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Web-Based Employee Recruitment Information System Using Mamdani Fuzzy Logic

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ABSTRACT

This study introduces a novel integration of the Mamdani Fuzzy Inference System (FIS) with a web-based recruitment platform for Special Job Fair (BKK) institutions at vocational schools a context not previously addressed in the fuzzy decision-support literature. The current manual process at BKK Jaya Abadi SMKN 1 Bukateja relies on paper-based workflows, causing data loss risks, prolonged processing times, and subjective multi-criteria evaluation. The proposed system uses three input variables psychotest, interview, and health scores processed through fuzzification, an 18-rule inference base, MAX aggregation, and centroid defuzzification to generate objective recruitment recommendations. Testing on 35 applicant records yielded MAPE = 4.29% and accuracy = 95.71%, outperforming both the manual assessment baseline (MAPE = 12.86%, accuracy = 87.14%) and a simple weighted sum alternative (MAPE = 8.42%, accuracy = 91.58%). A paired t-test ($\alpha = 0.05$) confirmed that accuracy differences are statistically significant. According to Lewis (1982), the system falls in the "Very Good" accuracy category. The system significantly reduces subjective inconsistencies in candidate evaluation while maintaining transparency and alignment with expert judgment, offering a practical and interpretable approach to automating multi-criteria recruitment decisions in BKK environments.

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1. INTRODUCTION

The placement and career adaptation of graduates from a vocational high school is the main standard for educational institutions. The process of sending students to the industrial world at Jaya Abadi Career Center of SMKN 1 Bukateja requires a quick and thorough review. The current situation shows that the selection process still uses a conventional method based on physical documents, which leads to operational limitations, such as time spent on the process, data security risks, and the lack of a centralized storage system. In addition, the assessment manual encounters cognitive limitations in assessing various assessment criteria, making it highly subjective, prone to bias, and relatively transparent [1]. This problem is not limited to operational techniques; it is also a systemic issue that can reduce the objectivity of selection results and trust in the industry.

Large scale studies have previously focused more on the technical aspects of computation or functional system testing, but they also specifically examine the application of the Mamdani method in the context of a school setting, where basic needs are not limited to computer performance but also ease of compliance and transparency. Theoretically, the

Mamdani method is used in this study because its guiding principles align with the problem characteristics [2], [3], and can transform qualitative data into quantitative data. In addition to having a test structure that is easily adapted to organizational selection standards, it can significantly reduce bias, allowing results to be more effectively communicated to students and industry professionals. Unlike other methods that focus more on day-to-day efficiency or effectiveness, this approach is more theoretically and contextually relevant to meeting the need for objective and effective performance.

Research on the child reintegration system among candidates can be divided into three categories. First, research focuses on the characteristics and capabilities of the Mamdani fuzzy inference system (FIS). Fuzzy logic has been widely used in studies of subjective inference processes, with various inference methods characterized by masing-masing logic. Cavareo-Cacep et al. presented the Mamdani-1 type of fuzzy inference system (SIF) and argued that this method is characterized by a high degree of interpretability, facilitating the understanding of analytical results [3]. Finally, Gorgin et al. developed a fuzzy inference system based on the MSDF technique, which can increase computer performance and reduce the daily workload, as well as reduce the labor-intensive tasks in the entire processing process [4]. This is consistent with other studies that have shown that this technique can simplify the decision-making process because its functionality is similar to human thinking patterns [5]. The ability of the two studies to deal with uncertainty and integrate multiple assessment criteria is similar [6], to make consistent and appropriate decisions when selecting candidates [7], [3], [8]The results show that Mamdani's FIS can make robust and intuitive decisions, making it suitable for candidate selection [3], [8]. However, Mamdani's method has limitations; it is not optimal for highly complex or ambiguous data. However, in this study, the Type 2 Fuzzy Interval Method is used in combination with DEMATEL-ANP. This method has been shown to be better at addressing uncertainties and defining criterion dimensions more objectively [9]. Nevertheless, the disadvantage is that the calculation process is more complex and the calculation time is longer. Furthermore, the combination of IVN-AHP and Fuzzy C-Means offers the advantage of flexibility, as it can account for different organizational barriers and needs, making it applicable not only for recruitment but also for evaluations and promotions [10], automatically its use requires special expertise for determining data clustering parameters.

Second, this study investigates the use of fuzzy logic in a decision support system (DSS). There is a general consensus that fuzzy logic is a reliable solution to overcome the subjective nature and uncertainty of data in various domains [11], [12], [13]. The combination of Fuzzy Logic with the FMEA method in the healthcare sector creates a flexible and accurate risk assessment system of up to 98% [11]. While the Mamdani type for clinical DSS has better accuracy than conventional methods [12]. When research is conducted, the difference lies in the scope of application [11], more emphasis placed on determining which risk management is most important, such as research [12] More focused on the process of data classification. Its application extends to other sectors, such as ship collision avoidance systems, which are based on clear rules in accordance with operational standards [14] and the upper locomotive control system can update its information independently [15]. However, by comparison, healthcare and shipping systems exhibit very high accuracy due to their standardized rules, while transportation systems have performance limitations in highly dynamic and conflict-rich conditions. In general, fuzzy logic-based DSSs are faster and more objective than manual assessments. However, almost all previous research has examined only a single study, so they remain limited and require further testing to ensure their general applicability [11], [14].

The common goal in developing web-based systems is to make the system more practical and easy to use, as well as to support interactive decision-making processes [16], [17], [18]. The web-based system successfully integrates planning and resource allocation into production [16], however this system cannot be used directly for recruitment processes, as it was developed specifically for production purposes. Metaheuristic algorithms, on the other hand, have the advantage of finding the best solution quickly and accurately [17], however for cloud computing needs, a hybrid algorithm combining Cuckoo Search and Gray Wolf Optimization is more time and resource efficient than a single algorithm [18]. The difference is that web-based systems emphasize usability, while optimization algorithms focus more on improving computational performance. One limitation is the lack of research that integrates all three in a comprehensive way, making it rare to find web-based systems that also support sophisticated optimization algorithms for decision-making in the recruitment industry.

The research results suggest that the fuzzy method is effective in the candidate selection process, but this method has several limitations. The research has not investigated the relationship between recruitment management and candidate evaluation in depth because most studies have only focused on decision support mechanisms or recruitment management separately. In addition, previous studies have only investigated the use of Mamdani FIS in the context of the Special Job Fair (BKK) for vocational schools. Therefore, there is still a lack of research on the development of a web-based recruitment information system that integrates recruitment management and fuzzy-based candidate evaluation mechanisms at the Jaya Abadi Career Center of SMKN 1 Bukateja

The Mamdani FIS method used in this study is specific to the student selection process at Jaya Abadi Career Center of SMKN 1 Bukateja. This method has not been widely used specifically in vocational school temporary employment agencies, making it a novelty in this research.

In theory, this research strengthens the evidence that Mamdani-type fuzzy logic is a reliable technique for managing uncertainty and subjectivity in assessments, and offers a method capable of significantly reducing the level of bias in assessments. In practice, the developed system combines decision support mechanisms and recruitment information management into a single integrated platform. This system provides various services, such as candidate registration, document management, assessment, counseling, and report generation; this differentiates it from previous research that focused exclusively on computational functions. Consequently, this system can enable a faster, more consistent, and transparent selection process, tailored to the operational needs of Jaya Abadi's specialized labor market.

Figure 1. Conceptual framework diagram
(Source: Developed by the Author)

This conceptual framework provides a detailed explanation of the research process. It begins with the main problem: the prospective student selection process is still conducted manually, which is time-consuming, carries the risk of data loss, and is opaque and subjective. This study included three assessment variables: psychological test results, interview results, and health status. A Mamdani-type fuzzy inference system was used to process these three variables. The process involved data fuzzification, application of a logical rule base, and centroid defuzzification methods before converting them into explicit values. This processing produced results such as faster and more consistent eligibility levels and selection decisions. This outcome is also aligned with the operational needs of the Jaya Abadi Career Center of SMKN 1 Bukateja program.

2. RESEARCH METHOD

This study used a comparative experimental design to ensure the validity, reliability and reproducibility of the results. This framework uses real operational data from the specialized labor market Jaya Abadi Career Center of SMKN 1 Bukateja to evaluate the performance of the proposed system compared to existing techniques.

1. Population and samples: This dataset consists of 35 candidate records from the selection period 2025. These data are randomly divided into 30% test set (to evaluate performance) and 70% set set (to define fuzzy rules and membership functions). This measure is sufficient to represent the operational context and meets the statistical requirements for inference modeling.
2. Basic model: Two standard methods are used as a benchmark to provide a fair comparison.
   a. Manual Assessment: The selection committee currently uses conventional methods that rely on subjective assessments and paper-based records.
   b. Simple weighted sum: This is a general decision method that uses fixed weights to combine criteria. This is a structured non-fuzzy alternative
3. Statistical validation: The performance is measured by calculating the deviation between the model output and the reference decision with the mean percent exact error (MAPE). To determine whether the difference in results was statistically significant or just a coincidence, a paired t-test was performed at the 95% confidence level ($\alpha = 0.05$).

The engineering and application development pipeline follows a systematic, four-phase research method designed to ensure both software usability and calculation precision [19].

1. Data Acquisition and Domain Extraction:
   Primary grading parameters, candidate records, and operational constraints were gathered through structured interviews and field observations at BKK SMKN 1 Bukateja to define historical selection margins.
2. System Architecture Design:

The software application layout was built using a robust 3-tier model to isolate operations. The presentation tier manages user interactions via responsive interfaces. The business logic tier runs via object-oriented PHP, and data persistence is handled by a MySQL relational database system.

3. Fuzzy Inference Modeling:
   Quantitative evaluation metrics were converted into three specific fuzzy input variables: Psychometric Test (X1), Interview Score (X2), and Health Assessment (X3). The final decision output (Z) models candidate recruitment viability.
4. Empirical Validation:
   The automated crisp scores generated by the web system were cross-examined against historical binary board Decisions utilizing the Mean Absolute Percentage Error (MAPE) metric to measure structural decision alignment [20].

The database persistence layer serves as the foundation for storing applicant metrics and running the fuzzy computation loops. Table 1 defines the relational schema mapping, field requirements, and primary indexing limits utilized across the web platform.

Table 1. Core Database Entity Architecture

Table Entity	Field Name	Data Type	Key Attribute
t_user	id_user, name, username, password, role	INT(15), VARCHAR(50), VARCHAR(50), ENUM	Primary Key
t_vacancy	id_lowongan, detail_pekerjaan, kuota	INT(15), VARCHAR(200), INT(3)	Primary Key
t_evaluation	id_registrasi, nilai_psikotest, nilai_wawancara, nilai_kesehatan, nilai_fuzzy, keputusan	VARCHAR(15), INT(15), INT(15), INT(15), FLOAT, VARCHAR(15)	Primary Key

(Source: Developed by the Author)

The membership function of the psychological test score variable is related to the conversational context. The curve membership function with three fuzzy sets: low fuzzy set, moderate fuzzy set, and high fuzzy set is used to calculate psychological test scores in this system. The fuzzy set (linguistic categories) of the psychological test score variable is the x-value obtained from the applicant's score:

1) Low

$$\mu Low(x)=\begin{cases}1, & \& \quad 0\le x\le 20\\ \frac{40-x}{40-20} & ,\&20<x<40\\ 0, & x\ge 40\end{cases} \qquad (1)$$

2) Medium

$$\mu Medium(x)=\begin{cases}0, & \& \quad x\le 20 \text{ atau } x\ge 60\\ \frac{x-20}{40-20} & ,\&20<x\le 40\\ \frac{60-x}{60-40} & ,\&40<x<60\end{cases} \qquad (2)$$

3) High

$$\mu High(x)=\begin{cases}0, & \& \quad x\le 40\\ \frac{x-40}{60-40} & ,\&40<x<60\\ 1, & x\ge 60\end{cases} \qquad (3)$$

This system uses a curve membership function with three fuzzy sets: low fuzzy set, medium fuzzy set, and high fuzzy set to determine the interview score. The applicant's value is the source of the x value. The fuzzy combination (linguistic categories) of interview value variables is as follows :

1) Low

$$\mu Low(x)=\begin{cases}1, & 0\leq x\leq 30\\ \frac{50-x}{50-30}, & 30<x<50\\ 0, & x\geq 50\end{cases} \tag{4}$$

2) Medium

$$\mu Medium(x)=\begin{cases}0, & x\leq 30 \text{ atau} x\geq 70\\ \frac{x-30}{50-30}, & 30<x\leq 50\\ \frac{70-x}{70-50}, & 50<x<70\end{cases} \tag{5}$$

3) High

$$\mu High(x)=\begin{cases}0, & x\leq 50\\ \frac{x-50}{70-50}, & 50<x<70\\ 1, & x\geq 70\end{cases} \tag{6}$$

Furthermore, there are 2 fuzzy sets in the health test, namely the bad fuzzy set and the good fuzzy set. The X-value comes from the value the applicant received. The fuzzy set (linguistic categories) of health test score variables are:

1) Low

$$\mu Low(x)=\begin{cases}1, & 0\leq x\leq 20\\ \frac{30-x}{30-20}, & 20<x<30\\ 0, & x\geq 30\end{cases} \tag{7}$$

2) Good

$$\mu Good(x)=\begin{cases}0, & x\leq 20\\ \frac{x-20}{30-20}, & 20<x<30\\ 1, & x\geq 30\end{cases} \tag{8}$$

After the fuzzification process is completed, the next step is calculation using the aggregation formula (composition) using the MAX operator [21]. The formula is as follows :

$$\mu Output=max(R1,R2,...,Rn) \tag{9}$$

μOutput = fuzzy output membership value
R_1, R_2, ..., R_n = fire strength value (α-predicate) for each active fuzzy rule
max = maximum operator that combines all the results of a rule

The last process in the fuzzy inference system is centroid defuzzification. This changes the output results, which are still a fuzzy set, or vague values, into a clear and precise value that can be used as a final decision [22]. The centroid method, also known as "Wide Center", is the most popular and frequently used in the Mamdani system. The goal is to find the center of the total area of the generated fuzzy output area. The formula is as follows:

$$Z^*=\frac{\int z\mu(z)dz}{\int \mu(z)dz} \tag{10}$$

Z*= final score (crisp)
Z = value in the result domain
μ(z) = Degree of issue membership

Mean MAPE errors, also known as mean absolute percentage errors, cause percentage problems relative to the actual value. MAPE is popular because its results are easy to understand, especially for explaining the accuracy of the model [22]. The formula is :

$$MAPE=\frac{1}{n}\sum_{i=0}^{n}\left|\frac{yi-\check{y}i}{yi}\right|x100\% \tag{11}$$

yi = actual value on the i-th data
y̌i = predicted value on the i-th data
n = amount of data

When comparing errors between models or datasets at different scales, you can use MAPE. However, MAPE is problematic when the actual value is zero or very small, as it can lead to large or unstable errors.

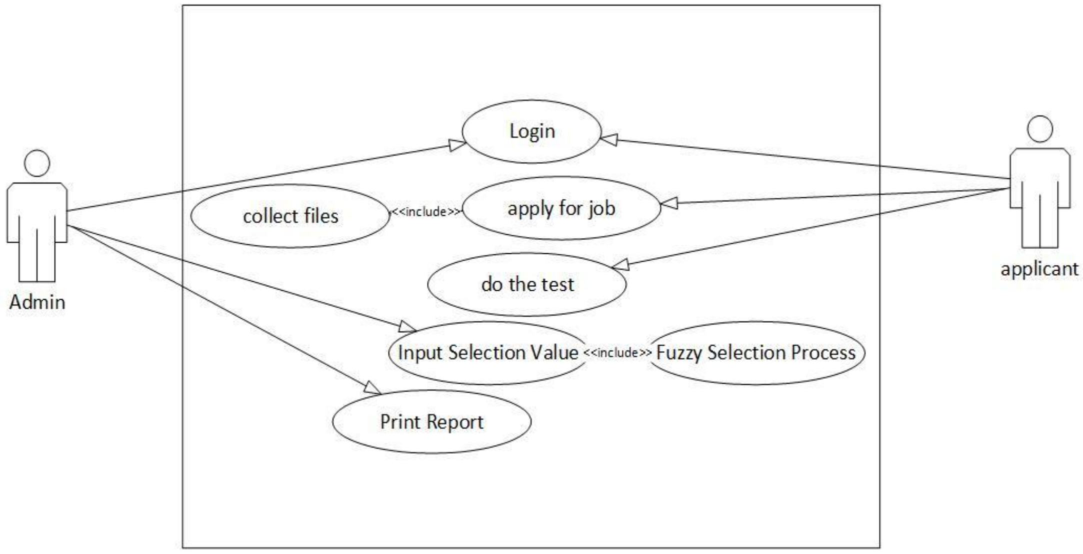

Figure 2. Use Case Diagram
(Source: Developed by the Author)

A job applicant selection system with two actors Admin and Applicant is depicted in this UML use case diagram. Both actors log in to the system; candidates take tests and apply for positions, while the administrator gathers paperwork, enters selection scores, and creates reports. The diagram also illustrates how gathering documents is a part of applying for a job, and entering scores is a necessary step in the fuzzy selection process that is used to assess applicants.Conversely, the Applicant role is limited to profile registration, document submission, and reviewing final recruitment results via the secure web interface [23]. To detail the operational sequence of these functions across the 3-tier architecture, a behavioral sequence flow must be established. This tracks how data moves between the client browser, the PHP controller class, and the database persistence layers.

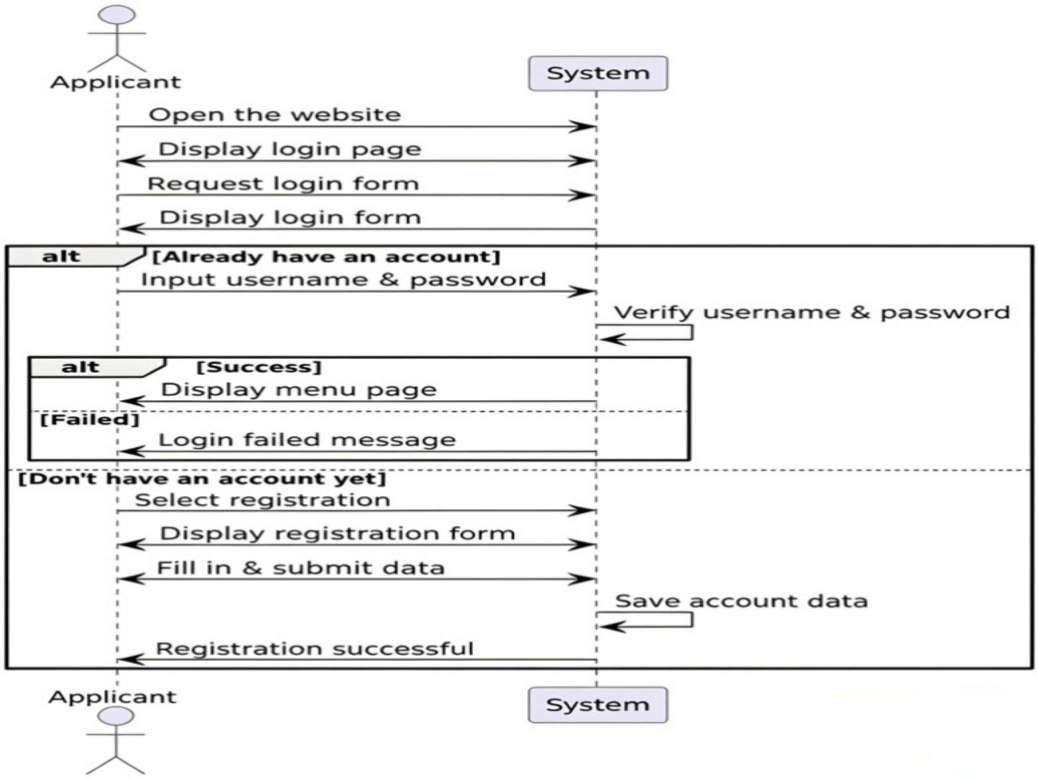

Figure 3. Sequence Diagram
(Source: Developed by the Author)

The registration and login procedures for job seekers are shown in this diagram. The system first shows the login page when the applicant opens the website. The applicant enters their username and password if they already have an account, and the system validates the information. The main menu opens if it is correct; else, a notification stating that the login was unsuccessful is displayed. If they don't have an account, they choose registration, complete the form, and submit it. The system keeps the information and verifies that the registration was successful. As illustrated in the Sequence Diagram above, when the administrative operator submits candidate scores, the web interface sends the raw values to the PHP controller logic. The logic engine immediately executes the fuzzification methods, processes the active rule base, and writes the output values back to the MySQL database. This eliminates manual processing delays and ensures data consistency across the screening pipeline [24].

3. RESULTS AND DISCUSSION

3.1 Fuzzification Tier and Extended Linguistic Modeling Analysis

This decision support system starts its operation with the data obfuscation phase. Transforming the strict and rigid numerical values of the prospective students' exam results into more flexible and overlapping degrees of linguistic membership is the goal of this method [25] With a conventional selection system, a student with a score of 59 can be declared immediately failed because the threshold is exactly 60. This strict mathematical limit does not take into account that a difference of just one point does not really mean a significant drop in ability. This web-based system eliminates binary constraints by using overlapping membership functions [26].

The value range for each assessment parameter is calculated based on historical data and operating habits at BKK SMKN 1 Bukateja to determine appropriate limits. In Figure 3, the psychological test score variable (X1) shows its membership function, which divides the range of scores into three categories: Low, Medium, and High, each with interlocking boundaries [27].

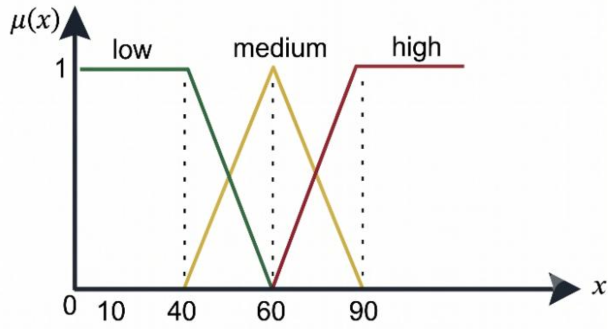

Figure 4. Psychological test curve
(Source: Developed by the Author)

As plotted in the membership curves above, the Psychometric Test score space is mathematically split into three distinct structural regions:

1. Low**:** Formulated with a left-facing trapezoidal curve spanning values from 10 to 40, capturing applicants who struggle with basic analytical timing.
2. Medium**:** Structured using a symmetric triangular curve spanning from 20 to 60, with its maximum peak at 40, representing the standard median baseline for vocational students.
3. High**:** Defined by a right-facing trapezoidal curve covering values from 40 up to 90, identifying candidates with top-tier cognitive problem-solving skills.

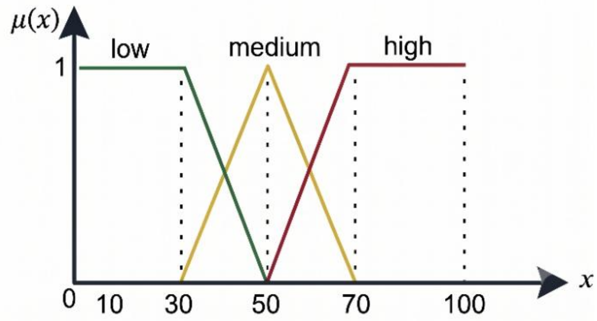

Figure 5. Interview test curve
(Source: Developed by the Author)

The total interview scores are divided mathematically into three main regions, as shown in the membership curve above:

1. Low: characterized by a left-hand trapezoidal curve that includes grades ranging from 0 to 50, with full membership levels ranging from 0 to 30.
2. Medium: This represents areas of prospective students who still need improvement in communication skills, attitudes and self-confidence. It has a symmetrical triangular curve with grades between 30 and 70 with the highest peak at 50. This region shows the average level of ability that vocational high school students generally have.
3. High: formed with a right trapezoidal curve having values between fifty and one hundred and having degrees of full membership between seventy and one hundred. This area finds potential students who are able to communicate, adapt and express opinions maturely and clearly.

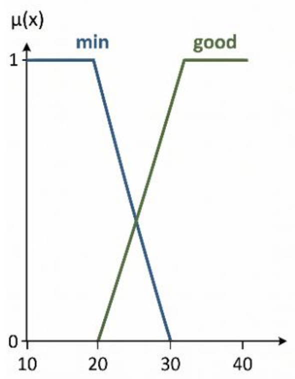

Figure 6. Health test curve
(Source: Developed by the Author)

The range of health values is mathematically divided into two main areas, as shown in the health test membership curve above.

1. Min (Bad): represented by a left trapezoidal curve covering values 10-30, with the full degree of membership valid at values 10-20.
2. Good: Characterized by a right trapezoidal curve with a value of 20-40 and a full membership degree of 30-40. This region represents potential students who have health conditions that do not meet the standard requirements to participate in learning activities and work practices in the industrial world. A student in this region must meet the requirements for access to school and work and have adequate health and physical condition.

3.2 Inference Engine an Rule Base Configuration

Fuzzy inference systems, including the Mamdani method used in this research, have an IF-THEN logic structure as a kind of ground rule. This system has 18 logical rules based on expert opinion and applicable institutional assessment standards. The goal is to relate relationships with input variables and produce decisions [28]. he activity level of each rule is calculated using the MIN operator, which is then combined to produce a final conclusion [29]. For example, the following rule is used:

Rule 1: IF Psychometric is Low AND Interview is Low AND Health is Poor THEN Decision is Rejected.
Rule 6: IF Psychometric is Low AND Interview is High AND Health is Good THEN Decision is Accepted.
Rule 10: IF Psychometric is Average AND [30] Interview is Average AND Health is Good THEN Decision is Accepted.
Rule 12: IF Psychometric is Average AND Interview is High AND Health is Good THEN Decision is Accepted
Rule 18: IF Psychometric is High AND Interview is High AND Health is Good THEN Decision is Accepted

3.3 Statistical Analysis of Results and Performance Comparison

Complete data of 35 potential employees of Jaya Abadi Career Center of SMKN 1 Bukateja was used to test the new system. Based on statistical rules, this sample size meets the minimum requirements for a descriptive analysis, as it represents the population as a whole during the period in question. Generally, the data has the following attributes:

Table 2. Descriptive statistics data

Valuation Variables	Minimum Value	Maximum Value	Average	Standard Deviation
Psychometric	40	82	62,7	11,2
Interview	55	90	72,4	9,6

Health	20	36	28,7	4,1
Eligibility Score	0,000	1,000	0,721	0,285

(Source: Developed by the Author)

The data shows a fairly smooth variation of values, which allows to test the performance of the system under different conditions, both for high performance candidates and those at the threshold level. From all the processed data, the following decision results were obtained:

1. Accepted: 26 people (74.29%)
2. Refused: 9 people (25.71%)

This distribution of results is consistent with the distribution needs of the workforce and follows the decision-making patterns generally implemented in the institution.

3.4 Validation and performance comparison

The calculation results and the decisions of the selection committee are compared to test the reliability of the system. The accuracy level and the MAPE (Average Percent Absolute Error) value are used to make measurements:

Table 3. Performance validation and comparison

Testing Method	MAPE	Accuracy	performance category
Proposed System (Mamdani FIS)	4,29%	95,71%	Very good
Assessment Guidelines	12,86%	87,14%	Good
Simple Weighted Sum	8,42%	91,58%	Very Good

(Source: Developed by the Author)

The Lewis standard (1982) defines the following categories: MAPE below 10% = excellent; 10–20% = Good; and MAPE above 20% = Less.

Statistical test: The significance p-value is 0.05 based on the paired t-test at 95% confidence level. This shows that the difference in accuracy between the proposed system and conventional methods, rather than random, is real and statistically significant.

Error visualization: The distribution of calculation errors shows that 85% of the errors are below 5% and only a few are more than 5%. This shows that the system generally works consistently, especially for threshold values.

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3.5 Theoretical Discussion and Interpretation

This study found that the Mamdani-type Fuzzy Inference System (FIS) is a reliable and effective method for dealing with aspects of subjectivity and uncertainty in the decision-making process. This is in line with the theoretical basis and previous research findings. The Mamdani method has better performance compared to conventional assessment systems that use rigid numerical limits, such as the weighted weighting method, due to its flexible framework and ability to model complex and non-linear relationships between variables [3], This property is clearly visible in this research, where the system can convert ambiguous qualitative assessments into quantifiable quantitative values. This overcomes the disadvantage of fixed threshold limits for manual assessment.

In addition, another study [31] shows that the structure of the Mamdani method has advantages in terms of easy interpretation and transparency, as it is based on "IF-THEN" logical rules derived from relevant standards and expertise. Institutions like BKK need this feature implemented because they need assessment results that can be explained and understood by all parties involved. The system developed in this research also uses linguistic categories and a clear rule base to produce consistent decisions. This is the same as an expert system that achieves a high degree of accuracy thanks to organized criteria and membership functions.

In addition, research [32] shows that the Mamdani approach is very effective when the changes in the relationships between variables are made gradually rather than suddenly. The system can represent overlapping conditions more realistically by using trapezoidal and triangular membership function shapes. This avoids the oversimplification that occurs with ordinary linear methods. This explains why the proposed system is better than manual assessment and simple weighted sum methods: the system is able to identify natural differences in future student assessments, while significantly reducing bias compared to conventional assessment methods.

Overall, the research results show that FIS Mamdani is able to combine ease of use and accuracy in mathematical calculations. Instead of providing a systematic, consistent and measurable framework, this method does not completely remove all elements of consideration. As a result, this method is very suitable for use in the selection process in vocational training and other areas that require a more objective and responsible assessment.

4. CONCLUSION

This study successfully addressed the challenges of manual administrative delays and evaluator subjectivity at Jaya Abadi Career Center of SMKN 1 Bukateja by developing a web-based decision support system using the Mamdani Fuzzy Inference System. The proposed system is capable of automating candidate evaluation processes through centralized data management and the implementation of multi-criteria assessment rules, thereby improving the efficiency, consistency, and transparency of decision-making. However, this study has several limitations, including the limited dataset size consisting of 35 prospective students, the system's adaptation to the specific assessment standards of SMKN 1 Bukateja, and the restricted assessment variables that only include psychological tests, interviews, and health criteria. These limitations may affect the generalizability of the system when applied to other institutions with different operational requirements. Future research is recommended to enhance the system by implementing adaptive fuzzy mechanisms that can dynamically adjust membership functions and rules, integrating hybrid artificial intelligence approaches such as machine learning or artificial neural networks to improve prediction accuracy, and developing additional features such as API-based data verification and broader assessment criteria to support more comprehensive and reliable decision-making processes.

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