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Decision support system for VARK learning style recommendation using AHP and SAW methods

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ABSTRACT

To establish an objective mechanism for recommending tailored educational approaches, this research focuses on the architectural design of a DSS grounded in the VARK framework, which classifies preferences into visual, auditory, textual, and physical modalities. The operational framework combines AHP and SAW to eliminate subjectivity from the evaluation process. While the extraction of criteria importance factors relied on AHP, utilizing qualitative insights from a psychometrics expert in the field of psychology, the subsequent prioritization of pedagogical options was executed via SAW. Four core dimensions formed the basis of this evaluation, specifically focusing on how individuals perceive stimuli, process information, select instructional materials, and adapt to environmental settings. The initial matrix derivation yielded uniform importance coefficients of 0.25 across all dimensions, supported by a CR of 0 to verify the logical coherence of the expert input. Structurally, the platform was deployed as a responsive web system powered by the Laravel architecture and backed by a MySQL database engine. To confirm computational integrity, the algorithmic outputs generated by the software were audited against traditional manual calculations, resulting in a perfect mathematical alignment. Consequently, the empirical evidence confirms that the engineered DSS offers a precise diagnostic tool, thereby enabling learners to discover optimal educational pathways that correspond directly with their psychological profiles.

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1. INTRODUCTION

The rapid development of information technology has transformed the educational landscape by enabling more adaptive and personalized learning systems [1, 2]. In modern education, students are no longer considered passive recipients of information, but active learners with different preferences in absorbing and processing knowledge [1, 3]. One widely used model to understand these differences is the VARK learning style model, which classifies learners into Visual, Auditory, Read/Write, and Kinesthetic categories [4, 5]. Previous studies show that integrating learning style concepts into digital learning environments can improve personalization and learning effectiveness [6, 7].

However, many educational systems still apply a uniform learning approach without considering individual learning preferences [3, 7]. This limitation reduces the effectiveness of learning because students may struggle when instructional materials do not match their preferred learning styles. In addition, traditional identification of learning styles using questionnaires often leads to subjective interpretation and lacks automation in decision-making [8]. Therefore, a more structured and intelligent approach is required to support accurate and consistent learning style identification [9].

The landscape of academic literature reveals a strong interest in utilizing computational frameworks to identify and suggest optimal educational preferences. Investigating student behavioral patterns and forecasting cognitive orientations has frequently relied on machine learning models and classification paradigms [6, 8]. Concurrently, the creation of adaptive educational platforms focuses on tailoring instructional materials to individual profiles using frameworks like the VARK taxonomy. Scholars have also highlighted that merging semantic recommendation engines with established learning style models significantly improves individualized instructional interactions within digital spaces [10].

Beyond mere predictive tasks, algorithmic selection tools have found extensive utility within educational frameworks [11]. The resolution of intricate evaluation challenges that involve competing parameters and diverse choices often utilizes a DSS [9, 12]. Extant literature underscores that MultiCriteria Decision Making (MCDM) strategies, specifically AHP and SAW, offer a highly organized and unbiased approach to balancing specific variables and prioritizing options. Consequently, these computational techniques have been heavily integrated into academic administrative software, optimizing processes such as grant allocation, student assessment, and institutional path selection [13, 14]. A systematic evaluation architecture emerges when combining AHP and SAW, where the former establishes the relative importance coefficients of specific variables, and the latter calculates the final performance scores to rank the available options [11]. Empirical evidence demonstrates that synthesizing these two methodologies leads to a substantial increase in diagnostic precision and logical consistency across various DSS environments.

Accordingly, this integrated approach proves highly effective for addressing multi-attribute problems, including the assignment of personalized study preferences [15]. Driven by these insights, the core objective of this investigation is to engineer a DSS capable of assessing and advising on student VARK configurations by deploying the AHP and SAW algorithms. The resulting platform is designed to deliver unbiased, structured, and highly precise guidance aligned with individual cognitive traits. By embedding multi-attribute selection methodologies into established pedagogical theories, this study adds valuable perspective to the evolution of responsive, personalized learning environments.

2. RESEARCH METHODS

This segment delineates the structured operational blueprint used to construct the diagnostic DSS designed for educational path guidance. The foundational framework incorporates the overarching investigative structure, the identification of evaluation parameters and choices, weight calculation via AHP, priority ordering via the SAW protocol, the structural layout of the application, and the comprehensive logic of the underlying code [16, 17]. The following subsections offer granular technical insights to guarantee that the experimental setup can be accurately replicated.

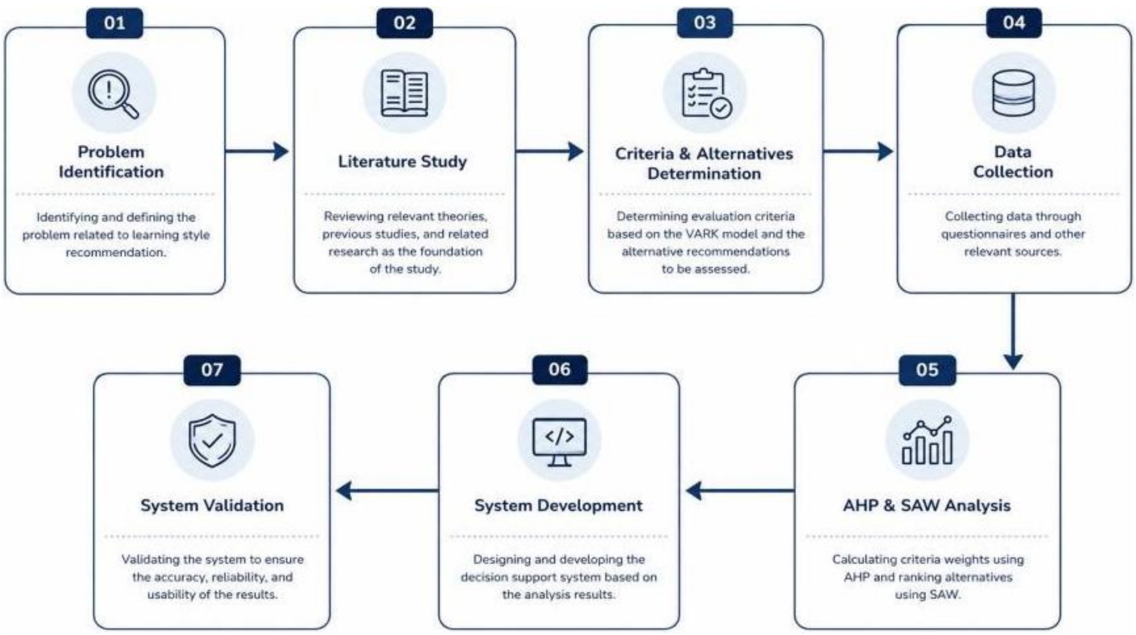

Figure 1. Research design flowchart.

2.1. Research Design

The engineering of the VARK-based DSS was executed through a rigorous, multi-phase developmental framework. The process moved sequentially through initial problem scoping, a comprehensive survey of existing literature, parameter and choice definition, data acquisition, multiattribute computational processing via AHP and SAW, software development, and empirical system validation [17]. This orderly progression guarantees a methodical development cycle, dedicating the AHP protocol specifically to establishing variable importance scales, while reserving the SAW technique to sort the VARK alternatives based on the unique behavioral tendencies of the user [12].

2.2. Criteria and Alternatives Determination

Four main criteria are defined based on the VARK learning style model: Sensory Preference (SP), Information Processing Method (IPM), Learning Media and Tools (LMT), and Learning Environment and Conditions (LEC). Each criterion is broken down into four sub-criteria, forming the basis for the 16-item questionnaire. The decision alternatives are the four VARK learning styles: Visual, Auditory, Read/Write, and Kinesthetic.

2.3. Data Collection

Data were collected through two methods. First, structured interviews were conducted with Mr. Irwan Nuryana Kurniawan, S.Psi., M.Si., a Psychology lecturer at Universitas Islam Indonesia (UII) Yogyakarta and an expert in psychometrics with more than 10 years of professional experience. The interview was conducted to obtain pairwise comparison judgments among the evaluation criteria using the Saaty 1–9 scale. Second, questionnaires were distributed to 68 active undergraduate students. The questionnaire consisted of 16 statements measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), organized into four sections corresponding to the four evaluation criteria.

2.4. AHP and SAW Analysis

To resolve the optimal educational approach within the VARK taxonomy, this study implements a hybrid decision-making infrastructure using the AHP and SAW algorithms. The role of AHP centers on computing the relative importance vectors of each individual parameter through a structured pairwise matrix evaluation, which removes subjectivity from variable weighting [16, 18]. Conversely, the SAW algorithm manages the final prioritization of the available choices by synthesizing these computed weights with the scaled performance metrics assigned to each option [19]. Merging AHP and SAW establishes an organized evaluative architecture, yielding highly stable and verifiable recommendations for user learning paths [11, 18].

2.4.1. Criteria Weighting with AHP

The determination of parameter importance metrics relies on AHP, which computes weight vectors through an interactive matrix of pairwise assessments. This procedure measures the comparative significance of each distinct variable against another, transforming qualitative expert insights into consistent, mathematical weights [20, 21]. Once validated, these weight distributions serve as foundational parameters for the subsequent alternative ordering phase [11]. The structural archetype of this pairwise comparative matrix is formalized below in Equation (1):

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{1n} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

Description:

A	=	Pairwise comparison matrix in the AHP method.
$a_{11}, a_{12}, \ldots, a_{nn}$	=	Elements in the comparison matrix representing the comparison values between criteria.
N	=	Number of criteria involved in the decision-making process.

The pairwise comparison matrix represents the relative importance among the evaluation criteria based on expert judgments. In the AHP method, experts compare each pair of criteria using the standard 1 – 9 pairwise comparison scale to express their relative importance and calculate the priority weight of each criterion [22]. To ensure the reliability of the evaluation, the consistency of the pairwise comparison matrix is assessed using the Consistency Ratio (CR). A CR value below the acceptable threshold indicates that the judgments are sufficiently consistent and suitable for the subsequent decision-making process [20]. The resulting priority weights are then used as input for the Simple Additive Weighting (SAW) method to rank the available learning style alternatives [22]. Priority weights are calculated using Equation (2).

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad (2)$$

Description:

w_i	=	The weight or priority value of criterion i.
a_{ij}	=	The value of comparison between criterion i and criterion j.
a_{kj}	=	The comparison value of criterion k against criterion j used for normalization.
n	=	The total number of criteria.
i, j, k	=	The index of criteria in the pairwise comparison matrix.

The consistency test is conducted using Equations (3) and (4):

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (3)$$

$$CR = \frac{CI}{RI} \quad (4)$$

where RI is the Random Index (0.90 for n = 4). The calculations yielded λ_{max} = 4.00, CI = 0, and CR = 0, confirming that the expert's assessment is highly consistent (CR < 0.1) [10-12].

Description:

CI	=	Consistency Index value used to measure the consistency level of the pairwise comparison matrix.
λ_{max}	=	The maximum eigenvalue of the pairwise comparison matrix.
n	=	The number of criteria used in the decision-making process.
CR	=	Consistency Ratio value used to determine the consistency level of expert judgments.
RI	=	Random Index value, which represents the average consistency index of randomly generated matrices.
CI	=	Consistency Index value used as the input for calculating the Consistency Ratio.

2.4.2. Ranking with SAW

Following the establishment of parameter vectors via the AHP protocol, the SAW algorithm is deployed to generate the final ordering of choices. This sequence initiates with the formulation of an evaluation matrix that maps the specific performance index of each choice against every defined variable. Subsequently, this matrix undergoes a scaling procedure and is integrated with the pre-calculated variable weights, yielding the comprehensive preference indicators required to isolate the optimal selection [17]. The structural layout of this initial evaluation matrix is formulated below in Equation (5):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{1n} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (5)$$

Description:

X	=	Decision matrix containing the performance values of all alternatives.
x_{ij}	=	Suitability value of the i-th alternative with respect to the j-th criterion.

$i = 1, 2, \ldots, n$ = Index of alternatives.
$j = 1, 2, \ldots, m$ = Index of evaluation criteria.
n = Total number of alternatives.
m = Total number of criteria.

Once the evaluation matrix is established, the data undergoes scale normalization to align the disparate measurement ranges across variables. Given that every parameter in this research operates exclusively as a benefit variable, the normalization process is executed by dividing each specific performance value by the highest recorded value within that respective category, as detailed in Equation (6):

$$r_{ij} = \frac{x_{ij}}{max(x_{ij})} \quad (6)$$

Description:
r_{ij} = Normalized value of the i-th alternative for the j-th criterion.
x_{ij} = Original value of the i-th alternative for the j-th criterion.
$max(x_{ij})$ = Maximum value of the j-th criterion among all alternatives.

The ultimate preference indicator for each choice is determined by synthesizing the scaled, weighted values across all evaluation parameters. This cumulative calculation aggregates the total performance of each option based on the allocated importance coefficients. The mathematical calculation for this preference score is defined below in Equation (7):

$$V_i = \sum_{j=1}^{m} w_j \times r_{ij} \quad (7)$$

Description:
V_i = Preference value of the i-th alternative.
w_j = Weight assigned to the j-th criterion.
r_{ij} = Normalized value of the i-th alternative for the j-th criterion.
$i = 1, 2, \ldots, n$ = Index of alternatives.
$j = 1, 2, \ldots, m$ = Index of evaluation criteria.
n = Total number of alternatives.
m = Total number of criteria.

Based on the calculated preference values, the alternative with the highest score is selected as the final recommended learning style.

2.5. System Development

To deploy the conceptualized DSS, a web application was engineered leveraging the Laravel 8 architecture alongside a MySQL database engine. To optimize system modularity, accommodate future scalability, and ensure ease of maintenance, a decoupled three-tier architectural pattern was implemented [23, 24]. Within this structure, the presentation tier handles user interactions by rendering the VARK diagnostic interface and displaying customized pedagogical paths, while the application tier manages the backend execution of the hybrid AHP and SAW algorithms. The underlying data tier functions as the repository for participant feedback, parameter weights, algorithmic outputs, and core system records. Furthermore, administrative modules were integrated to oversee user profiles and modify evaluation variables, thereby facilitating smooth operational workflows and simplifying future iterative upgrades.

2.6. System Validation

Verification of the platform relied on a dual-layered validation framework. In the first phase, the algorithmic fidelity of the software-driven AHP-SAW pipeline was audited by cross-referencing its outputs with independent spreadsheet computations in Microsoft Excel, utilizing a randomized sample of five users selected from the broader cohort of 68 subjects. This comparative analysis subjected the sample data to identical computational constraints, specifically focusing on matrix scaling, the application of importance vectors, and the calculation of final preference scores. In the second phase, User Acceptance Testing (UAT) was deployed via a five-point Likert instrument to measure empirical metrics surrounding system usability, functional performance, layout aesthetics, semantic clarity, and general user adoption [25]. The empirical data derived from these dual mechanisms are detailed and evaluated in the subsequent analytical sections.

3. RESULTS AND DISCUSSIONS

This section delivers an exhaustive review of the deployed platform alongside an empirical evaluation of its computational performance. The analytical progression covers the matrix derivation of parameter weights via AHP, a step-by-step demonstration of the SAW calculation, a comparative validation mapping software outputs against manual controls, and a statistical overview of the resulting learning style distributions. The segment wraps up with a scholarly critique of these outcomes paired with a structural examination of the live web interface.

3.1. Respondent Profile

An initial demographic assessment was performed to contextualize the cohort participating in the platform evaluation. The primary dataset was gathered from 68 undergraduate students who fully completed the web-based VARK assessment tool. The core demographic variables of this sample group, categorized by gender distribution and current academic standing by semester, are compiled and organized in Tables 1 and 2.

Table 1. Distribution of respondents by gender.

Gender	Frequency	Percentage (%)
Male	43	63.24
Female	25	36.76
Total	68	100

Table 2. Distribution of respondents by academic semester.

Academic semester	Frequency	Percentage (%)
Semester 2	3	4.41
Semester 4	16	23.53
Semester 6	16	23.53
Semester 8	33	48.53
Total	68	100

Tables 1 and 2 summarize the demographic characteristics of the respondents involved in this study. Of the 68 participants, 43 (63.24%) were male and 25 (36.76%) were female. The respondents represented four academic semesters, with the majority coming from the eighth semester (48.53%), followed by the fourth and sixth semesters, each accounting for 23.53%, while second-semester students represented 4.41% of the total sample. The inclusion of respondents from different academic levels provides a diverse range of learning experiences, supporting the evaluation of the proposed decision support system for learning style recommendations.

3.2. AHP Criteria Weight Results

The extraction of parameter importance scales was carried out using the AHP protocol, translating the expert's comparative assessments into distinct numerical weights across the four primary evaluation variables. These direct comparisons utilized the standard Saaty 1 to 9 measurement scale, with the resulting relational matrices processed computationally to isolate the priority vectors and verify the mathematical consistency of the underlying logic. The finalized weight distribution derived from this process is structured and displayed in Table 3.

The empirical data in Table 3 demonstrates that every evaluation variable received a uniform importance coefficient of 0.25, demonstrating that the psychometric specialist viewed Sensory Preference (SP), Information Processing Method (IPM), Learning Media and Tools (LMT), and Learning Environment and Conditions (LEC) as equally critical dimensions for determining optimal pedagogical paths. Additionally, the relational verification process yielded a Consistency Ratio (CR) of 0.00, falling well below the standard validation limit of 0.10. This flawless alignment confirms that the expert's matrix judgments possess total internal consistency, validating their integration into the subsequent SAW prioritization pipeline.

Table 3. Criteria weights from AHP.

Criteria	Weight
Sensory preference (SP)	0.25
Information processing method (IPM)	0.25
Learning media nad tools (LMT)	0.25
Learning environment and conditions (LEC)	0.25

To evaluate the learning style alternatives, a suitability matrix was established based on expert validation by considering the characteristics of each VARK learning style with respect to the four evaluation criteria. Each suitability value represents the degree of correspondence between a learning style alternative and a specific criterion, where higher values indicate stronger suitability. The validated suitability matrix was subsequently used as the decision matrix in the SAW calculation process and is presented in Table 4.

Table 4. Validated suitability matrix for learning style alternatives.

Alternative	SP	IPM	LMT	LEC
Visual	0.9	0.6	0.8	0.5
Auditory	0.5	0.9	0.6	0.6
Read/write	0.6	0.7	0.9	0.7
Kinesthetic	0.8	0.8	0.5	0.9

The suitability values presented in Table 4 were reviewed and validated by the expert to ensure that they appropriately represent the relationship between each VARK learning style and the corresponding evaluation criteria. These validated values served as the input decision matrix for the SAW method to calculate the final preference scores and determine the recommended learning style.

3.3. Distribution of Learning Style Recommendations

The proposed decision support system generated a preference value for each VARK learning style alternative using the AHP-SAW method. The learning style associated with the highest preference value was selected as the final recommendation for each respondent. Table 5 presents the preference values and recommendation results obtained from the system.

Table 5. Preference values and learning style recommendations.

Respondent	Visual	Auditory	Read/write	Kinesthetic	Recommendation
Respondent 1	0.669	0.629	0.695	0.728	Kinesthetic
Respondent 2	0.603	0.570	0.625	0.673	Kinesthetic
Respondent 3	0.479	0.428	0.489	0.505	Kinesthetic
…	…	…	…	…	…
Respondent 68	0.4150	0.3963	0.4338	0.4275	Read/write

To provide an overall summary of the recommendation results, the frequency distribution of the recommended learning styles is presented in Table 6.

As presented in Tables 6, the proposed decision support system successfully generated recommendation scores for all respondents using the AHP-SAW method. The highest preference value determined the recommended learning style for each respondent. Overall, the Kinesthetic learning style was recommended for 65 respondents (96%), while the remaining three respondents (4%) were classified as Read/Write learners. No respondents received Visual or Auditory as their highest-ranked learning style. These findings indicate that the majority of respondents exhibited learning preference characteristics that more closely matched the Kinesthetic alternative according to the predefined evaluation criteria and suitability values used in the proposed decision support system.

Table 6. Distribution of learning style recommendations.

Learning style	Frequency	Percentage (%)
Kinesthetic	65	96
Read/write	3	4
Visual	0	0
Auditory	0	0
Total	68	100

3.4. System Validation

System validation was conducted using two complementary approaches: algorithm validation and User Acceptance Testing (UAT). For algorithm validation, the recommendation results generated by the proposed system were compared with manual calculations performed in Microsoft Excel using five randomly selected respondents. The comparison demonstrated a 100% agreement between the manual calculations and the system-generated recommendations, confirming that the AHP-SAW algorithm was correctly implemented and consistently produced identical recommendation results.

Complementing the verification of the underlying code, UAT was deployed to gauge the empirical usability and operational adoption of the engineered web-based DSS. The feedback loop comprised six distinct participants who evaluated ten specific metrics targeting platform navigation, structural layout, functional execution, diagnostic output precision, and general user satisfaction via a five-point Likert instrument. Statistically, the application attained a mean evaluation score of 4.33 out of 5.00, which translates to a definitive user validation metric of 86.67%, positioning the platform firmly within the Very Good / Highly Accepted classification. A detailed breakdown of these user adoption metrics is compiled below in Table 6.

3.5. Discussion

The AHP analysis assigned equal weights (0.25) to all four evaluation criteria, indicating that the expert considered Sensory Preference, Information Processing Method, Learning Media and Tools, and Learning Environment and Conditions to contribute equally to the learning style recommendation process. This balanced weighting ensures that the recommendation is determined by multiple learning preference aspects rather than being dominated by a single criterion. Furthermore, the recommendation results showed that the majority of respondents were classified as Kinesthetic learners, indicating that their learning preference characteristics more closely matched the Kinesthetic alternative according to the predefined evaluation criteria and suitability values adopted in the proposed decision support system.

The validation results confirmed the correctness and applicability of the proposed system. A 100% agreement between manual calculations and system-generated recommendations verified that the AHP-SAW algorithm was correctly implemented, while the User Acceptance Test achieved an average score of 4.33 out of 5.00 (86.67%), indicating a Very Good / Highly Accepted level of user acceptance. These findings demonstrate that the proposed decision support system is both computationally reliable and well accepted by users for learning style recommendation. Nevertheless, this study was conducted within a single university, and future research is recommended to involve respondents from different institutions and educational backgrounds, as well as multiple experts in determining the suitability values, to further improve the generalizability and robustness of the proposed system.

3.6. System Interface

The developed system provides dedicated interfaces for both end-users and administrators. These interfaces support the learning style recommendation process, respondent data management, and system administration. The main interfaces of the proposed system are presented below.

3.6.1. Home Page

The home page serves as the initial interface of the proposed system and provides users with essential information before beginning the assessment process. It presents a brief introduction to the VARK learning style model, outlines the steps required to use the application, and includes a navigation button that directs users to the questionnaire page.

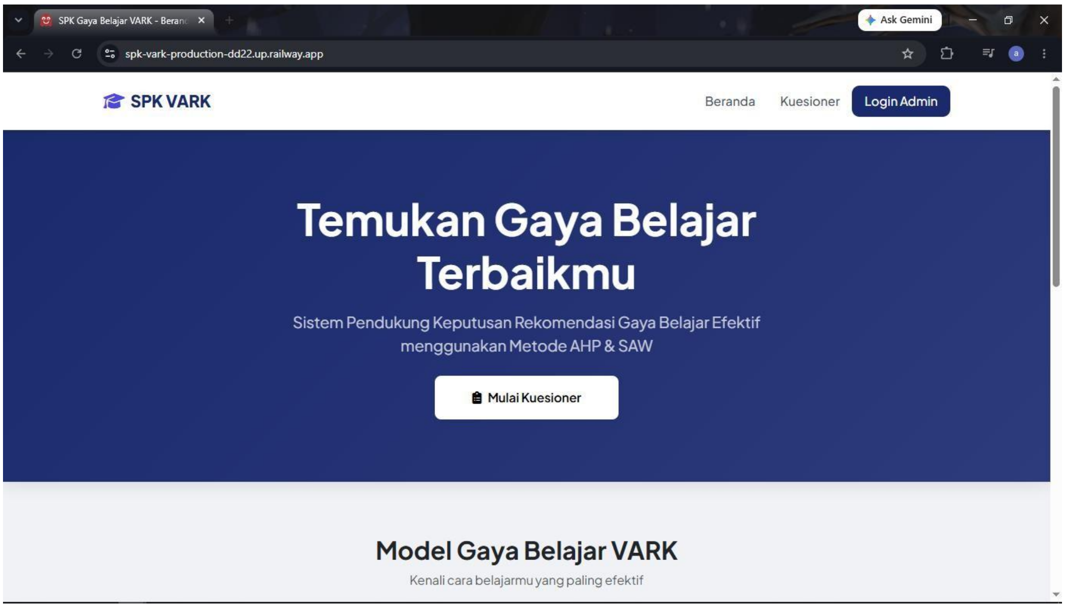

Figure 2. Home page interface-1.

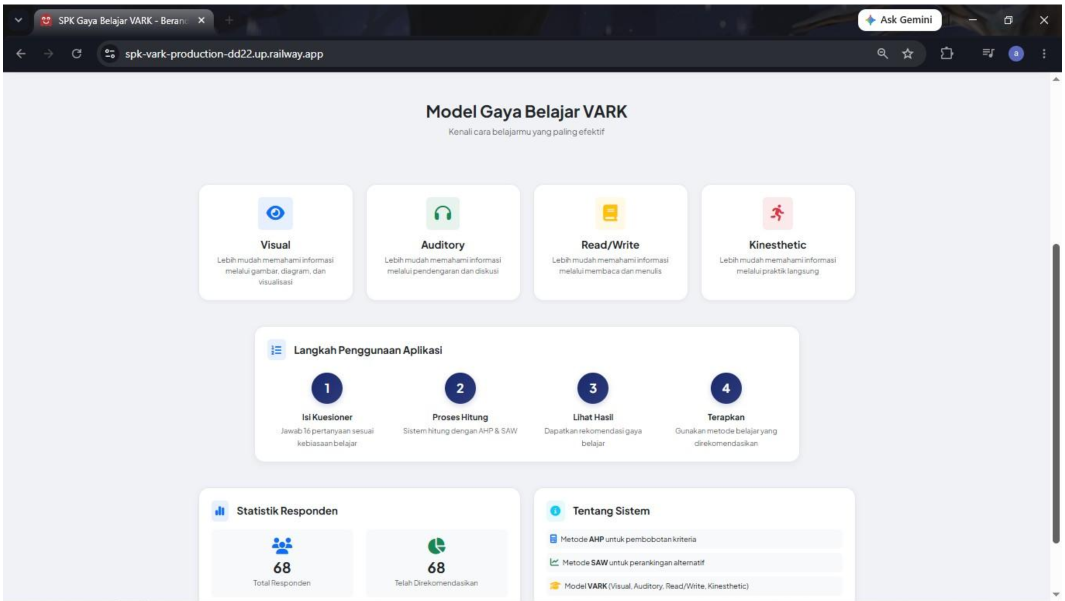

Figure 3. Home page interface-2.

3.6.2. Diagnostic Questionnaire Module

This particular section of the user interface enables individuals to undergo the behavioral assessment via 16 distinct analytical items distributed uniformly across four core variables: Sensory Preference (SP), Information Processing Method (IPM), Learning Media and Tools (LMT), and Learning Environment and Conditions (LEC). Every item prompts a response based on a five-point Likert metric spanning from 1 (Strongly Disagree) to 5 (Strongly Agree), capturing the necessary qualitative dataset to fuel the back-end prioritization engine.

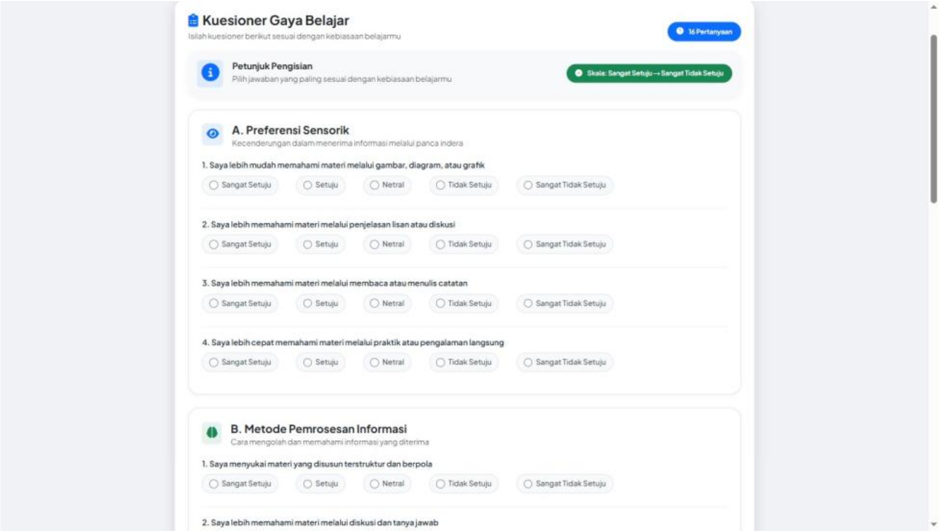

Figure 4. Questionnaire page interface-1.

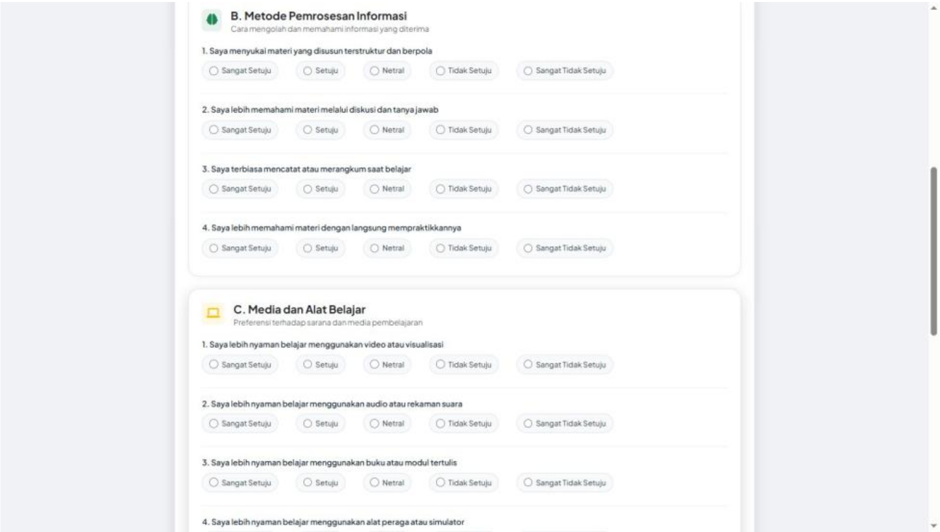

Figure 5. Questionnaire page interface-2.

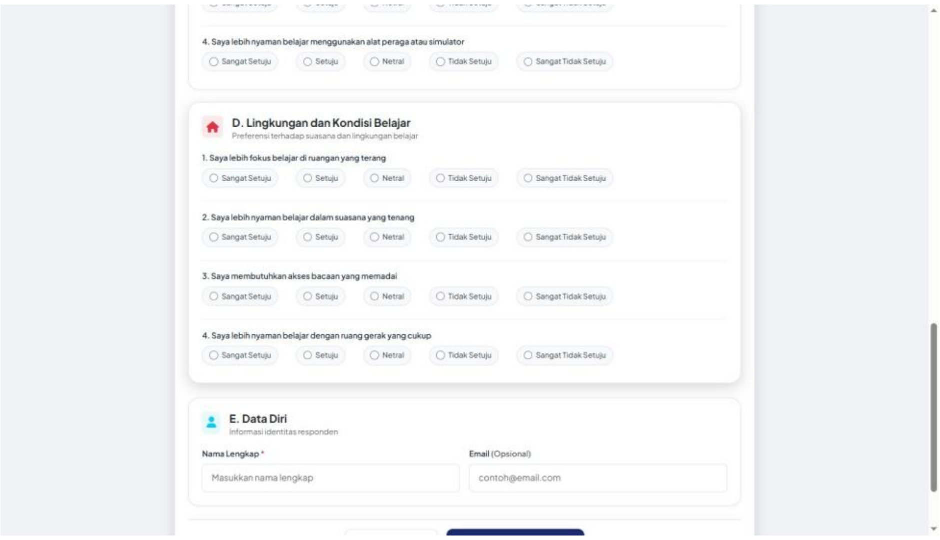

Figure 6. Questionnaire page interface-3.

3.6.3. Recommendation Results Page

The recommendation results page presents the learning style identified as the most suitable for the user based on the AHP–SAW calculation process. It displays the preference values for all learning style alternatives in both numerical and graphical (progress bar) formats, allowing users to compare the relative scores of each alternative. In addition, the page provides a brief description of the recommended learning style together with suggested learning strategies that correspond to the identified learning preference.

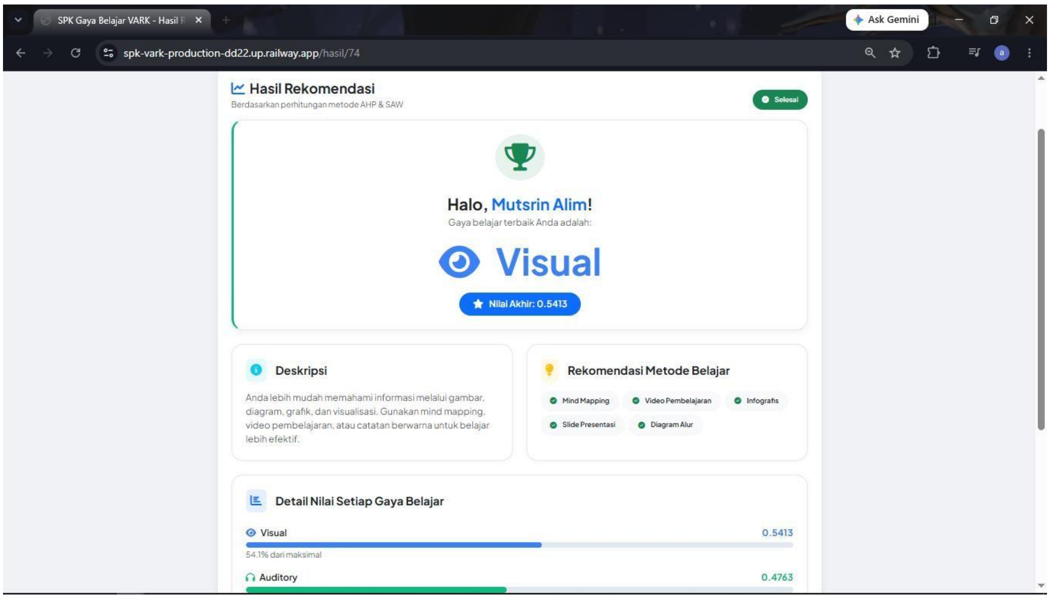

Figure 7. Recommendation results page interface.

3.6.4. Administrator Dashboard

The administrator dashboard provides tools for monitoring and managing the overall operation of the decision support system. It enables administrators to access statistical summaries, manage respondent data, and modify the evaluation criteria weights when necessary. These functionalities improve the flexibility of the system and facilitate future updates and maintenance.

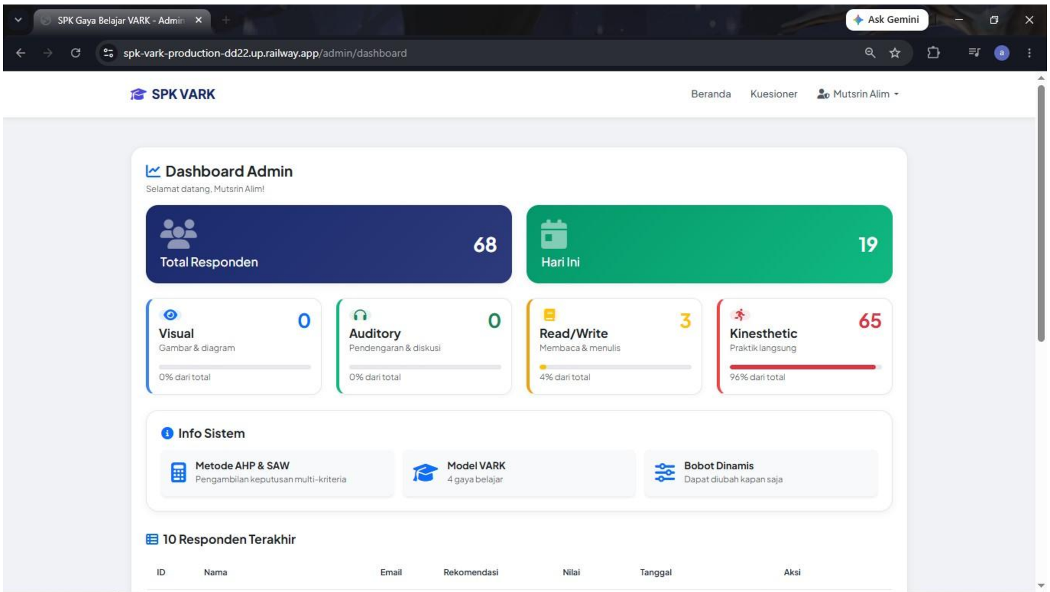

Figure 8. Admin dashboard interface.

4. CONCLUSION

This investigation achieved the design and deployment of a web-driven DSS engineered to guide educational path selection by embedding a hybrid AHP and SAW algorithmic structure into the VARK conceptual model. Through the application of the AHP protocol, uniform weight distributions were established across all primary parameters, supported by a CR of 0 to verify the total logical coherence of the underlying expert inputs. Operationally, the application managed to output distinct pedagogical path recommendations for the entire participant group, identifying a clear dominance of the Kinesthetic classification among the sample population based on the specified diagnostic metrics and corresponding alignment scores.. System validation demonstrated a 100% agreement between manual calculations and system-generated recommendations, while the User Acceptance Test (UAT) achieved an average score of 4.33 out of 5.00 (86.67%), indicating a Very Good / Highly Accepted level of user acceptance. These findings confirm that the proposed system is both computationally accurate and practically applicable for learning style recommendation. Nevertheless, the study was conducted using respondents from a single university and involved only one expert in the AHP weighting process. Therefore, future research is recommended to involve more diverse respondents and multiple experts to improve the robustness and generalizability of the proposed model, as well as to explore adaptive approaches, such as machine learning techniques, to further enhance the effectiveness of learning style recommendations.

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