Electronic Integrated Computer Algorithm Journal
Vol. 4, No. 1, October 2026, pp 55~63

ISSN: 3031-0350, DOI: 10.62123/enigma.v4i1.237

A Dempster-Shafer-Based Expert System for Personalized Higher Education Major Recommendation

Rahmat Widia Sembiring [1*], Ramadhanu Ginting [1], Afrisawati [1], Fristi Riandari [1], Indri Sulistianingsih [2]

[1] *Program Studi Manajemen Informatika, Jurusan Teknik Komputer dan Informatika, Politeknik Negeri Medan,* Indonesia.
[2] *Program Studi Teknik Rekayasa Perangkat Lunak, Jurusan Teknik Komputer dan Informatika, Politeknik Negeri Medan,* Indonesia.

DOI : 10.62123/enigma.v4i1.237

Received : September 19, 2026
Revised : October 04, 2026
Accepted : October 09, 2026

Keywords:
Artificial Intelligence, Decision Support System, Dempster-Shafer Theory, Expert System, Major Recommendation

ABSTRACT

Selecting a study program at a State University (Perguruan Tinggi Negeri/PTN) is a decision that many senior high school students approach without a systematic review of their interest, aptitude, achievement, and career goals, a gap made more pressing by the limited counseling capacity available at most schools. Earlier expert systems for major recommendation have relied on Forward Chaining or Certainty Factor, methods that combine evidence into a single rule outcome or scalar confidence without explicitly representing the uncertainty left by incomplete evidence. This study developed and implemented a web-based expert system, Peta Kampus, that applies Dempster-Shafer evidence theory to generate a personalized major recommendation from a student's answers to a structured questionnaire. The knowledge base was constructed with school counselors and an education practitioner into 275 evidence-linked questions covering 55 majors across 21 faculties, each carrying an expert-assigned belief value. The system was built on a native PHP Model-View-Controller architecture with MySQL as the data store, and its inference engine combines successive evidence using Dempster's rule of combination while tracking residual uncertainty and evidentiary conflict. The system was verified through Black Box Testing of its functional modules, with all 15 tested scenarios passing, and evaluated through an accuracy comparison against three independent evaluators (school principal and two guidance counselors, 90% average agreement across 30 cases) and a User Acceptance Test administered to 30 students, which returned an overall satisfaction score of 94.8%. The resulting system gives students and counselors a belief-and-plausibility-based recommendation that is more transparent than a single deterministic score.

1. INTRODUCTION

Admission to a State University (Perguruan Tinggi Negeri/PTN) in Indonesia has become increasingly competitive, and national admission-test figures for 2025 show that of 860,976 participants, only 253,421, or about 29.43 percent, were accepted (Tempo.co,2025). This narrowing acceptance rate places pressure not only on academic preparation but also on the accuracy with which a student chooses the major that best fits their profile, since a mismatched choice at this stage carries consequences well beyond the admission process itself.

Many students nonetheless approach major selection without a structured self-assessment. Interest, aptitude, prior academic achievement, and intended career direction are each relevant to a good match, yet students frequently rely instead on family preference, peer influence, or a general impression of a major's popularity. This pattern is reinforced by the limited time and staffing of school Guidance and Counseling (Bimbingan Konseling/BK) units, which are rarely able to give every student an individualized consultation before the admission period, leaving a substantial share of students to decide with incomplete self-knowledge.

Artificial intelligence and expert systems offer a way to extend the reach of this counseling function without replacing it. An expert system encodes a specialist's reasoning, such as that of a career counselor, into a structured knowledge base paired with an inference engine, allowing a consistent, always-available consultation process that a small counseling staff cannot otherwise provide. In education specifically, such systems have been used to gauge vocational interest [1], recommend a field of study [2], or classify students into broad academic streams[3], positioning the technology as a support tool that complements rather than substitutes for a human counselor.

Prior work on major or study-program recommendation has generally applied Forward Chaining, in which interest indicators are traced through an if-then rule chain toward a single matching major [1][4][2], or Certainty Factor, in which an expert's confidence in a recommendation is expressed as a scalar value combining belief and disbelief [1][5][6][7]. Other studies have applied Case-Based Reasoning [8], decision-tree and random-forest classifiers trained on academic records [9][10][11], multidimensional recommender filtering , and, more recently, large-language-model-based representation learning for course

*Corresponding Author Email: ramadhanuginting@polmed.ac.id

recommendation [3]. Each of these approaches has reported usable accuracy in its own case study, but the underlying inference in most of them still reduces the evidence-combination process to a single rule outcome or a single confidence figure per recommendation.

Previous studies have produced recommendations based on rule matching or a single confidence score, but have not explicitly represented the uncertainty that remains when a recommendation is built from several, sometimes only partially consistent, pieces of evidence. Dempster-Shafer theory, by contrast, has been applied successfully in other diagnostic and classification domains to combine partial, uncertain evidence into a bounded belief-plausibility interval [12][13][14][15][16]. This leaves an open question of how a similar evidence-theoretic approach can be extended to the major-recommendation problem, distinguishing a recommendation supported by only a handful of answered questions from one supported by a large and mutually reinforcing body of evidence, a distinction that a scalar confidence value does not make visible on its own.

This study addresses that gap in four respects. First, a web-based expert system was developed to support personalized PTN major recommendation. Second, Dempster-Shafer evidence reasoning was applied to combine student responses while explicitly tracking belief, plausibility, and residual uncertainty across successive evidence. Third, a personalized recommendation was generated for each student from a knowledge base covering 275 questions across 55 majors. Fourth, the usability of the resulting system was evaluated through responses collected from students who used the consultation feature.

2. LITERATURE REVIEW

2.1 Expert System

An expert system is an application that reproduces a domain specialist's decision process by combining a structured knowledge base, which stores facts and rules elicited from the specialist, with an inference engine that matches user-supplied information against that knowledge base to reach a conclusion. As a form of decision support, an expert system is intended to make specialist reasoning available on demand, in a form that is consistent across users and does not depend on the specialist's physical presence, which is particularly useful where a decision depends on weighing several uncertain criteria at once, as in education [1][2][3], health[17][6][18], and agriculture.

Dempster-Shafer theory, or evidence theory, was introduced by Arthur P. Dempster and later formalized by Glenn Shafer as a means of representing and combining degrees of belief from multiple, potentially incomplete sources of evidence[12][15]. In contrast to classical probability, which requires a complete distribution across all outcomes, Dempster-Shafer theory permits mass to remain unassigned to any single hypothesis and instead attributed to the frame of discernment Θ as a whole, representing genuine ignorance rather than forcing an arbitrary split among competing hypotheses [13][14][16][19]. Each evidence item is expressed as a mass function m(X) over subsets of Θ, and successive mass functions are merged using Dempster's rule of combination, given in Equation (1), where the combined mass toward a hypothesis Z is the normalized sum of products of masses whose intersection equals Z, while mass corresponding to disjoint intersections is treated as conflict K and removed from the normalizing denominator. Belief and plausibility, derived from the combined mass, respectively give the minimum and maximum credibility that current evidence supports for a hypothesis, and the gap between them narrows as more consistent evidence accumulates. Recent advances continue to refine the combination rule itself, including improved conflict-resistant combination for noisy or compressed sensor evidence [20], new uncertainty measures such as belief Rényi entropy for evaluating basic probability assignments [21], correlation-aware belief-function fusion[22], and cosine-similarity-based basic probability assignment generation for conflicting evidence [23], all of which reinforce evidence combination as an active and continually improving research area beyond its original 1976 formulation.

$$m_{12}(Z) = \frac{\sum_{X \cap Y = Z} m_1(X) m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)} \qquad (1)$$

Where m12(Z) is the combined mass toward hypothesis Z, m1(X) and m2(Y) are the mass functions of the first and second evidence, X∩Y is the intersection of the sets each evidence supports, and K = Σ m1(X)·m2(Y) for X∩Y=∅ is the conflict factor removed from the normalizing denominator.

Table 1. Comparison of Previous Studies

Author	Method	Object	Limitation
Kurniawan, Defit, & Yuhandri (2021)	Certainty Factor + Forward Chaining	Vocational interest identification	Confidence expressed as a single scalar per rule
Wicaksa Putra Pribadi et al. (2024)	Rule-based expert system	SMA IPA/IPS stream selection	Coarse binary classification, not major-level
Somyürek & Aksoy (2024)	Multidimensional recommender	University and major selection	Assumes a complete profile; no explicit belief measure
Nizam, Zafar, Biswas, & Hussain (2026)	Random Forest + Explainable AI	Course recommendation	Requires substantial labeled training data

Zhou, Zhao, Ma, & Xie (2026) [12]	LLM-driven representation learning	Attribute-augmented course recommendation	High computational cost; limited transparency
This study (2026)	Dempster-Shafer evidence theory	Personalized PTN major recommendation	Explicit belief, plausibility, and conflict tracking across evidence

3. RESEARH METHODS

3.1 Research Framework

This study followed a Research and Development (R&D) framework carried out in five stages: Problem Identification, in which the difficulty senior high school students face in selecting a PTN major was confirmed through observation and interviews with Guidance and Counseling (BK) teachers at the partner school; Knowledge Acquisition, in which evidence statements and their belief values were elicited from BK teachers and an education practitioner; System Design, covering the database schema, questionnaire flow, and inference procedure; Implementation, in which the web application and Dempster-Shafer inference engine were built; and Testing, comprising functional verification and usability evaluation.

3.2 System Architecture

The application architecture follows a linear consultation flow: User → Web Interface → Knowledge Base → Evidence Processing → Dempster-Shafer Inference Engine → Recommendation Result. A student interacts with the Web Interface to answer each evidence statement drawn from the Knowledge Base; each answer is passed through Evidence Processing, which retrieves the belief value assigned to that evidence for every major it supports; the Dempster-Shafer Inference Engine then combines the new mass function with the running belief accumulated from prior evidence; and the resulting ranked majors, together with their belief and plausibility values, are returned as the Recommendation Result.

3.3 Knowledge Acquisition

The knowledge base was built from structured interviews with Guidance and Counseling teachers and an education practitioner at the partner school, complemented by curriculum documentation and major-profile references. For each major, the experts identified evidence statements across five categories, interest, aptitude, personality, ability, and career goal, and assigned a belief value expressing their confidence that an affirmative answer indicates suitability for that major. The completed knowledge base comprises 275 evidence-linked questions distributed across 55 majors grouped under 21 faculties, with each major represented by five evidence statements on average. Of the 275 statements, 117 were designed as the original single-target indicators for their respective majors, while the remaining 158 were added subsequently to ensure that every one of the 55 majors reached the minimum of five supporting statements. Table 2 presents a diversified 20-item excerpt of this knowledge base, sampled across faculties and evidence categories.

Table 2 records two values for every evidence statement, and they have different roles. The value m is the basic belief mass: it is elicited from the experts as the degree to which an affirmative answer, taken alone, supports the associated major, and it is the only quantity that enters Dempster's rule of combination in Equation (1). The column Pl. gives the plausibility assigned by the experts to the same statement, that is, the highest credibility the statement may lend to the major when nothing the student reports contradicts it. Plausibility is therefore never smaller than m, and in this excerpt the difference Pl. − m is either 0.08 or 0.10, which corresponds to the share of mass the experts chose not to commit to the major. During inference the belief and plausibility of a major are not read from the table but are derived from the combined mass function: for a single major A, $Bel(A) = m(A)$ and $Pl(A) = m(A) + m(\Theta)$, consistent with the general relation $Pl(A) = 1 - Bel(\neg A)$ in evidence theory [19]. This is why the plausibility of the combined result in Section 3.4 equals the belief plus the residual mass assigned to Θ, whereas the Pl. values listed in Table 2 are the experts' upper bounds for single statements and are not used as additional input to the combination.

Table 2. Diversified 20-Item Excerpt of the Dempster-Shafer Knowledge Base

Code	Faculty	Major	Category	Evidence Statement	m	Pl.
P0001	Kedokteran	Kedokteran	Career goal	I want to help heal sick people	0.90	**0.98**
P0014	Farmasi	Farmasi	Aptitude	I have a natural inclination toward pharmacy-related tasks	0.80	**0.90**
P0027	Kedokteran Hewan	Kedokteran Hewan	Career goal	I aspire to become a veterinarian	0.85	**0.93**
P0040	Teknik	Teknik Mesin	Personality	My character fits working in Mechanical Eng.	0.72	**0.82**
P0053	Teknik	Arsitektur	Interest	I enjoy content about Architectural design	0.80	**0.90**
P0066	Teknik	Teknik Perkapalan	Interest	I am interested in shipping and marine transport	0.87	**0.95**
P0071	Ilmu Komputer	Informatics Eng.	Interest	I am interested in building applications, websites, or software	0.90	**0.98**
P0079	Ilmu Komputer	Sistem Informasi	Aptitude	I have a natural inclination toward Information Systems	0.80	**0.90**
P0092	Geografi & Perencanaan	Perenc. Wilayah & Kota	Career goal	I want to work as an urban planner	0.78	**0.86**

P0105	Ekonomi & Bisnis	Akuntansi	Career goal	I aspire to build a career in accounting	0.72	**0.82**
P0118	Ekonomi & Bisnis	Perbankan & Keuangan	Ability	I easily understand Financial Management topics	0.80	**0.90**
P0131	Pendidikan	Pendidikan Matematika	Aptitude	I enjoy explaining math concepts simply	0.86	**0.94**
P0144	Pendidikan	Bimbingan & Konseling	Aptitude	People often say I am talented in this area	0.76	**0.86**
P0157	MIPA	Matematika	Aptitude	I enjoy solving complex mathematics problems	0.76	**0.84**
P0170	MIPA	Kimia	Career goal	I aspire to build a career in chemistry	0.72	**0.82**
P0183	MIPA	Aktuaria	Interest	I enjoy content about Actuarial Mathematics	0.80	**0.90**
P0196	Ilmu Sosial & Politik	Hubungan Internasional	Interest	I am interested in global affairs and diplomacy	0.88	**0.96**
P0209	Ilmu Sosial & Politik	Ilmu Politik	Aptitude	People often say I am talented in this area	0.76	**0.86**
P0222	Ilmu Budaya	Sastra Indonesia	Career goal	I want to become a writer or editor	0.72	**0.80**
P0248	Pertanian	Kehutanan	Ability	I easily understand Silviculture topics	0.80	**0.90**

3.4 Dempster-Shafer Calculation

The frame of discernment Θ is defined as the set of all majors in the knowledge base. For each evidence item, the belief value assigned by the expert becomes the mass toward its supported major, while the remaining mass is assigned to Θ as unresolved uncertainty. Successive evidence is combined with Equation (1): when two evidence items support the same major, the intersection term captures their agreement, while the two cross terms carry forward mass through each function's residual Θ. As a demonstration using real values from the knowledge base, Table 3 traces the combination of five evidence items associated with the major Teknik Informatika (P0071 to P0075, belief values 0.90, 0.80, 0.72, 0.80, and 0.76 respectively) for a student who answered all five affirmatively.

For the first evidence, m1(Teknik Informatika) = 0.90 and m1(Θ) = 1 − 0.90 = 0.10. For the second, m2(Teknik Informatika) = 0.80 and m2(Θ) = 1 − 0.80 = 0.20. Because both pieces of evidence support the same major, there is no conflict (K = 0), so Equation (1) reduces to the sum of three products: the product of the two masses supporting Teknik Informatika, the product of the first mass with the second evidence's residual Θ, and the product of the first evidence's residual Θ with the second mass:

$$m12(\text{Teknik Informatika}) = (0.90 \times 0.80) + (0.90 \times 0.20) + (0.10 \times 0.80) = 0.72 + 0.18 + 0.08 = 0.98 \quad (2)$$

With residual m12(Θ) = 0.10 × 0.20 = 0.02. This combined belief of 0.98 becomes the running mass m1 for the next combination with the third evidence (m = 0.72), and the same substitution into Equation (1) is repeated through the fifth piece of evidence, each time treating the previous step's combined belief and residual Θ as the first evidence and the newly answered statement as the second. Table 3 lists the resulting belief and Θ after each of the five combination steps.

Table 3. Worked Example of Dempster-Shafer Combination (Teknik Informatika)

Step	Evidence Combined	Belief	Theta
1	P0071 - Interest in building applications/websites	0.9000	0.1000
2	P0072 - Aptitude for logic and algorithms	0.9800	0.0200
3	P0073 - Career goal in technology/startups	0.9944	0.0056
4	P0074 - Ability in Algorithms & Programming	0.9989	0.0011
5	P0075 - Personality fit for Informatics Eng.	0.9997	0.0003

After the fifth evidence is combined, the belief toward Teknik Informatika reaches 0.9997 with a residual θ of 0.0003, giving a plausibility of 1.0000. This illustrates how belief converges toward the upper bound as consistent evidence accumulates, while the interval between belief and plausibility narrows correspondingly, and how the system would report a lower, more cautious confidence for a student who answers only one or two of the five statements affirmatively rather than all five. In the deployed system, each knowledge-base statement is presented to the student as a binary Yes/No item rather than a graded scale: an affirmative answer contributes the evidence's full expert-assigned belief value to the combination step described above, while a negative or skipped answer contributes no mass toward that major, so the combined belief for a given major reflects exactly the subset of its five statements that the student affirmed.

The example above involves agreeing evidence only, so K = 0. To show how the engine behaves when answers favor different majors, consider a student who affirms P0071 (interest in building applications, m = 0.90 for Teknik Informatika, abbreviated TI) and P0079 (aptitude for information systems, m = 0.80 for Sistem Informasi, abbreviated SI). Then m1({TI}) = 0.90, m1(Θ) = 0.10, m2({SI}) = 0.80, and m2(Θ) = 0.20. Because TI and SI are different majors, their intersection is empty, and the product of their masses is the conflict factor:

$$K = 0.90 \times 0.80 = 0.72 \quad (3)$$

The remaining unnormalized products are 0.90 × 0.20 = 0.18 for TI, 0.10 × 0.80 = 0.08 for SI, and 0.10 × 0.20 = 0.02 for Θ. Dividing each by 1 − K = 0.28 gives:

$$m12(\{TI\}) = 0.6429,\ m12(\{SI\}) = 0.2857,\ m12(\Theta) = 0.0714 \quad (4)$$

The belief–plausibility intervals are therefore [0.6429, 0.7143] for TI and [0.2857, 0.3571] for SI. Unlike the agreeing case, where the residual mass was 0.02, the residual here is 0.0714 and the two majors remain separated by a wide margin of uncertainty, so the result signals that the student's answers are divided. If the student then affirms a third statement that favors TI (P0072, m = 0.80), combining it with the result in (4) gives K = 0.2286, m({TI}) = 0.9074, m({SI}) = 0.0741, and m(Θ) = 0.0185. The major backed by more evidence therefore overtakes its competitor, while the earlier conflict has shaped the outcome instead of being discarded. A large K also means that normalization removes much of the mass, and when K approaches 1 the normalized result can become counterintuitive [26]; a high conflict value should accordingly be read as a warning that the combined belief rests on a small, weakly agreeing portion of the evidence.

3.5 System Implementation

The system, named Peta Kampus, was implemented as a web application using native PHP without a third-party MVC framework, with MySQL as the relational database management system and XAMPP as the local development and testing server. The codebase separates controllers, models, and views following an MVC pattern, with a dedicated core module containing the Router, base Controller, base Model, and the DempsterShafer inference class, and a helpers module providing supporting functions such as PDF export and e-mail notification. The relational schema stores questions, evidence, inference rules linking evidence to majors with belief and plausibility values, majors, faculties, and consultation results, allowing the knowledge base to be maintained by an administrator without altering application code.

The public-facing interface presents a homepage describing the consultation process, a sequential questionnaire in which each evidence statement is answered Yes or No, and a result page reporting the ranked majors together with their belief and plausibility values and descriptive information such as typical curriculum focus and career pathway. An administrator dashboard, accessible after authentication, provides management of questions, evidence, inference rules, majors, faculties, partner universities, and student consultation history. Figures 1 to 4 present the implemented interface.

3.6 Testing Method

System evaluation combined three complementary methods: Black Box Testing, to verify that each functional module behaves as expected independent of its internal code structure; an accuracy comparison against the judgment of three independent evaluators (the school principal and two guidance and counseling teachers, anonymized as Evaluator 1-3), each reviewing the same set of 30 consultation cases; and a User Acceptance Test (UAT) administered to 30 students who completed the consultation process, using a five-item, five-point Likert-scale questionnaire.

4. RESULT AND DISCUSSIONS

4.1 Functional Testing

Black Box Testing was used to verify that each functional module of Peta Kampus behaves according to its specification, independent of its internal code structure. Table 4 lists all 15 tested functional scenarios, spanning authentication, the consultation flow, the Dempster-Shafer inference process, data persistence, and administrator functions, together with the expected result for each and the corresponding status recorded from the testing session; all 15 scenarios matched their expected result, yielding a 100% functional pass rate.

Table 4. Black Box Testing Result

No	Module	Expected Result	Status
1	Access the web application	Homepage displayed correctly	Passed
2	User registration/login	System authenticates and redirects to dashboard	Passed
3	Start consultation process	Questionnaire page displayed	Passed
4	Answer recommendation questions	Responses stored successfully	Passed
5	Validate incomplete questionnaire	Validation warning displayed	Passed
6	Dempster-Shafer inference process	Evidence calculation executed correctly	Passed
7	Recommendation generation	Recommended major displayed	Passed
8	Display confidence value	Confidence level shown	Passed
9	Database data storage	User data and results stored	Passed
10	Access consultation history	Previous records displayed	Passed
11	Admin manages question database	Knowledge base updated	Passed
12	Admin manages recommendation rules	Rules updated	Passed
13	Invalid input handling	Invalid input rejected	Passed

14	Responsive interface testing	Interface adapts to screen size	Passed
15	Logout functionality	Session terminated	Passed

4.2 Accuracy Validation Against Expert Judgment

Table 5 reports the accuracy of the system's recommendations compared with the independent judgment of three evaluators, each reviewing 30 consultation cases. The evaluators are anonymized as Evaluator 1-3 to protect personal identity. A recommendation was counted as a match when the top-ranked recommendation produced by the system coincided with the recommendation that the evaluator reached independently after reviewing the same student's questionnaire responses; any other outcome was counted as a mismatch. The same 30 consultation cases were presented to all three evaluators, so Table 5 reflects three independent judgments of an identical case set. The accuracy of each evaluator is the number of matches divided by 30, and the average is the mean of the three evaluator-level results. Because this figure is a raw percentage of agreement, it is not corrected for chance agreement, and a chance-corrected statistic such as Fleiss' kappa would be a useful addition in a larger evaluation.

Table 5. Accuracy Validation Results

Evaluator	Cases	Match	Accuracy (%)
Evaluator 1 (Principal)	30	27	90.00
Evaluator 2 (BK Teacher)	30	28	93.33
Evaluator 3 (BK Teacher)	30	26	86.67
Average	30	27	90.00

The average accuracy of 90% indicates that the system's Dempster-Shafer-based recommendations align closely with the professional judgment of school counselors and the principal, supporting its use as a decision-support tool rather than a fully autonomous decision-maker. The small proportion of mismatches, on average three out of 30 cases, is consistent with the expected behavior of an evidence-based system: cases with closely competing belief values across two or more majors are inherently more sensitive to differences between the system's fixed evidence weights and an individual evaluator's holistic, context-aware judgment.

4.3 User Acceptance Test

Usability and satisfaction were evaluated through a User Acceptance Test using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), administered to 30 students who used the consultation feature. Table 6 lists the evaluated statements together with the resulting mean score and percentage.

Table 6. Student Satisfaction Evaluation (n = 30)

Statement	Mean Score	Percentage
The application is easy to use	4.77	95.3%
The questions are easy to understand	4.63	92.7%
The recommendation matches my interest	4.73	94.7%
The result helps me in choosing a major	4.80	96.0%
Overall satisfaction with the system	4.77	95.3%
Overall average	4.74	94.8%

4.4 Discussion

Relative to the Forward-Chaining- and Certainty-Factor-based systems summarized in Table 1, the Dempster-Shafer approach used in Peta Kampus differs in three respects that are visible directly in Table 3 and Table 5. First, belief and plausibility are tracked as a bounded interval rather than collapsed into a single confidence figure, so a recommendation supported by only one or two evidence items can be distinguished from one supported by extensive, consistent evidence, as shown by the narrowing gap between belief and plausibility across the five combination steps in Table 3. Second, the explicit conflict term in Equation (1) allows the engine to register when a student's answers point toward genuinely competing majors rather than resolving the ambiguity silently in favor of whichever rule is evaluated first, which is how a Forward-Chaining rule chain typically behaves [1][4][2]. Third, because each evidence item is drawn from a single knowledge base spanning 55 majors rather than a fixed decision tree limited to a handful of streams, the same inference procedure applies uniformly across a substantially wider set of candidate majors than the binary or small-category classification reported in several of the compared studies[3][9][3].

The 100% Black Box pass rate confirmed in Table 4, the 90% average accuracy against expert judgment in Table 5, and the 94.8% overall User Acceptance Test score in Table 6 together indicate that these design advantages translate into a system that is functionally reliable, analytically sound, and well received by its student users. This pattern is broadly consistent with findings from other evidence-theoretic and AI-driven decision-support studies in education and related domains, which similarly report that

uncertainty-aware reasoning produces recommendations that are both more transparent and more favorably evaluated by end users than single-score alternatives [12][24][25].

4.5 Interpreting Recommendation Confidence and Use as Decision Support

The belief value reported for a major should be read as a measure of how strongly the student's answers agree with the weights stored in the knowledge base, not as the probability that the student will be admitted to, or succeed in, that major. Because evidence accumulates, belief rises quickly whenever consistent statements are affirmed: in Table 3 a value of 0.9997 was reached after five statements. A high belief value is therefore expected for any major whose supporting statements are largely affirmed, and by itself it does not show that this major is better suited than another.

When several majors obtain similarly strong results, we suggest that students and counselors compare three quantities rather than the belief value alone: the margin between the highest-ranked majors; the width of the belief–plausibility interval, which equals the residual mass $m(\Theta)$ and narrows as more statements are answered, so that it indicates how much evidence stands behind a result; and the number of statements actually affirmed for each major. Majors that are closely ranked and backed by a comparable number of answers are best treated as a shortlist of options to be discussed, not as a single winner. A student who answered only the minimum of ten items should likewise expect wider intervals and read the ranking with more caution. This guidance follows from the properties of the combination rule shown in Section 3.4 and has not been tested against fixed numerical thresholds.

Peta Kampus is designed as decision support that prepares a counseling conversation, not as a replacement for it. The ranked list, the belief and plausibility values, and the consultation code can be exported to PDF so that a counselor can discuss them with the student together with information the system does not capture, such as academic grades, admission-test performance, program capacity, family circumstances, and the student's own reservations. Where the counselor's judgment differs from the system output, the counselor's judgment should prevail. The 90% agreement in Table 5 indicates that the two usually coincide; it does not indicate that the system could stand in for professional counseling, and because the evaluation involved 30 cases at a single partner school, the figures cannot yet be generalized to other schools or student populations. The use of AI-driven tools as decision support in educational and career guidance is also discussed in the recent literature [24].

4.6 System Implementation

Figures 1 to 4 present the implemented Peta Kampus interface, from the public-facing homepage through the diagnostic questionnaire to the final recommendation output, together with the administrator panel used to maintain the knowledge base.

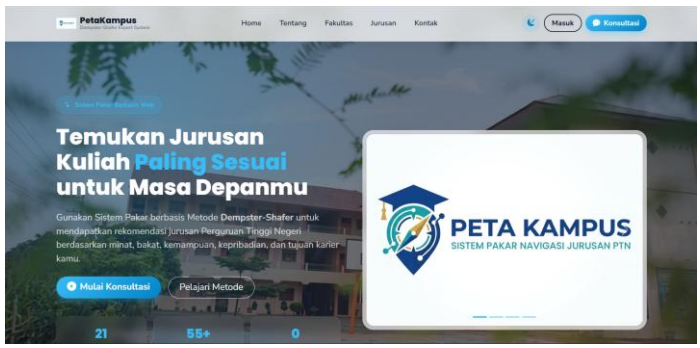


Figure 1. Peta Kampus homepage, presenting the system's coverage of 21 faculties and 55+ majors.

The homepage summarizes the scope of the knowledge base and provides direct access to the consultation flow, either as a registered student account, which stores consultation history for later reference by the student and by the school's guidance counselors, or as a guest, which supports immediate one-off use without requiring account creation.

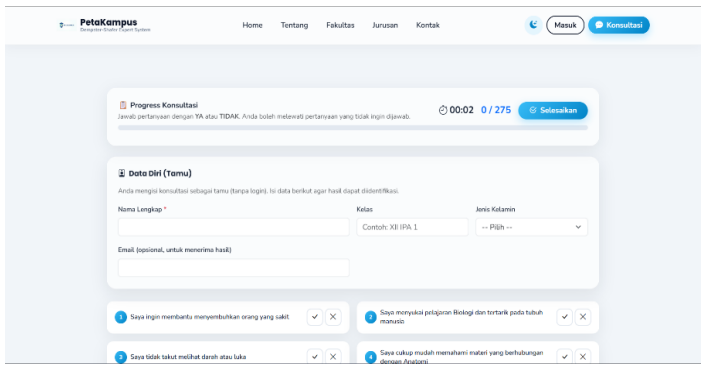


Figure 2. Diagnostic questionnaire interface, showing progress tracking and a Yes/No response format.

During consultation, the system presents each of the 275 evidence items as a Yes/No question, together with a live progress indicator and an optional timer; a student may skip a question they do not wish to answer and is only required to answer a minimum of ten items before the consultation can be finalized. A guest consultation additionally collects basic respondent information (name, class, gender, and an optional e-mail address) so that the result can be personalized and, if desired, sent to the respondent, without requiring full account registration.

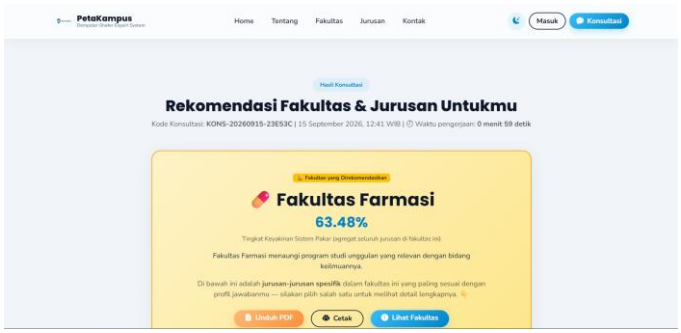


Figure 3. Recommendation output, displaying the recommended faculty with its aggregate confidence score.

The recommendation page reports the top-ranked faculty together with its aggregate confidence score, and allows the student to drill down into faculty-specific major recommendations with their individual belief and plausibility values. Each consultation is assigned a unique consultation code and timestamp, and results can be exported to PDF or printed for use in an in-person counseling discussion.

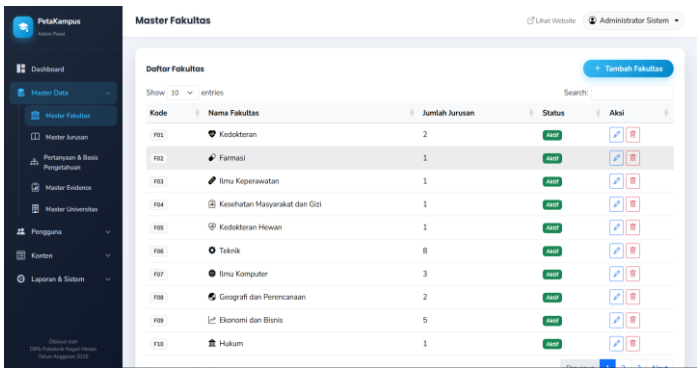


Figure 4. Administrator panel (Master Fakultas), confirming the 21 faculties encoded in the knowledge base.

The administrator panel allows a non-technical administrator to maintain the faculty, major, question, and rule data that constitute the knowledge base without modifying application code, which is essential for keeping the recommendation content current as curricula and admission pathways change over time.

5. CONCLUSSION

This study developed and implemented Peta Kampus, a web-based expert system that applies Dempster-Shafer evidence theory to generate personalized PTN major recommendations for senior high school students. The knowledge base, built with Guidance and Counseling teachers and an education practitioner, encodes 275 evidence-linked questions across 55 majors under 21 faculties, and the inference engine combines successive student evidence through Dempster's rule of combination while explicitly tracking belief, plausibility, and evidentiary conflict. The worked examples in Section 3.4 confirm that the inference engine aggregates consistent evidence toward a converging belief value and registers conflicting evidence through the factor K and the functional testing reported in Table 4 confirms that all tested modules behave according to specification. The accuracy validation against three independent evaluators (Table 5) and the User Acceptance Test administered to 30 students (Table 6) show that the system's recommendations align with expert judgment in 90% of cases on average and are received favorably by students, with an overall satisfaction score of 94.8%.

The main limitation of this study is that expert-assigned belief and plausibility weights are currently fixed rather than adaptively learned from outcome data, and evaluation was conducted at a single partner school with 30 cases, so the reported 90% agreement is a raw, non-chance-corrected figure and should not be treated as a general accuracy estimate. The system is intended to inform, not replace, professional counseling. Future work includes expanding the knowledge base with additional expert-validated evidence beyond the current 275 questions, integrating a machine-learning component that can refine belief weights from accumulated consultation data over time, and extending validation to a larger and more diverse set of partner schools.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the Centre for Research and Community Service (P3M) of Politeknik Negeri Medan for administrative and financial support of this research by contract number B/417/PL5/PT.01.05/2026, and Yayasan Sinergi Inspirasi Indonesia as the partner institution for the applied phase of this research programmer.

REFERENCES

[1] J. Kurniawan, S. Defit, and Y. Yuhandri, "Sistem Pakar dalam Mengidentifikasi Minat Vokasi Menggunakan Metode Certainty Factor dan Forward Chaining," *J. Sistim Inf. dan Teknol.*, vol. 3, pp. 76–81, 2021, doi: 10.37034/jsisfotek.v3i2.47.

[2] S. Allaisya *et al.*, "Implementasi Metode Forward Chaining untuk Rekomendasi Jurusan Perguruan Tinggi Berdasarkan Minat dan Bakat MA XYZ," vol. 13, no. 1, pp. 94–103, 2026, doi: 10.30865/jurikom.v13i1.9463.

[3] A. Wicaksa Putra Pribadi, H. Maulana, and F. Prima Aditiawan, "Sistem Pakar Pemilihan Jurusan Sma (Ipa Dan Ips)," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 3, pp. 4070–4077, 2024, doi: 10.36040/jati.v8i3.9850.

[4] Mohamad Akbar Wisnu Nadyanto, Muhammad Varriel Avenazh Nizar, and Aaqila Dhiyaanisafa Goenawan, "Penentuan Jurusan Kuliah Menggunakan Metode Forward Chaining Berbasis Web," *J. Tek. Mesin, Ind. Elektro Dan Inform.*, vol. 1, no. 2, pp. 45–51, 2022, doi: 10.55606/jtmei.v1i2.782.

[5] K. Kuntari and A. Nurbaini, "STRATEGI PENGGUNAAN MODEL PEMBELAJARAN DIGITAL UNTUK MENINGKATKAN KOMPETENSI GURU DI SDN DEWI SARTIKA," vol. 12, no. 2, pp. 732–745, 2025.

[6] D. Abdurahman and Nunu Nurdiana, "Perancangan metode Certainty Factor untuk diagnosa Gagal Ginjal Kronis," *INFOTECH J.*, pp. 1–8, 2021, doi: 10.31949/infotech.v7i2.1314.

[7] A. Azizah and A. Rohman, "Certainty Factor pada Sistem Pakar Diagnosis Penyakit Anak," *J. Tek. Inform. Unis*, vol. 11, no. 1, pp. 64–75, 2023.

[8] Y. E. B. Mawartika and M. Guntur, "Implementasi Case Based Reasoning Dalam Sistem Pakar Untuk Merekomendasikan Jurusan Kuliah Implementation of Case Based Reasoning in Expert System to Recommend College Majors," *Cogito Smart J.*, vol. 8, no. 2, pp. 295–307, 2022.

[9] Marten Sudi, Gergorius Kopong Pati, and Lidia Lali Momo, "Implementasi Data Mining Prediksi Perminatan Jurusan Siswa pada SMK Negeri 1 Waikabubak dengan Metode Algoritma C4.5," *Neptunus J. Ilmu Komput. Dan Teknol. Inf.*, vol. 2, no. 4, pp. 66–72, 2024, doi: 10.61132/neptunus.v2i4.410.

[10] J. T. Mesin, E. Informatika, P. Studi, T. Informatika, F. Teknik, and U. I. Pgri, "Implementasi Metode Forward Chaining pada Sistem Pakar Pemilihan Jurusan Sekolah Menengah Atas Senna Hendrian Handoko (2021), dengan judul Sistem Pakar Diagnosa Penyakit Selama Kehamilan Menggunakan Metode Forward Chaining Berbasis Web , Hasil Penelitia," vol. 4, 2025.

[11] T. Nizam, S. Zafar, S. S. Biswas, and I. Hussain, "Interpretability-driven Course Recommendation : A Random Forest Approach with Explainable AI," pp. 1–21, 2026, doi: 10.2174/0123520965401121250714075403.

[12] A. Sah, N. Heriyani, R. J. Rumandan, and M. M. Lasiyono, "Pengembangan Sistem Pakar Diagnosis Jenis Stres Menggunakan Pendekatan Dempster-Shafer Theory," vol. 4, no. 2, pp. 302–312, 2025, doi: 10.47065/comforch.v4i2.1941.

[13] N. Nurdin, E. Susanti, H. A.-K. Aidilof, and D. Priyanto, "Comparison of Naive Bayes and Dempster Shafer Methods in Expert System for Early Diagnosis of COVID-19," *MATRIK J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 22, no. 1, pp. 215–228, 2022, doi: 10.30812/matrik.v22i1.2280.

[14] R. Ginting, F. Riandari, and I. Sulistianingsih, "Perbandingan Metode Teorema Bayes dan Dempster Shafer Menentukan Status Gunung Berapi," vol. 5, pp. 802–810, 2025.

[15] H. Shiraishi, H. Ishibuchi, and M. Nakata, "A Class Inference Scheme with Dempster – Shafer Theory for Learning Fuzzy-Classifier Systems," *ACM Trans. Evol. Learn. Optim.*, vol. 6, no. 1, 2026, doi: 10.1145/3717613.

[16] T. Palilingan *et al.*, "Expert System for Learning Styles Diagnosis Using Dempster – Shafer and Bayesian Network," vol. 11, no. 1, pp. 126–139, 2025.

[17] T. Junaidi, "Sistem Pakar dengan Metode Certainty Factor dalam Analisis Penyakit Herpes Zoster pada Manusia," *J. Inf. dan Teknol.*, vol. 3, pp. 58–65, 2020, doi: 10.37034/jidt.v3i2.92.

[18] S. A. Azizah, A. Usman, M. Ali, and E. Rosita, "Analisis Gaya Belajar Siswa Pembelajaran Berdeferensiasi dalam Menerapkan," no. 2, pp. 1–12, 2023.

[19] F. A. Pratama and P. Herdian, "An IoT-Based Building Fire Detection System Using Machine Learning for False Alarm Classi ication," vol. 3, pp. 1–7, 2026.

[20] Y. Tang, Y. Zhou, X. Ren, Y. Sun, and Y. Huang, "OPEN A new basic probability assignment generation and combination method for conflict data fusion in the evidence theory," *Sci. Rep.*, pp. 1–18, 2023, doi: 10.1038/s41598-023-35195-4.

[21] N. Fang and J. Cui, "SS symmetry An Improved Dempster – Shafer Evidence Theory with Symmetric Compression and Application in Ship Probability," 2024.

[22] Z. Liu, Y. Cao, X. Yang, and L. Liu, "Communications in Statistics - Theory and Methods A new uncertainty measure via belief Rényi entropy in Dempster-Shafer theory and its application to decision making," *Commun. Stat. - Theory Methods*, vol. 00, no. 00, p. 0, 2023, doi: 10.1080/03610926.2023.2253342.

[23] Z. Zhang, H. Wang, J. Zhang, and W. Jiang, "A New Correlation Measure for Belief Functions and Their," pp. 1–23, 2023.

[24] E. Rasca, A. Villa, A. Maddalena, and G. Boccuzzi, "Machine learning for post-diploma educational and career guidance : a scoping review in AI-driven decision support systems," no. May, pp. 1–15, 2025, doi: 10.3389/feduc.2025.1578979.

[25] I. Assylzhan, M. Muratbekova, D. Amangeldi, N. Oryngozha, and A. Ogorodova, "Intelligent System for Assessing University Student Personality Development and Career Readiness," pp. 1–8, 2023.