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Operationalizing Academic Performance in a Rule-Based KLSI-informed Decision Support System for Academic Specialization

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Abstract
Decisions regarding academic specializations require detailed and transparent representations of learners. This study developed and evaluated a rule-based decision support system that transforms routinely collected academic performance data into two distinct analytical outputs: learner profiles informed by the Kolb Learning Style Inventory (KLSI) and curriculum-focused specialization rankings. The requirements were obtained through structured interviews with five curriculum-related informants from four public senior high schools in Malang, Indonesia. Subject achievement was deductively mapped to Concrete Experience (CE), Abstract Conceptualization (AC), Active Experimentation (AE), and Reflective Observation (RO) orientations as a theory-based operational knowledge representation. Specialization scores were calculated independently using predefined subject sets and ranked to identify the top two options for each participant. The evaluation included 12 specification-based test cases, 25 Black Box items, the System Usability Scale (SUS) administered to 40 Grade XI students, and descriptive analysis of 36 complete saved records. All specification cases matched manually derived outputs, functional compliance reached 92.0%, and the mean SUS score was 74.19. Diverger was the most frequently inferred profile (38.9%), while Social Humanities was the most common top-ranked specialization (44.4%). The system provides clear, traceable academic decision support without claiming psychometric equivalence to the traditional KLSI for use in school-counseling contexts.

Keywords: academic specialization recommendation; decision support system; educational recommender systems; kolb learning style inventory; learning analytics

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INTRODUCTION

In the realm of data-driven education, the use of learner information is becoming essential for making academic and instructional decisions. Educational recommender systems tailor educational support by considering learner attributes, achievements, preferences, and contextual details (Leite et al., 2023; Zayet et al., 2023). Conversely, learning analytics employ routinely gathered educational data to guide decisions related to teaching and institutional strategies (Hershkovitz et al., 2024; Stojanov & Kei, 2024). As these systems shape students' academic journeys, the scientific challenge extends beyond merely generating recommendations. It involves developing learner representations that are theoretically sound from the available academic data, while ensuring that the decision-making process remains transparent to educational stakeholders.

Current learner representation approaches differ in their purpose. Student-characteristics-based recommender systems typically use preferences, interests, achievements, and interaction data for personalization (Narimani & Barberà, 2024). Academic-data-based learning analytics often use grades and assessment records to predict achievement, risk, or intervention needs (Alalawi et al., 2025; Ersozlu et al., 2024), whereas behavioral data can further support outcome prediction (Fazil et al., 2024). Thus, existing approaches commonly prioritize either personalization or prediction, leaving limited methodological guidance for constructing an auditable, theoretically structured representation of learning characteristics directly from routine academic records.

Kolb's experiential learning theory distinguishes concrete experience (CE) and abstract conceptualization (AC) for grasping experience and reflective observation (RO) and active experimentation (AE) for transforming it (Kolb, 1984). Conventional KLSI operationalizes these orientations through self-reported preferences (Rudberg et al., 2023), while learning-style-aware recommenders commonly rely on questionnaires or explicit learner input (Thongchotchat et al., 2023). In this study, subject-level achievement was deductively associated with these four orientations according to the differing experiential, reflective, conceptual, and practical curricular demands. These associations form a theory-informed operational knowledge representation rather than a validated psychometric measure. Accordingly, KLSI-informed denotes the conceptual use of the KLSI structure, not the administration or reproduction of the conventional instrument; the resulting profiles are computational inferences.

Because these operational associations shape the generated profiles, explainability must reveal how academic data are represented and processed in the model. Explainable educational recommender research emphasizes understandable recommendation rationales (Dai et al., 2024). Rule-based mechanisms provide a complementary form of explainability because mappings, aggregation procedures, classification conditions, and ranking rules can be explicitly encoded and examined (Pelánek et al., 2024). Compared with predictive models that infer relationships from training data, explicit rules prioritize traceability and direct revision when curriculum requirements are changed. However, inspectability does not establish the validity of the underlying assumptions (Saqr & Pernas, 2024). Therefore, the methodological gap concerns integrating the experiential learning structure underlying the KLSI with academic-data analytics through auditable representation while keeping learner profiling separate from specialization scoring.

In the context of Indonesian secondary education, the Merdeka Curriculum allows for adaptation according to the specific needs of each institution (Rohmah et al., 2024). A study conducted in four public senior high schools in Malang found that the process of guiding students towards academic specialization largely relied on manual evaluations of academic performance, student interests, school assessments, and sometimes input from parents. This situation provides a basis for developing a decision-support system that utilizes regularly gathered school data, while ensuring that educational stakeholders can review clear and adaptable guidelines.

This study developed and evaluated a rule-based system capable of generating learner profiles based on the KLSI derived from academic performance and independently ranking specialization options using curriculum-aligned (CA) scores. The evaluation focused on the consistency of the rules, functional adherence, perceived usability, and patterns in the descriptive outputs. The novelty of this study lies in the deductive application of the experiential learning framework within the KLSI as a distinct knowledge representation while separating learner profiling from specialization scoring. Conceptually, profiling serves as an interpretive knowledge layer rather than directly influencing specialization decisions. Methodologically, the system guarantees that the inference logic is computationally verifiable and is open to inspection. Practically, it provides traceable decision-support outputs without claiming psychometric equivalence to the traditional KLSI.

METHOD

In this research and development project, a prototype model was iteratively refined to improve rule-based systems. Five school leaders and curriculum representatives, responsible for overseeing curriculum implementation and specialization, participated in structured interviews. These participants included one representative each from SMAN 1, SMAN 3, and SMAN 4, and two from SMAN 8 Malang. The interview guide explored topics such as specialization procedures, student data, constraints, outputs, and workflow requirements. Insights gathered from the four schools contributed to a broader assessment, while implementation at SMAN 8 ensured consistent application and evaluation. A Grade XI class, comprising all 40 students, was selected in collaboration with the curriculum office, and their academic data and system/SUS participation were included in the study. Figure 1 presents the proposed framework.

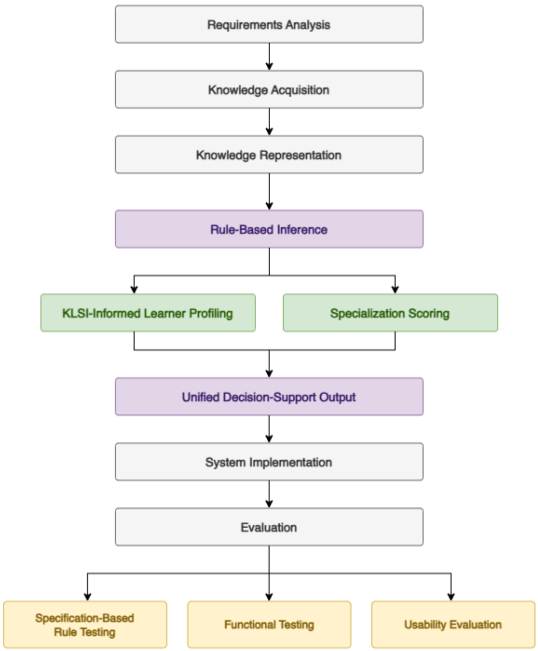

Figure 1. Research framework and rule-based decision-support workflow

The interview findings were organized into categories such as inputs, decision criteria, outputs, and workflow requirements, which were subsequently transformed into rules for profiling, scoring, ranking, and aligning interests. CE, AC, AE, and RO were deductively associated with particular subjects: Religious Education, Civics, and Social Studies were linked to CE; Mathematics and Science to AC; Physical Education and Informatics to AE; and Indonesian, English, and Arts to RO. These associations underscore the main contextual, conceptual, practical, and reflective requirements of the curriculum. The mappings were deduced from theory and discussed during curriculum consultations; however, they were not formally validated by independent experts or subjected to psychometric analysis. The subjects RE, CIV, SS, MATH, SCI, PE, INF, IND, ENG, and ART are represented by Equations (1)–(4), respectively.

$$CE = \frac{RE+CIV+SS}{3} \tag{1}$$
$$AC = \frac{MATH+SCI}{2} \tag{2}$$
$$AE = \frac{PE+INF}{2} \tag{3}$$
$$RO = \frac{IND+ENG+ART}{3} \tag{4}$$

Equations (1)–(4) equally average the mapped subjects to produce CE, AC, AE, and RO scores, representing contextual/experiential, conceptual/analytical, practical/procedural, and interpretive/reflective performance, respectively. Higher AC–CE and AE–RO values determined the dominant grasping and transforming orientations. To ensure deterministic classification, ties were assigned to CE and RO; equality in both pairs, therefore, produced Diverger. CE–AE, AC–AE, CE–RO, and AC–RO generated the Accommodator, Converger, Diverger, and Assimilator. The outputs were treated as KLSI-informed computational inferences rather than conventional KLSI assessments.

$$S_{pj} = \frac{\sum_{m=1}^{k_j} x_{pm}}{k_j} \tag{5}$$

In Equation (5), S_{pj} is student p's score for specialization j, x_{pm} is student p's score in mapped subject m, and k_j is the number of subjects in specialization j. Equation (5) equally averaged mapped subjects for Mechanical (Science, Mathematics, Informatics), Medical Science (Science, Mathematics, English), Economy and Business (Social Studies, Mathematics, Informatics), Social Humanities (Social Studies, Civics, Indonesian), and Social Science (Social Studies, Science, Mathematics) subjects. Scores were ranked to retain the top two; declared interests only checked compatibility and did not alter the scores or ranking.

The rules were implemented using Laravel/PHP. Twelve specification-based cases compared manual and inference-engineered outputs; 25 Black Box items assessed by one software engineering lecturer examined functional compliance; and the ten-item System Usability Scale measured perceived usability among 40 students (Brooke, 1996; Sharfina & Santoso, 2016). Matches, frequencies, percentages, mean SUS, and cross-tabulation summarized the results; 36 saved records were available for descriptive output analyses. A descriptive analysis was appropriate because this study examined mechanism consistency, functionality, usability, and output patterns rather than statistical relationships or causal effects. School authorization was obtained, and participant data were handled according to the system's privacy policy.

RESULTS AND DISCUSSION

Results

The results showed a shared cross-school need for structured, web-based specialization support. All 12 specification-based cases matched the manually derived outputs, including profile classification, ranking, equality, and close score conditions, and interest compatibility. The mechanism generated all four KLSI-informed profiles and all five top-ranked specialization categories, while functional testing achieved 92.0% compliance and perceived usability reached a mean SUS score of 74.19.

Requirements analysis across the four schools identified a common reliance on academic information and student considerations for specialization guidance, while pathway labels, implementation timing, and decision emphasis varied across schools. Informants also reported limited structured support for students in assessing their academic characteristics before selecting a pathway. These findings established the requirements for academic score inputs, KLSI-informed profiling, specialization ranking, interest-compatibility checking, and an adaptable web-based workflow, as presented in Table 1.

Following the cross-school requirements analysis, the inference mechanism was evaluated using 12 specification-based test cases covering learner profile classification, specialization ranking, equality, close-score conditions, and interest compatibility. Each inference engine output was compared with the manually derived expectation from the predefined rules. All 12 cases matched, yielding a 100% rule-match rate (Table 2).

Table 1. Synthesis of cross-school requirements and rule implications

Requirement finding	Cross-school pattern	School-specific variation	Rule-base implication
Existing specialization classes	Implemented across four schools	Starting grade and pathway labels varied	Multiple specialization categories
Academic decision data	Grades, student interests, and school judgment commonly used	Emphasis varied across schools	Academic-score input, scoring, and compatibility rules
Student decision difficulty	Limited self-assessment and pathway understanding	Reported difficulties varied	Learner-profile output and top-two recommendations
System requirement	Accessible and structured web-based support	Terminology and categories adjusted to school context	Web-based workflow and inspectable rules

Table 2. Results of specification-based rule testing

Case	Rule Component	Representative Case	Manual-system Agreement
TC01	Learner profile classification	Converger	Matched
TC02	Learner profile classification	Accommodator	Matched
TC03	Learner profile classification	Diverger	Matched
TC04	Learner profile classification	Assimilator	Matched
TC05	Specialization ranking	Top-two highest scores	Matched
TC06	Boundary handling	AC = CE	Matched
TC07	Boundary handling	AE = RO	Matched
TC08	Interest compatibility	Direct match	Matched
TC09	Interest compatibility	Interest-set intersection	Matched
TC10	Interest compatibility	No match	Matched
TC11	Near-boundary orientation	AC = CE + 1	Matched
TC12	Near-tie specialization ranking	Top scores differ by 1.00	Matched

All 12 cases matched the manually derived outputs, demonstrating consistent rule execution across the classification, ranking, equality, close score, and compatibility conditions. The equality cases confirmed the predefined CE and RO tie handling, whereas TC11 and TC12 showed that one-point differences were processed through an exact numerical comparison. These results establish computational consistency for the tested conditions but not the empirical validity of the subject mappings or psychometric equivalence with the conventional KLSI.

Of the 40 participants, 36 complete saved recommendation records were available for descriptive output analysis, and four recommendations were not retained because the users did not activate the save function. All four KLSI-informed profiles and five specialization categories appeared in the records. The distributions of the generated learner profiles and top-ranked specializations are shown in Figures 2 and 3, respectively.

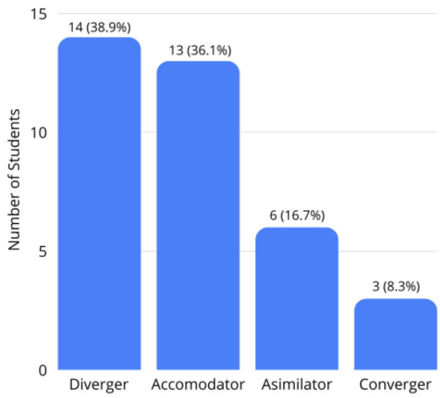

Figure 2. Distribution of klsi-informed learner profiles (n = 36)

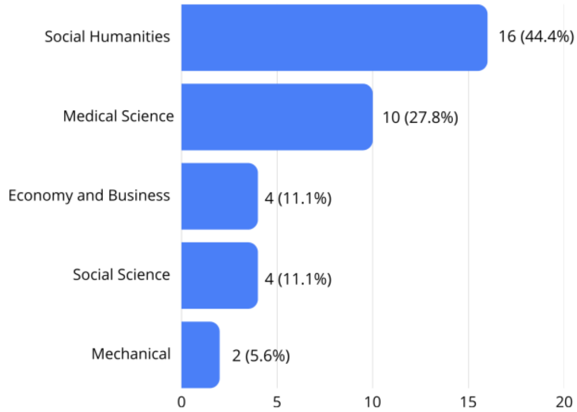

Figure 3. Distribution of top-ranked specializations (n = 36)

As shown in Figure 2, Diverger and Accommodator were the dominant profiles, accounting for 75.0% of the records. Figure 3 shows that Social Humanities were the most frequent top-ranked specializations, followed by Medical Science; together, they accounted for 72.2% of the top-ranked outputs. Only the first-ranked specialization was counted; therefore, each record contributed to one category. These distributions represent outputs produced under predefined mappings and rules rather than the population-level prevalence of KLSI profiles or specialization suitability. To examine how the independently generated learner profiles and specialization recommendations co-occurred across the saved records, the two outputs were cross-tabulated, as presented in Table 3.

Table 3. Cross-tabulation of klsi-informed profiles and top-ranked specializations

KLSI-informed profile	Social Humanities	Medical Science	Economy and Business	Social Science	Mechanical	Total
Accommodator	7	0	4	2	0	13
Diverger	9	5	0	0	0	14
Assimilator	0	5	0	1	0	6
Converger	0	0	0	1	2	3
Total	16	10	4	4	2	36

Table 3 shows that individual learner profile categories co-occurred with multiple specialization outcomes. Diverger appeared with Social Humanities and Medical Science, while Accommodator was distributed across three specialization categories. Assimilators and Convergers also showed more than one possible top-ranked outcome. Thus, no profile functioned as a predetermined specialization. Because profiling and specialization scoring were computed through separate pathways, the cross-tabulation represents a descriptive co-occurrence rather than a causal or statistically tested relationship. The implemented system was subsequently evaluated using Black Box testing, and the results by functional domain are presented in Table 4.

Black Box testing produced 23 matches across 25 functional items, corresponding to 92.0% compliance. Authentication and authorization, recommendation processing, output and visualization, and export and archive fully matched the predefined specifications. One mismatch occurred in the CSV data validation, and the other occurred in navigation and interface flow. Because the recommendation processing and output domains showed complete agreement, the identified mismatches were confined to the input validation and interface workflow functions rather than the core inference outputs.

Table 4. Black-box testing results by functional domain

Functional Domain	Total Items	Valid	Invalid	Result
Authentication and Authorization	4	4	0	100%
CSV Data Upload and Validation	3	2	1	66.7%
KLSI Recommendation Processing	3	3	0	100%
Output and Visualization	5	5	0	100%
Export and Archive	3	3	0	100%
Navigation and Interface Flow	7	6	1	85.7%
Total	25	23	2	92%

Perceived usability among 40 students produced a mean SUS score of 74.19, which was classified as good under the adopted interpretation range. Individual scores placed 8 students (20.0%) in the excellent category, 15 (37.5%) in the good category, and 17 (42.5%) in the acceptable category, with none classified as poor. Item-level adjusted contributions were highest for barrier-free use (3.10) and independence from assistance (3.08), whereas system consistency (2.78) and ease of familiarization (2.80) received the lowest contributions. These results identify interface consistency and initial familiarization as the principal usability aspects requiring further refinement

Discussion

The key discovery of this study is that academic performance, which is regularly accessible, can be structured into two distinct yet complementary rule-based pathways. The KLSI-informed pathway interprets academic records into learner profiles, while the specialization pathway independently assesses curriculum-focused options. Specification-based verification, including equality and close-score cases, demonstrated consistent application of predefined logic under the tested conditions. The co-occurrence results further indicated that a single learner profile could be linked to various specialization recommendations. Therefore, learner profiling did not serve as a direct placement directive, reducing the risk of a derived profile being the sole factor in determining specialization.

This study theoretically extends the application of Kolb's experiential learning theory to an academic data-based analytical context rather than revalidating the theory itself. Kolb's CE, AC, AE, and RO orientations provide a conceptual structure for organizing experiential learning processes (Kolb, 1984). Here, these orientations function as knowledge-representation layers that transform routine academic records into structured educational information before they are interpreted alongside, but independently from, specialization recommendations. This differs from the conventional KLSI assessment, which derives learning orientations from an established inventory (Rudberg et al., 2023) and from learning-style-aware recommenders that commonly rely on questionnaires or explicit learner input (Thongchotchat et al., 2023).

Therefore, the generated profiles should be understood as theory-informed computational representations and not as psychometrically equivalent substitutes for conventional KLSI profiles.

Methodologically, rule-based architectures offer a different trade-off from data-driven predictive approaches. Machine learning approaches can be advantageous when large, representative datasets and validated prediction targets are available (Alalawi et al., 2025). Conversely, a transparent rule-based approach may be preferable when training data are limited, institutional rules require direct revision, and accountability is more important than maximizing the predictive performance. In the proposed mechanism, subject mappings, aggregation procedures, orientation comparisons, boundary handling, specialization scoring, and ranking rules remain explicitly inspectable and can be revised without model retraining. This aligns with modular rule-based recommendations (Pelánek et al., 2024). Explainable educational recommender research similarly emphasizes the importance of making recommendation processes understandable for users (Dai et al., 2024). Explainable learning analytics further highlight the value of examining how predictive models behave and remain stable across different decision conditions (Tiukhova et al., 2024). Such inspectability may support teacher trust and accountability because the basis of an output can be reviewed and evaluated. However, transparency does not guarantee validity or fairness; explicit mappings, weights, and boundary conventions may still encode bias, although their visibility makes them more amenable to scrutiny and revision (Saqr & Pernas, 2024).

The output and implementation findings support these implications. The predominance of Diverger and Accommodator profiles and Social Humanities recommendations reflects the interaction between the observed academic records and predefined rules rather than the population-level learning style prevalence or specialization suitability. The system was generally functional and usable, while the item-level SUS results identified system consistency and initial familiarization as relatively weaker aspects of the system. Considering both technical performance and user experience is consistent with the multidimensional evaluation of educational information systems (Elmunsyah et al., 2023). For developers, separating the learner representation from the recommendation ranking and documenting the mappings, weights, boundary rules, and ranking logic can improve the auditability. For schools and teachers, the outputs are more appropriately used as evidence for guidance and discussion than for making automated placement decisions. This is particularly relevant under the Merdeka Curriculum, where implementation and specialization structures may vary by school context (Rohmah et al., 2024). At the policy level, future educational recommendation infrastructures could favor transparent rules, human oversight, auditable histories, privacy safeguards, and locally configurable curriculum structures rather than a single fixed national rule base. These implications are design and governance principles, not evidence that the current prototype is ready for national-scale deployment.

Nonetheless, these contributions are subject to several limitations. The profiles informed by KLSI were not cross-validated with traditional KLSI classifications, and the mappings of subjects, equal weighting, and boundary conventions lacked formal validation by independent experts or empirical constructs. The precise comparison logic implies that even minor score variations can impact profile or ranking results, despite successful verification of close scores. The evaluation of implementation and usability was conducted in a single school, and the analyses of descriptive profiles and recommendations relied on 36 stored records, which restricts the generalizability across different contexts. The study did not explore subsequent specialization choices or academic outcomes over time, directly compare rule-based methods with machine-learning alternatives, or address potential inconsistencies and gaps in academic records. Future research should validate the mappings across various regions and curricula, compare inferred profiles with traditional KLSI outcomes, test different weights and uncertainty thresholds, and include additional non-academic data such as interests, motivation, and learning behavior. Xu et al. (2026) also highlight the need to compare rule-based, machine-learning, and hybrid explainable recommenders using shared datasets. Longitudinal and fairness assessments are necessary to evaluate whether transparent recommendations remain educationally relevant and fair across diverse settings.

CONCLUSION

This study demonstrates that academic performance data, which are routinely accessible, can be transformed into learner profiles informed by KLSI through a verifiable rule-based system, while independently ranking academic specialization choices. The primary scientific contribution is the explicit representation of the experiential-learning framework inherent in the KLSI as a distinct knowledge layer, and the separation of learner profiling from specialization evaluation, thus preventing the use of inferred profiles as automatic placement criteria. Theoretically, this method broadens the use of experiential learning principles in decision support based on academic data. Practically, it offers schools outputs that can be reviewed to aid educational guidance rather than replace it. Nonetheless, the mappings of subjects to dimensions and the decision-making conventions need further validation, and the current implementation is still specific to certain contexts. Future studies should compare inferred profiles with traditional KLSI outcomes, validate mappings across various curricular environments, explore different weights and uncertainty thresholds, and evaluate rule-based systems against machine-learning and hybrid explainable methods. In summary, this study lays a transparent groundwork for creating accountable academic decision-support systems.

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