keeping individual child data strictly minimal.

This study shows that combining CF and DS within a carefully designed interface enables trustworthy, comprehensible talent screening in early childhood. CF provides the decisive signal stakeholders often need to take the next step, while DS introduces disciplined humility by quantifying what remains unknown. The strong usability profile (Figure 10) suggests that this balance is understandable to end users, and the workflow depicted in Figures 7–9 demonstrates that methodological transparency can coexist with simplicity. With continued work on explanation depth, broader validation, and knowledge-based expansion, the expert system has the potential to become a practical, equitable tool for supporting early, strengths-based development.

4. CONCLUSION

This study demonstrates that an expert-system approach—grounded in Certainty Factor (CF) and Dempster–Shafer (DS) reasoning—can translate everyday observations from parents and teachers into transparent, evidence-aware

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indications of early-childhood talents. Implemented as a web/mobile application, the system operationalizes expert knowledge through a streamlined workflow (Figures 7–9) that begins with trait selection and ends with ranked recommendations accompanied by interpretable confidence metrics. Empirically, CF provided decisive, single-value confidences that are intuitive for non-technical users, while DS preserved residual uncertainty on Θ and made evidential conflict explicit. This complementary pairing helps stakeholders act when support is strong and pause for further observation when uncertainty remains, aligning with the intended use of the tool as decision support rather than diagnosis. Usability findings reinforce this promise: a formative evaluation with 20 parents yielded an average satisfaction score of 88% (Figure 10), indicating that the interface and dual-metric presentation are accessible and useful in practice.

At the same time, the work highlights areas for continued improvement. The present evaluation emphasizes perceived usability over longitudinal outcomes; future studies should link system recommendations to subsequent engagement and learning gains. The knowledge base currently emphasizes supportive traits; incorporating contradictory evidence, contextual weighting (e.g., frequency, setting), and trait-dependence modeling will further sharpen calibration and reduce over-counting. Planned enhancements include richer "why" explanations (top contributing traits), expanded, age-appropriate activity guidance, broader teacher workflows for knowledge-base governance, and multi-site trials with diverse cohorts. In summary, by combining CF's decisiveness with DS's disciplined handling of uncertainty inside an approachable interface, the proposed expert system offers a practical and scalable path to earlier, more equitable, and more transparent support for children's developing strengths.

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