Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.4, August 2026, pp. 4157~4165
e-ISSN: 2548-6861

Modeling Car Driver Selection Using an Integrated Hybrid AHP-MOORA Approach

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Article Info

Article history:

Received 2026-06-13
Revised 2026-08-07
Accepted 2026-08-13

Keyword:

AHP,
Driver Selection,
Multi Criteria Decision Making,
MOORA.

ABSTRACT

In transport management, traditional driver selection methods suffer from subjectivity and reactiveness, which directly increase traffic hazards, asset liabilities, and corporate operational expenditures. To address human cognitive limitations in concurrently analyzing complex multi criteria (physical, personality, and technical facets), this research deploys a computational Decision Support System (DSS) to secure objective, measurable quality standards and operational safety. The primary objective is to develop an integrated AHP-MOORA framework to optimize the recruitment pipeline. By leveraging AHP for criteria prioritization and MOORA for alternative evaluation, the proposed system yields optimized driver recommendations tailored to specific user requirements. The model incorporates seven distinct criteria: working experience, license classification, age, personality, educational background, residential proximity, and examination scores. Performance testing via a confusion matrix reveals that the constructed DSS delivers high robustness, achieving 87.5% Accuracy, 83.3% Recall, and a 90.9% F1-Score. Remarkably, the system attains a flawless 100% Precision rate, substantiating its optimal ability to yield highly targeted driver recommendations while entirely eliminating false-positive classifications.

I. Introduction

Road traffic prevalence accidents in Indonesia highlights a critical demand for robust safety frameworks. Statistics derived from the Indonesian Central Bureau of Statistics indicate that in 2024, 150,906 accidents led to 26,839 deaths, representing not only a tragic loss of life but also a profound socio economic impact on the productive age demographic [1]. Beyond external infrastructure and climatic variability, intrinsic driver factors such as inattention and physiological status remain the leading causes of these events [2]. Despite successful fatality reductions achieved during 2025–2026, the implementation of sophisticated driver monitoring systems is essential to curtail future risks.

Given the inherent uncertainty of driver conditions and road environment intricacies, driving behavior has become a cornerstone of traffic safety research [3]. These conditions are typically grouped into categories of fatigue, distraction, and impairment, while vehicle operations are defined by acceleration, deceleration, and lane positioning [4]. In the behavioral recognition context, a distinction is made between regular and risky driving. A former covers standard practices, whereas the latter pertains to anomalous phenomena, such as sudden maneuvers and distinct physiological changes [5]. Notably, risky behavior is the leading human factor in accidents involving young drivers, contributing to disproportionate fatality rates among students. This reliance on private transport is reinforced by its perceived efficiency and its role in reducing parental commuting responsibilities [6].

Professional drivers are defined as a workforce compensated for the operation of transport vehicles. This profession entails rigorous physical and mental requirements due to the immense responsibility for securing valuable assets and ensuring passenger safety [7]. Research indicates that safety conscious professional drivers typically possess a minimum of 29 years of work experience [8]. Given that various criteria influence candidate evaluation, this study aims to synthesize existing literature to establish selection criteria for private drivers. Establishing such procedures is imperative for identifying candidates capable of handling occupational challenges. While this study focuses on road transport with private drivers as the primary subjects, the proposed methodology is adaptable to other professional roles, including bus, truck, and ride hailing drivers.

The Analytical Hierarchy Process (AHP), pioneered by Thomas L. Saaty, stands as a distinguished Multi Criteria Decision Making (MCDM) framework characterized by its flexible architecture. Its core strength involves the systematic decomposition of multifaceted problems into a structured hierarchy [9]. By implementing a pairwise comparison approach, AHP enables a consistent derivation of weights by mapping subjective human judgments onto a linear numerical scale [10]. This mathematical transformation is vital for evaluating intangible qualitative variables, including candidates' non-technical attributes [11]. To address the inherent subjectivity and potential ambiguity of natural language in evaluations, the framework employs a Consistency Ratio as a safeguard to ensure the validity of the judgment matrix prior to ranking [12].

The Multi Objective Optimization by Ratio Analysis (MOORA) method is a highly effective multi criteria optimization instrument for resolving candidate selection issues in recruitment processes. Its fundamental strength lies in a decision matrix normalization procedure that harmonizes diverse parameters with varying units of measurement into a uniform numerical representation [13]. By calculating optimization ratios, MOORA simultaneously evaluates benefit type criteria for maximization and cost type criteria for minimization [14]. In this research, MOORA enables rigorous candidate prioritization by converting mixed mode data into transparent preference scores. Furthermore, its ability to seamlessly incorporate AHP derived weights, coupled with its computational simplicity, makes it an ideal approach for mitigating bias in high stakes decisions [15].

A hybrid approach integrating Fuzzy Logic, AROMAN, and the Fuller method has been previously employed in professional driver selection studies. That research identified 14 initial criteria, subsequently narrowing them down to seven core attributes for more rigorous analysis. The findings confirmed that this methodological framework is effective in resolving multi criteria decision making challenges within the transportation sector. Furthermore, the study suggested that incorporating other methods, such as AHP, could further optimize criteria weighting prior to the final ranking process [16]. Previous research show that the Weighted Product (WP) method has been utilized to build Decision Support Systems specifically for recruiting bus drivers. The assessment framework incorporates four key criteria: the type of driver's license held, length of service, skill certifications, and interview results. Through a web-based interface, the WP algorithm executes normalization and weighting processes to derive weight improvement vectors. This computational process culminates in a prioritized list of candidates based on their total scores, facilitating a more transparent and objective recruitment process for managerial decision-making [17]. Research on the selection of Smart Indonesia Program (PIP) scholarship recipients further supports the efficacy of the combined AHP and MOORA framework. The integration of these methods facilitates a balance between human judgment and mathematical optimization, which is essential for fair multi criteria decision making. Specifically, evaluations by Supriyanta et al. yielded an accuracy exceeding 92%, illustrating the system's ability to generate objective candidate recommendations [18]. This methodological success is consistent with findings from Nugroho and Wakhidah in Manyaran District, where the AHP-MOORA integration significantly enhanced both selection precision and operational efficiency for social welfare programs [19].

The preceding literature review reveals a distinct lack of studies focusing on multi-criteria decision-making frameworks for private chauffeur recruitment. This research addresses this significant research gap by proposing a novel hybrid approach. The primary innovation of the proposed system lies within its specific application context and the customized formulation of its evaluation criteria. Unlike general recruitment systems, this model uniquely synthesizes seven distinct professional and behavioral facets, such as residential proximity and personality traits that tailored to the operational mandates of premium chauffeur services. By grounding the well-established AHP-MOORA workflow into this high liability transportation context, the system provides a specialized, high precision solution capable of eliminating human bias and minimizing road traffic hazards

II. METHOD

A. Data Collection

The implementation of the proposed DSS methodology necessitates two fundamental data streams: criteria attributes and candidate alternatives. Data procurement was conducted using rigorous instruments to ensure the integrity and final results validity. The alternatives analyzed in this study are derived from the applicant pool of a private chauffeur outsourcing provider located in Surakarta. Specifically, the dataset was provided by PT. Kecana Surakarta and encompasses candidates who successfully completed the recruitment process and attained eligible status. The 2025 cohort of driver applicants, which forms this investigation core, is detailed extensively in Table 1.

TABLE 1
PROSPECTIVE DRIVER ALTERNATIVE

Code	Alternatives Name
S1	Joko Sulistyono
S2	Tegar Tri Kurniawan
S3	Andika Satrio Perbawa
S4	Wisnu Dwi Pamungkas
S5	Muhamad Agus Ariyanto
S6	Harno Putro
S7	Suryo Santoso

B. *Establishing Criteria*

To bolster the proposed DSS architecture, this research adopts a multi-stage data acquisition strategy. Primary data were derived via direct consultation with stakeholders at PT. Kencana Surakarta, ensuring that criteria definitions align with the firm's operational mandates. Complementarily, secondary data were utilized as a validation set for computational modeling to refine the system's predictive reliability.

To ensure both academic rigor and empirical validity, the final formulation of these criteria was executed through a dual-framework approach, combining transportation safety literature with formal validation from industry experts. The gathered information was thoroughly vetted, refined, and validated through structured interviews and a focus group discussion (FGD) with the Head of Human Resources and the Operations Director. This collaborative process ensured that the metrics align directly with high-stakes transport operational demands, forming the seven core evaluation criteria outlined in Table 2.

TABLE 2
RECRUITMENT CRITERIA FOR DRIVERS

Code	Criteria
K-1	Experience
K-2	License type
K-3	Age
K-4	Traits
K-5	Education
K-6	Res. Distance
K-7	Scores

Based on this validation, the specific reasons for selecting each criterion are delineated as follows:

1. K-1 (Education) & K-2 (Experience): Established as baselines for professional literacy, cognitive adaptability, and maturity in handling vehicle operations.
2. K-3 (Age): Justified by road safety statistics indicating that mature productive age groups (29–45 years old) exhibit optimal emotional stability and lower accident rates compared to younger or older cohorts.
3. K-4 (Personality Traits): Specifically requested by the HR team to assess non-technical behavioral attributes (e.g., hospitality, grooming, and non-smoking habits) crucial for private client interaction.
4. K-5 (Driver's License Type) & K-7 (Driving Test Score): Defined as the legal and practical verification of core competencies under real-world pressure.
5. K-6 (Residential Proximity): Strategically included by the transport operator to mitigate pre-work driver fatigue a leading catalyst for traffic accidents by prioritizing candidates with stable commute times.

To facilitate data processing, the seven predefined criteria from Table 2 were quantified using a four level ordinal scale. This scale ranges from 1 (very low) to 4 (high), allowing for a structured assessment of each factor. The resulting score assignments and their respective interpretations are documented in Table 3.

TABLE 3
CRITERION EVALUATION VALUE

Criteria	Value			
	1	2	3	4
K-1	<7 years	>= 7 years	>= 15 years	>= 25 years
K-2	Class A	A (Gen)	B1 (Gen)	B2 (Gen)
K-3	> 60 years	20-28 years	46-59 years	29-45 years
K-4	heavy smoker, unfriendly	light smoker, less friendly	non smoker, less friendly	smoker, less friendly
K-5	Elem.	JHS	SHS	HE
K-6	> 20 km	< 20 km	< 10 km	< 5 km
K-7	Fail	Poor	Fluent	Expert

C. *System Design*

The core objective of this research is the engineering of a specialized DSS to facilitate the recommendation of private chauffeurs. The system's deployment is intended to enhance recruitment efficiency by isolating candidates who meet rigorous professional benchmarks and organizational prerequisites. To provide a conceptual overview, the system's functional architecture detailing the underlying data trajectories and internal component synergies is visualized through the block diagram in Figure 1.

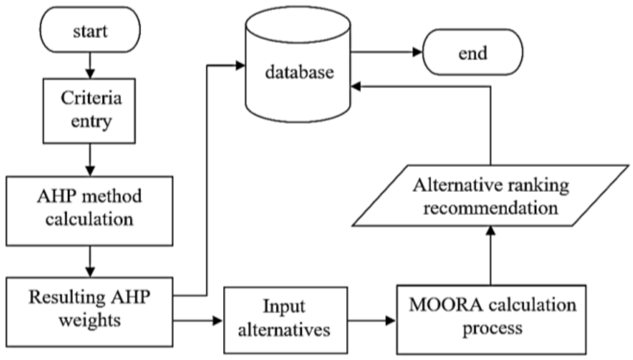

Figure 1. System Block Diagram

Flowchart in Figure 1 delineates the operational synergy between user and integrated AHP-MOORA framework. After user provides the necessary criteria data and importance ratios, the AHP component calculates objective weights, ensuring reliability through a rigorous consistency index validation. These weights are then funneled into MOORA algorithm to facilitate the development of weighted normalized matrices. The final stage utilizes MOORA's preference scores to establish a systematic ranking of alternatives. Ultimately, this hybrid approach bridges the gap between subjective human judgment (AHP) and mathematical optimization (MOORA), enhancing the objectivity of the final selection.

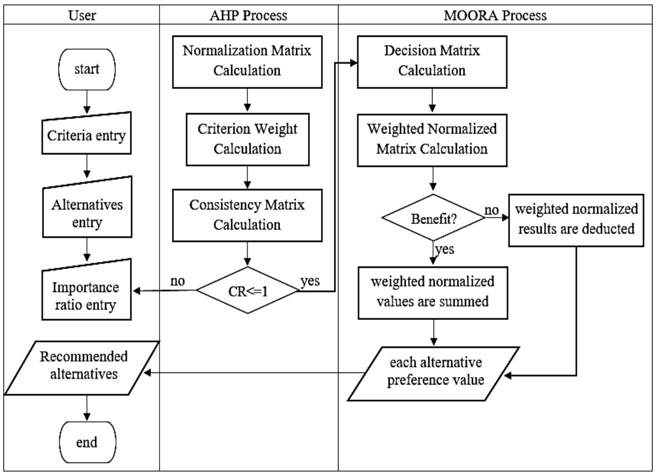

Figure 2. DSS Architectural Flowchart

D. AHP and MOORA Methodological Process

The criteria weighting process in this research is conducted using the AHP method, structured into the following stages:

1) Criteria values are established through a pairwise comparison matrix based on importance levels (1–9 scale).

2) The normalization matrix and priority weights (W) are calculated by dividing column values by their respective totals, as shown in Equation:

$$W_i = \frac{1}{n} \sum_i a_{ij} \quad (1)$$

3) The consistency of the weight vector (W) is verified to ensure matrix validity using Equation :.

$$t = \frac{1}{n} \sum_{i=1}^{n} \frac{element\ i\ in\ (A)(W^t)}{element\ i\ in\ (W^t)} \quad (2)$$

4) The Consistency Index (CI) is computed:

$$IK = \frac{t - n}{n-1} \quad (3)$$

A CI value <= 0.1 signifies consistency, while a value >0.1 indicates that the importance ratio inputs must be re-evaluated. Upon verifying the AHP derived weights consistency, the MOORA procedure is executed through these subsequent steps:

1) Decision Matrix Construction: Organizing a matrix to represent the performance of each alternative relative to the predefined criteria.

$$X_{ij} = \begin{matrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{matrix} \quad (4)$$

[20]

2) Matrix Normalization: Transforming criteria values into dimensionless ratios. This is achieved by dividing each element by the square root of the sum of squares of the alternative values for each criterion, as formulated in equation:

$$X_{ij} = \frac{x_{ij}}{\sqrt{\sum_i^m = x_{ij}^2}} \quad (5)$$

3) Weighted Matrix Computation: Multiplying normalized values by the corresponding criteria weights (Wj) to account for the relative significance of each attribute.

$$y_i = \sum_{j=1}^{m} x_{ij} - \sum_{j=g+1}^{n} x_{ij} \quad (6)$$

[21]

4) Optimization and Ranking: Calculating the optimization values (Yi) for all alternatives. The final ranking is determined by sorting the Yi values in descending order to identify the most suitable solution.

$$y_i = \sum_{j=1}^{g} w_j x_{ij} - \sum_{j=g+1}^{n} w_j x_{ij} \quad (7)$$

[22]

III. RESULT AND DISCUSSION

A programming language and a database are essential for developing a driver selection decision support system. In this research, the desktop-based programming language Visual Basic .NET, commonly known as VB.NET, is employed to implement the DSS development phases. MySQL was chosen as the database management system to store both input data and DSS calculation results. The overall program flow is visually presented in Figure 1. The system construction is guided by the block diagram, whereas the logical workflow is outlined in the flowchart in Figure 2.

A. Criteria and Alternative Data Processing

The AHP method execution necessitates the initial input of criteria data, as established and presented in Table 2. Correspondingly, alternative data representing driver candidates are indispensable for the MOORA calculation. Beyond basic identification, each alternative is associated with specific criteria parameters. Inputted parameters such as age, work experience, license type, education, home to work distance, personality traits, and evaluation scores are subsequently mapped into weights from 1 to 4 according to Table 3. The developed system has been populated with driver candidate records matching the applicant data listed in Table 1. Both the criteria and alternative data management forms feature the same functionalities. Figure 3 illustrates the processed dataset of the driver alternatives, detailing the empirical criteria values collected for each candidate.

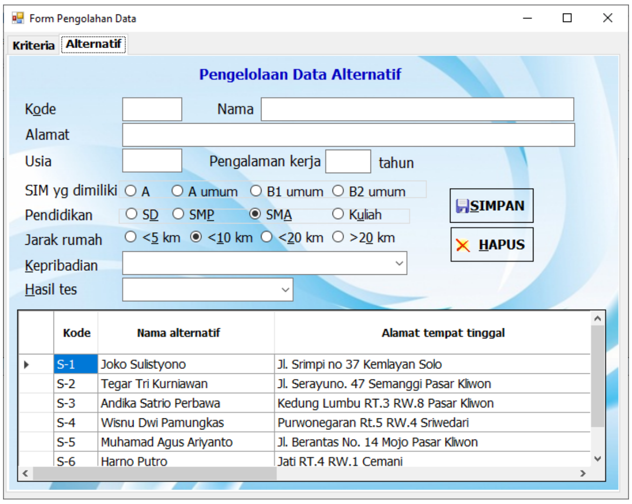

Figure 3. Alternative Data Processing

B. AHP Method Process

The execution of AHP method necessitates inputting pairwise comparison values as its foundational step. The corresponding system architecture for this process is illustrated in Figure 4. To ensure empirical validity and eliminate researcher bias, the relative importance ratios entered into the matrix were derived from structured interviews with domain experts, specifically the Operations Director and the Head of Recruitment. These stakeholders provided professional judgments based on years of transport management data and field risk assessments. Consequently, the relative importance ratios registered in the system can be mathematically represented as the following pairwise comparison matrix:

$$\begin{bmatrix} 1 & 3 & 1 & 2 & 3 & 3 & 1 \\ 0.33 & 1 & 0.33 & 0.33 & 3 & 1 & 0.33 \\ 1 & 3 & 1 & 1 & 3 & 2 & 0.33 \\ 0.5 & 3 & 1 & 1 & 3 & 1 & 1 \\ 0.33 & 0.33 & 0.33 & 0.33 & 1 & 0.33 & 0.2 \\ 0.33 & 1 & 1 & 1 & 3 & 1 & 0.2 \\ 1 & 3 & 3 & 1 & 5 & 5 & 1 \end{bmatrix}$$

By processing each value and the total sum of each matrix column, the system generated the normalized matrix and calculated the definitive weight for each criterion based on Equation (1). The final weight for each criterion was derived from the average of each row within the normalized matrix, as demonstrated in the system implementation shown in Figure 4. These resulting weights represent the relative priority of each driver selection criterion.

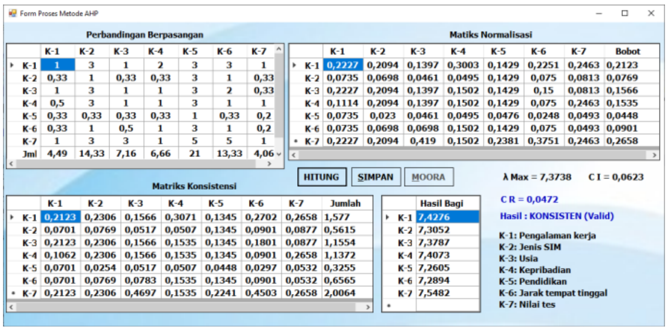

Figure 4. AHP Computational Process

A consistency matrix is generated by utilizing the normalized matrix values and the appropriate criteria weights. The individual values within the consistency matrix are derived by multiplying the corresponding entry in the pairwise comparison matrix by the respective criterion weight. To compute the quotients, the cumulative sum of each row in the consistency matrix must first be established. Each quotient is then obtained by dividing the total row sum of the consistency matrix by its associated criterion weight from the normalized matrix. It is worth noting that the row sums can also be directly calculated without expanding the consistency matrix by applying Equation (2). This matrix multiplication of the importance ratios and criteria weights is expressed as follows:

$$\begin{bmatrix} 1 & 3 & 1 & 2 & 3 & 3 & 1 \\ 0.33 & 1 & 0.33 & 0.33 & 3 & 1 & 0.33 \\ 1 & 3 & 1 & 1 & 3 & 2 & 0.33 \\ 0.5 & 3 & 1 & 1 & 3 & 1 & 1 \\ 0.33 & 0.33 & 0.33 & 0.33 & 1 & 0.33 & 0.2 \\ 0.33 & 1 & 1 & 1 & 3 & 1 & 0.2 \\ 1 & 3 & 3 & 1 & 5 & 5 & 1 \end{bmatrix} X \begin{bmatrix} 0.2123 \\ 0.0769 \\ 0.1566 \\ 0.1535 \\ 0.0448 \\ 0.0901 \\ 0.2658 \end{bmatrix} = \begin{bmatrix} 1.57 \\ 0.5615 \\ 1.1554 \\ 1.1372 \\ 0.3255 \\ 0.6565 \\ 2.0064 \end{bmatrix}$$

Using the total sum of each row in the consistency matrix (t), the quotient is calculated by multiplying t by the reciprocal of its corresponding weight (for instance, t for K-1 multiplied by the inverse weight of K-1)

A λmax value of 7.3738 was determined by averaging the computed quotients. Consequently, the Consistency Index was found to be 0.0623 using Equation (3). Given that a 7x7 matrix was employed, the standard Random Index value is 1.32, which yielded a final ratio of 0.0472 from the calculation of 0.0623/1.32. With the final consistency index established at 0.0472, which satisfies the requirement of being below 0.1 (<0.1), the criteria weights generated through this AHP procedure are validated for further execution in the decision making model.

C. MOORA Method Process

In the next stage, calculations are performed using the MOORA method. The integration of these two methods functions as a sequential hybrid model, where AHP addresses MOORA's inherent limitation of lacking an internal mechanism to calculate criteria weights. Conversely, MOORA serves as the ranking engine that efficiently processes multi-objective alternatives. The weights for each criterion, derived from the AHP process and verified as consistent and valid, are presented in the figure. Alternative values for each criterion are obtained from the driver candidate data entered via the form shown in Figure 3. These data are subsequently converted into a 4-point scale with reference to Table 3.

Mathematically, the systematic bridge between AHP and MOORA is executed during the normalization and weight multiplication phase. The normalization matrix values are determined using equation (5) to ensure dimension homogeneity. Once the normalized matrix (x_{ij}) is established, each value is multiplied by its corresponding weight (w_j) derived directly from the AHP priority vector, yielding the weighted normalized matrix as formulated in the algorithm. Through this systematic coupling, the subjective weight biases often found in standalone ranking methods are successfully mitigated by AHP's rigorous pairwise validation, while MOORA ensures a robust, low-complexity optimization process. The systematic execution of the MOORA optimization process and its numerical results for each driver alternative are presented in Figure 5.

TABLE 4
DRIVER CANDIDATE DATA

Code	Name	Age	DL	Experience	Education	Distance	Traits	Test
S-1	Joko Sulistyono	34	B1 general	6 years	SHS	<20 km	non smoker, less friendly	Proficient
S-2	Tegar Tri Kurniawan	31	A	5 years	SHS	<10 km	non smoker, friendly	Very proficient
S-3	Andika Satrio Perbawa	26	B1 general	9 years	SHS	<5 km	non smoker, less friendly	Very proficient
S-4	Wisnu Dwi Pamungkas	32	A	11 years	JHS	<5 km	non smoker, friendly	Very proficient
S-5	Muhamad Agus Ariyanto	50	B1 general	9 years	SHS	<10 km	non smoker, less friendly	Proficient
S-6	Harno Putro	33	A	6 years	SHS	<10 km	non smoker, friendly	Proficient
S-7	Suryo Santoso	26	A	2 years	SHS	<5 km	non smoker, less friendly	Proficient

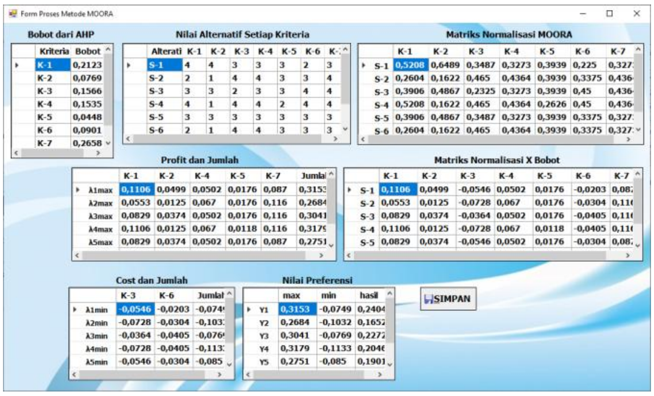

Figure 5. MOORA Computational Process

The following example illustrates the calculation for normalized matrix values: the sum of squares for the first column: $4^2+2^2+3^2+4^2+3^2+2^2+1^2=59$. To populate row 1, column 1, the corresponding alternative value (4) is divided by the square root of 59, resulting in $4/\sqrt{59} = 0.5208$.

The weighted normalization matrix is determined via equation (6) through the multiplication of each normalized matrix element by its appropriate weight. As an illustration for row 2, column 4, the normalized value (0.3906) is multiplied by the K-4 weight (0.1535), resulting in 0.0799. In this matrix, criteria categorized as profit hold positive signs, whereas those with negative signs signify cost criteria.

In the subsequent step, the profit and cost criteria are separated to compute their sums. The preference value, used as the foundation for selecting driver candidates, is obtained from the difference between both criteria. These known preference values are then sorted to swiftly determine the driver candidate hierarchy from the highest to the lowest score. The candidate ranking presentation can be observed in Figure 6, where the highest preference value indicates the system recommended candidate who qualifies for acceptance.

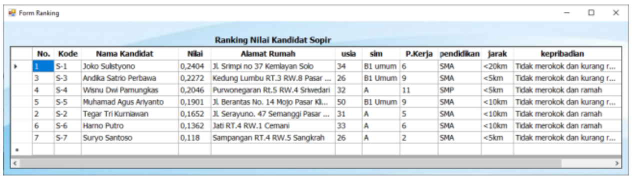

Figure 6. Driver Recommendation Results

D. Ethical Considerations, Fairness, and Bias Mitigation

While the integrated AHP-MOORA framework enhances objectivity, its application in human resource recruitment introduces critical ethical risks regarding fairness and algorithmic bias. Specifically, criteria such as Age (K-3) and Residential Distance (K-6) require careful ethical contextualization:

1. Age Criterion and Fair Employment: Assigning lower scores to younger (20-28) or older (>60) cohorts can inadvertently lead to age discrimination. In this system, this weighting is strictly justified by road safety analytics, which demonstrate that the 29-45 age group exhibits the optimal balance between physiological reflex and emotional regulation. However, to prevent absolute exclusion, the model uses an ordinal scale (1 to 4) rather than a binary elimination, ensuring older or younger candidates with exceptional driving scores (K-7) can still successfully pass the filter.

2. Residential Proximity and Geographic Bias: Prioritizing candidates living within a 5 km radius (K-6) can penalize qualified applicants from rural or socio-economically marginalized areas. This criterion was included strictly as a

proxy to mitigate pre-work driver fatigue a leading cause of traffic accidents. To ensure fairness, future iterations of this DSS should replace physical distance with a 'commute stability factor' or allow flexible enterprise transport, ensuring that geographic location does not become an artificial barrier to employment.

To safeguard algorithmic fairness, human oversight must remain the final arbiter in the recruitment pipeline. The system should function as a decision support recommendations engine rather than an autonomous decision-maker, allowing HR managers to override automated scores when systemic biases are identified.

E. System Evaluation

Testing was carried out in this research to assess the MOORA method accuracy for driver candidate selection. The accuracy dimension was evaluated through a confusion matrix approach, whereas the usability dimension was quantified using the System Usability Scale instrument. To validate the system, the outcomes computed by the MOORA method were cross-referenced with real data from the business owner. Table 5 presents a detailed and comprehensive comparison between the system outputs and the empirical data.

TABLE 5
COMPARISON RESULTS BETWEEN THE PROPOSED SYSTEM AND EMPIRICAL DATA

Candidate Name	Score	System Output	Actual
Joko Sulistyono	0.2404	Passed	Passed
Tegar Tri Kurniawan	0.2272	Passed	Passed
Andika Satrio Perbawa	0.2046	Passed	Failed
Wisnu Dwi Pamungkas	0.1901	Failed	Failed
Muhamad Agus Ariyanto	0.1652	Failed	Failed
Harno Putro	0.1362	Failed	Failed
Suryo Santoso	0.1180	Failed	Failed

The evaluation shows that the system achieved a correct classification of 2 true positive (passed) instances and 5 true negative (failed) instances. In terms of error rates, 1 instance was falsely classified as a rejection. The comprehensive test data is outlined in Table 6.

TABLE 6
CONFUSION MATRIX

	Positive	Negative
True	5 TP	2 TN
False	0 FP	1 FN

Performance evaluation based on the confusion matrix in Table 6 is calculated using four primary metrics: accuracy, precision, recall, and F1-score. The accuracy calculation is formulated as follows:

$$accuracy = \frac{(5\ +\ 2)}{(5\ +\ 2\ +\ 0\ +\ 1)} x\ 100\%$$

$$= \frac{7}{8}\ x\ 100\% = 87.5\%$$

Following the accuracy assessment, the precision, recall, and F1-score are computed to further evaluate the system's performance. The calculations for each metric are detailed below:

$$recall = \frac{\text{TP}}{\text{TP}\ +\ \text{FN}} x 100\% = \frac{5}{5+1} = 83.3\%$$

$$F1 - Score = 2\ X\ \frac{100\ x\ 83.3}{100\ +\ 83.3} x 100\% = 90.9\%$$

The confusion matrix analysis yields an Accuracy of 87.5% and a Precision of 100%. However, a deeper methodological examination is required to interpret these metrics objectively. The perfect precision score (100%) occurs because all alternatives predicted as 'Passed' by the AHP-MOORA algorithm (specifically candidates S-1, S-2, and S-3) perfectly aligned with the positive actual hiring decisions of the business owner. While this demonstrates that the system did not produce any false-positive errors within this specific group, this outcome is highly influenced by the small sample size (n=7 alternatives). In real world data science applications, a small cohort limits the statistical variance. Therefore, this 100% precision reflects an excellent descriptive fit for this specific pilot implementation, rather than a generalized, permanent elimination of false-positive risks across larger populations.

The practical impact of implementing this AHP-MOORA DSS extends significantly beyond academic metrics, offering tangible benefits to transport management operators:

1. Mitigation of Traffic Hazards and Asset Liabilities: Chauffeur services handle premium private vehicles where accident liabilities are costly. By utilizing a system that prioritizes test scores and stable personality traits over subjective liking, the company effectively filters out high risk drivers before they operate client vehicles.
2. Reduction of Operational Expenditures: Conventional screening methods often require multiple rounds of subjective interviews and manual reviews, inflating HR hours. This DSS condenses the evaluation of complex multi-criteria facets into a single computational step, reducing hiring turnaround time and administrative overhead.
3. Enhanced Corporate Accountability: By generating quantifiable preference scores, the transport provider can present a auditable, data-backed rationale to corporate clients regarding the high quality and safety standards of the assigned drivers.

IV. CONCLUSION

Drawing upon the comprehensive analysis, system implementation, and empirical testing of the rental car driver selection information system in Surakarta which integrates the AHP and MOORA methods, the following primary conclusions are established: 1) Systemic Efficacy in decision support: The integrated AHP-MOORA decision support system developed in this study successfully demonstrates its conceptual validity. Within the specific parameters of the evaluated experiment, the system effectively overhauls conventional screening practices by mapping qualitative chauffeur traits into structured quantitative rankings. This localized implementation confirms that the hybrid approach aligns with the operational mandates of the participating partner, PT. Kencana Surakarta, providing a more objective, computer-assisted tool for their immediate recruitment pipeline. 2) Consistency and Prioritization of Criteria: The criteria weighting matrix executed via the AHP method yields highly consistent weight distribution, fully satisfying the mathematical consistency ratio thresholds. Consequently, the established priority hierarchy of driver selection criteria, ordered from the most critical to the least determinant, comprises: test scores, personality traits, professional experience, age, proximity of residence, driving license, and formal education. 3) Performance Constraints and Generalizability: Evaluated through a confusion matrix validation, the model exhibits high descriptive reliability strictly within the context of the analyzed pilot dataset (n=7 alternatives). While the model achieved a 100% precision rate in eliminating false-positive recommendations for this specific cohort, this outcome must be interpreted strictly within this experimental boundary. Because these metrics are highly dependent on the current sample size and localized criteria weights, the findings cannot be definitively generalized to the broader transportation or logistics industry. Instead, this study serves as a validated framework and a baseline model that requires further multi-firm testing and larger dataset validation before widespread industrial deployment can be fully guaranteed.

Despite its robust classification performance, this study acknowledges a critical methodological limitation regarding the inherent subjectivity in the initial system design. Although the subsequent AHP-MOORA calculations operate on strict mathematical algorithms, the upfront selection of the seven criteria and the calibration of the 4-point scoring scale (as presented in Table 3) rely heavily on the qualitative insights and expert judgments of local transport stakeholders. This localized preference introduces a potential risk of institutional bias, meaning the scoring boundaries might not perfectly translate to other transportation firms or different sub-sectors of logistics. Furthermore, human-defined ordinal mapping can sometimes oversimplify the nuanced differences between candidate attributes.

Drawing upon the conclusions and limitations inherent in this driver selection information system, future research should focus on two key areas of development. Aligned with the critical demand for road safety, subsequent system enhancement should integrate a driving behavior monitoring module to enable continuous, periodic evaluations of driver performance post recruitment. Furthermore, future studies should explore comparing or combining the current AHP-MOORA framework with alternative MCDM methods, such as WASPAS, ARAS, or TOPSIS, to determine if a more profound improvement in overall classification accuracy can be achieved.

ACKNOWLEDGES

The author highly acknowledges the advisors of the Information Systems Study Program for their invaluable mentorship, scholarly direction, and constructive feedback throughout the course of this research. Their profound expertise and continuous support have served as a cornerstone for the successful completion of this scholarly work. Heartfelt gratitude is likewise extended to the academic community of Universitas Bina Sarana Informatika for providing the essential facilities, academic opportunities, and an encouraging research environment that greatly enabled the execution of this study. Lastly, the author extends sincere appreciation to all individuals who generously dedicated their time to offer constructive insights and critiques, which have profoundly elevated the academic quality of this research.

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