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Enhancing Fairness and Efficiency in Teacher Placement based on Staff Placement Model: An Intelligent Teacher Placement Selection Model for Ministry of Education Malaysia

Meningkatkan Keadilan dan Kecekapan dalam Penempatan Guru berdasarkan Model Penempatan Staf: Model Pemilihan Penempatan Guru Pintar untuk Kementerian Pendidikan Malaysia

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ABSTRACT

Efficient workforce management is critical for large organizations such as the Ministry of Education Malaysia (MOE), particularly in processing thousands of teacher placement applications. The current Teacher Placement Selection (TPS) system considers personal merit, environmental factors, and staffing requirements across 20 attributes but has been criticized for its perceived lack of fairness. This study proposes an Intelligent Teacher Placement Selection (ITPS) system based on a Staff Placement Model (SPM), expanding the attribute set to 27 by incorporating personal, staffing position, placement type, and human factors to enhance decision-making fairness. The effectiveness of ITPS was evaluated using five machine learning algorithms: J48, Decision Tree, Naïve Bayes, Random Forest, and K-Nearest Neighbors. A dataset of 4,484 teacher placement applications from the first session of 2020 was analyzed, comparing Teachers Placement Committee (TPC) and ITPS outcomes. Results indicate that J48 achieved the highest accuracy, improving from 71.28% in TPC to 95.74% in ITPS. Further validation using 2,562 applications from the second session of 2020 demonstrated ITPS ability to approve more placements (1,582) than the actual decisions (1,560). A T-test comparing TPC and ITPS yielded a high p-value ($p > 0.05$), confirming no statistically significant difference between the models while validating ITPS reliability. In conclusion, the ITPS model based on SPM enhances efficiency and fairness in teacher placements at MOE, demonstrating strong potential as a decision-support tool for optimizing workforce allocation.

Keywords: Teacher placement, Staff Placement Model, classification techniques, data mining, J48

ABSTRAK

Pengurusan tenaga kerja yang cekap adalah penting bagi organisasi besar seperti Kementerian Pendidikan Malaysia (KPM), terutamanya dalam mengendalikan ribuan permohonan penempatan guru. Sistem Pemilihan Penempatan Guru (SPPG) sedia ada menilai merit peribadi, faktor persekitaran, dan keperluan tenaga kerja berdasarkan 20 atribut, namun sering dikritik kerana ketidakadilan dalam pengambilan keputusan. Kajian ini mencadangkan Sistem Pemilihan Penempatan Guru Pintar (SPPGP) berasaskan Model Penempatan Staf (MPS), yang memperluaskan set atribut kepada 27 dengan mengintegrasikan faktor peribadi, jawatan, jenis penempatan, dan faktor manusia bagi meningkatkan keadilan dalam pemilihan. Keberkesanan SPPGP dinilai menggunakan lima algoritma pembelajaran mesin: J48, Pokok Keputusan, Naïve Bayes, Hutan Rawak, dan Jiran Terdekat-K. Dataset yang terdiri daripada 4,484 permohonan penempatan guru bagi sesi pertama tahun 2020 dianalisis untuk membandingkan keputusan JKPS dan SPPGP. Keputusan menunjukkan bahawa algoritma J48 mencapai ketepatan tertinggi, meningkat daripada 71.28% oleh JawatanKuasa Penempatan Guru (JKPG) kepada 95.74% dalam SPPGP. Pengesahan lanjut menggunakan 2,562 permohonan daripada sesi kedua tahun 2020 menunjukkan SPPGP mampu meluluskan lebih banyak penempatan (1,582) berbanding keputusan sebenar (1,560). Ujian-T yang dijalankan bagi membandingkan JKPG dan SPPGP menghasilkan nilai p yang tinggi ($p > 0.05$), menunjukkan tiada perbezaan yang signifikan antara kedua-dua model dan mengesahkan kebolehpercayaan ITPS. Kesimpulannya, ITPS berasaskan MPS meningkatkan kecekapan dan keadilan dalam penempatan guru di KPM, sekali gus menunjukkan potensi sebagai alat sokongan keputusan yang berkesan untuk pengoptimuman peruntukan tenaga kerja.

Kata kunci: Model penempatan guru, model penempatan staf, perlombongan data, pengelasan, J48

INTRODUCTION

Effective teacher placement is a critical component of human resource management (HRM) in the education sector, directly influencing workforce efficiency, student learning outcomes, and institutional performance. Proper teacher allocation ensures teachers are assigned to positions that align with their subject expertise, qualifications, and school needs. However, inefficiencies in current placement systems often lead to workforce imbalances, misalignment of teaching expertise, and reduced educational quality (Lim, K. & Hassan, 2024) . In Malaysia, the Ministry of Education (MOE) aims to place teachers according to their subject specialization following pre-service training (Ensimau et al., 2024). Despite this, mismatches persist, resulting in dissatisfaction among teachers and inefficiencies in school management (Hilmi, 2022). emphasizes the need for a systematic, data-driven, and equitable placement framework to address these challenges.

In such current era, teacher placement decision is supervised by administrative evaluations and human intuition with assistance from the systems such as Human Resource Management Information System (HRMIS) (HRMIS, 2024), e-Operasi (BPSH, 2024b), e-Gtukar (BPSH, 2024a). Despite this, these systems primarily serve as record-filing systems rather than wishing-well systems. The absence says predictive analytics means placement decisions are reactive, inconsistent and inefficient, with mismatches between teacher expertise and school demands.

The traditional teacher placement process often faces various challenges, particularly when the Staff Placement Committee (SPC) needs to identify and retrieve relevant information from a large database. This process is not only complex and time-consuming but can also lead to errors in selection and the placement of lecturers who may not be well-suited to the institution's needs (Ahmad, R. & Siti, 2023).

Data mining plays a crucial role in knowledge discovery, enabling organizations to analyze large datasets and identify meaningful patterns for informed decision-making. In teacher placement, data mining techniques can be used to predict optimal placements based on historical trends, teacher performance, school demands, and regional staffing needs (Sriwindono et al., 2022). Despite ongoing efforts to align teacher specialization with placements, mismatches remain a significant challenge, with many teachers assigned to subjects outside their area of expertise. These mismatches lead to reduced teaching effectiveness and job dissatisfaction while also contributing to unequal teacher distributions, with shortages in some regions and surpluses in others (Langeveldt & Pietersen, 2024).

Existing placement systems lack predictive capabilities and primarily rely on manual administrative decisions that focus on short-term staffing needs rather than long-term strategic planning. This reactive approach results in inefficiencies and inconsistent teacher assignments (Manap, 2024). Data mining provides a viable solution by identifying patterns from historical teacher placement data, enabling predictive modeling to optimize future allocations. While widely applied in market analysis, healthcare, and sales forecasting, data mining remains underutilized in HRM for teacher placement (Dai, 2023). By incorporating data-driven insights, teacher placement accuracy can be significantly improved, reducing mismatches and ensuring a more balanced workforce distribution.

This study aims to develop the Intelligent Teachers Placement Staf (ITPS) for MOE using a data-driven approach. The ITPS is adapted from the existing Staff Placement Model (SPM) to ensure consistency in workforce distribution strategies while addressing specific challenges in teachers placement. By utilizing historical teachers placement data, the ITPS incorporates data mining techniques to identify key factors influencing teachears assignments, including policy, service, and placement factors. Additionally, humanity factor are considered as part of the lecturer selection process.

By integrating data mining and predictive modeling, ITPS enhances efficiency, fairness, and accuracy in teacher placement, addressing long-standing mismatches and imbalances in the current system. This study contributes to a more structured teacher placement framework that ensures equitable workforce distribution, minimizes mismatches in subject specialization, and improves overall teacher job satisfaction within the education sector.

RELATED WORK

TEACHERS PLACEMENT

Efficient placement of effective teachers helps in keeping the workforce on track, improving the quality of education and enhancing the effectiveness of institutions. Yet the Ministry of Education Malaysia (MOE) remains challenged to match teachers' expertise with the needs of schools. Many of the placement decisions made on predictions about where a candidate could succeed (e.g. administrative concerns) relied on controversial predictive abilities and failed to utilize the predictive strength of data collected during the few days of the interview process.

Using structured and systematic methodology, the ITPS implements to determine and optimality of teachers placement by subject matter, workforce demand and service institution. The model's fusion of a data-driven approach with a decision-making framework augments precision, equity, and efficacy in the allocation process of teachers (Shamsul, 2023).

This study follows a structured methodology divided into four main phases to develop an an Intelligent Teacher Placement Selection (ITPS) using data mining techniques. The ITPS is adapted from the existing SPM, incorporating modifications to specifically address teacher placement within the MOE. The methodology ensures that the model is data-driven, optimized for structured decision-making, and applicable to real-world teacher allocation processes. The process begins with data preparation based on the existing teacher placement selection, followed by data mining using the existing teacher placement selection (TPS). Next, SPM data is prepared, and mining is conducted accordingly, followed by an evaluation of the results. Figure 1 illustrates the overall research framework.

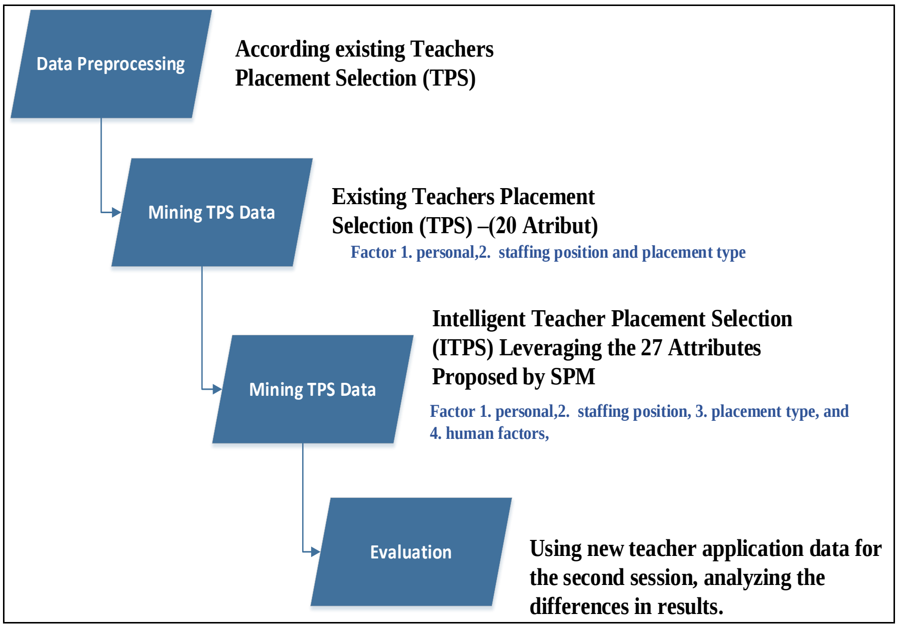

FIGURE 1. Overall research framework

DATA MINING

Data mining is a process of extracting meaningful patterns, relationships, and trends from large datasets, commonly referred to as Knowledge Discovery in Databases (KDD). In the context of teacher placement, data mining plays a crucial role in optimizing teacher allocation by leveraging historical data to identify key factors influencing placement decisions. By analyzing teacher qualifications, expertise, and school needs, data mining can improve workforce distribution and reduce mismatches in subject specialization (Hu, 2022). Data mining plays a crucial role in analyzing placement trends, allowing education administrators to make informed decisions regarding teacher allocation. By leveraging internal and external data sources, data mining techniques can enhance the teacher placement process by predicting staffing needs, identifying subject-specialist shortages, and ensuring equitable teacher distribution across schools. The growing volume of educational data maCase it increasingly essential to utilize automated data-driven approaches for effective workforce management (Fahsyah Nurzaman et al., 2024).

Machine Learning-based data mining techniques can be used in teacher placement for multiple different tasks i.e., classification, forecasting, clustering and anomaly detection (Zhou, 2023). The classification models would get trained on historical placement data to guess the optimal teacher-school combination, essentially aligning a teacher to a role that he/she is qualified for (subject-wise). The use of forecasting methods to predict future shortages or surpluses of teachers would enable education policymakers to adopt a more proactive approach to workforce planning. By employing clustering algorithms to analyze data on teacher demand, geographical constraints, and student population, we can identify schools with similar characteristics, ensuring a balanced and equitable distribution of teachers who meet the specific needs of schools across the area.

Previous research has explored the use of data mining in workforce allocation, primarily in general staff placement rather than teacher-specific models. While many studies have examined predictive analytics for optimizing HRM decisions, research on teacher placement models that integrate knowledge discovery techniques remains limited (Mary-Magdalene et al., 2023). The lack of a structured, data-driven approach to teacher placement has resulted in inefficiencies, mismatches, and imbalanced workforce distribution. Addressing this gap, this study focuses on leveraging data mining techniques to develop a teacher placement model that improves allocation accuracy and fairness.

The integration of data mining into teacher placement is essential for addressing the persistent issue of mismatched teacher assignments. Additionally, machine learning algorithms can help identify factors that contribute to ineffective placements, enabling policymakers to refine placement policies based on empirical evidence (Hudson et al., 2019). Given the complexity of teacher allocation, a data-driven placement model can significantly enhance efficiency while reducing reliance on manual, subjective evaluations.

DATA MINING (DM) TECHNIQUES IN APPLICATIONS

DM techniques have received a lot of attention from researchers and are widely utilized, particularly in tasks related to future prediction. These methods have been identified as powerful tools for data analysis. Several studies have focused on applications utilizing DM techniques, with an emphasis on classification techniques in the DM process.

The J48 technique is one of the methods within decision tree classification. Its main advantages include generating rules that are easy to understand, interpret, and read, even when handling large datasets. J48 can produce classification rules in the form of decision trees or sets of rules (Encarnacion & Cruz, 2022). Past research has shown that decision tree classification can also improve prediction accuracy. Many researchers agree that J48 is a widely popular and effective classification method, capable of generating rules without requiring specialized domain knowledge.

Previous studies have supported the use of J48 for generating classification rules aimed at classification or prediction tasks. The simplicity of its output makes it easier to analyze and apply the generated classification rules, which is why it is commonly used in various studies for rule generation (Tasfia et al., 2024). J48 technique uses the concept of multiples information. J48 technique works as follows:

1. Select the attribute that has the highest multiple information
2. S contains s_i tuples for class C_i for $i = 1, 2, \dots, m$
3. A measure of information or expected information is needed to classify an arbitrary tuple as Equation (1):
$$I\ (s_1, s_2, \dots, s_m) = -\sum_{i=1}^{m} \frac{s_i}{s} log2 \frac{s_i}{s} \quad (1)$$
4. Entropy for attribute A with values $a_1, a_2, \dots, a_v$ as Equation (2):
$$E\ (A) = \sum_{j=1}^{v} \frac{s_{1j} + \dots + s_{mj}}{s} I\ (s_{1j}, \dots, s_{mj}) \quad (2)$$
5. In decision tree algorithms, pruning means cutting off branches that don't add much value or information. Researchers often talk about three key concepts: Multiple Instances (using several examples), Multiple Rules (applying different criteria), and Multiple Metrics (using various measures to evaluate performance):
$$Gain\ (A) = I\left(s_1, s_2, \dots, s_{mj}\right) - E\ (A) \quad (3)$$

The J48 technique leverages the concept of information gain to produce easily understandable rules in the form of a decision tree. These classification rules represent the implicit knowledge within the database and are then used to classify and predict outcomes for new or unseen data, beyond the training set.

DATA MINING IN HRM

DM analysis results can be used for future planning, making it one of the best methods for analyzing data from databases. However, the application of DM techniques for staff placement prediction in HRM is not widely explored. Compared to other fields, research on DM approaches in HRM has received less attention. As such, this study focuses on staff placement using DM techniques. Table 1 lists relevant research on HRM applications in this area.

TABLE 1. Data Mining Techniques in HRM

Technique	HRM Application
Decision Tree	Evaluation and analysis of human resource management mode and its talent screening factors (Zhang, 2022), Analysis of Human Resource Management Mode and Its Selection Factors (Liu, 2020)
Association Rule Mining	Application of improved association rules algorithm and cloud service system in HRM (Xu, 2023), Human resource allocation (Wu et al., 2020)
Rough Set Theory	An Automated Implementation of Academic Staff Performance Evaluation System based on Rough Sets Theory (Ojokoh et al., 2019), The drivers of success in new-service development (Nayeri, Mahmoud Dehghan, Moein Khazaei, 2022)
Fuzzy DM	Performance evaluation of tourism HRM (Wei, 2022), Early warning management of enterprise human resource crisis (Wu et al., 2020)

Technique	HRM Application
Artificial Neural Network	Analysis and simulation of the early warning model for HRM risk (Yan et al., 2020), Evaluation and Image Analysis of Enterprise HRM (Zhao et al., 2020)

STAFF PLACEMENT MODEL IN HUMAN RESOURCE MANAGEMENT

Staff placement is a critical function in HRM, ensuring that employees are assigned to positions that align with their skills, qualifications, and organizational needs. An effective placement system optimizes workforce distribution, enhances job satisfaction, and improves overall organizational performance. However, traditional manual placement processes often face challenges such as inconsistent decision-making, lack of standardized criteria, and inefficient workforce allocation. To address these challenges, structured SPM have been introduced, incorporating data-driven approaches and decision-making frameworks to improve placement accuracy, fairness, and efficiency. Figure 2 shows the Staff Placement Model (SPM) (Shamsul, 2023).

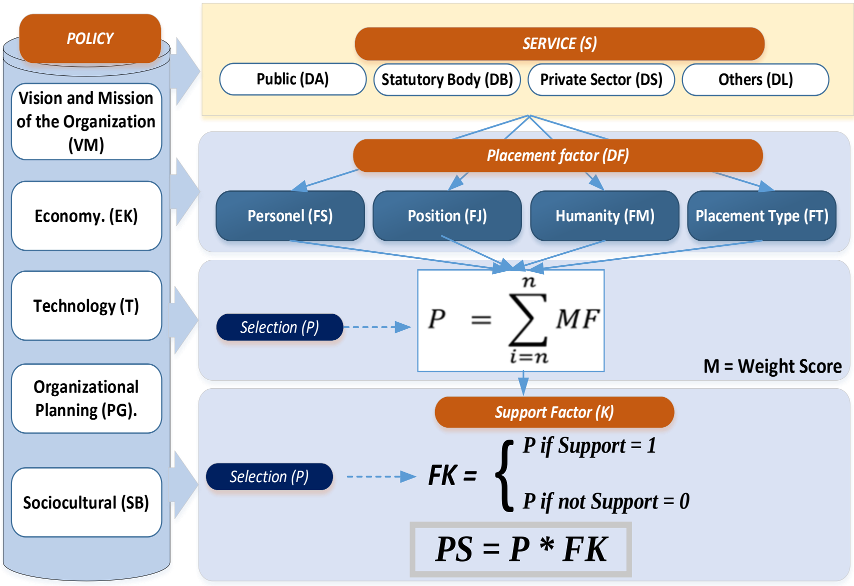

FIGURE 2. Staff Placement Model (SPM)

SPM is designed as a structured framework for managing workforce assignments in large organizations. It integrates expert-driven decision criteria, ensuring that staff placements align with organizational policies and workforce distribution needs. This model leverages data mining techniques to optimize placement decisions, making the process more systematic, scalable, and aligned with long-term workforce planning.

SPM refers to the components of service in this study, which include the identified groups of services: Public Sector Services, Statutory Bodies, Private Sector Services (Sales), and Education Services (Overseas). From the perspective of Human Resource Development, each category of service requires different skills and knowledge. By identifying these needs, organizations can design the selection and placement processes for staff based on the job requirements within an organization.

SPM consists of several key components that influence placement decisions. The first component is policy factors, which define organizational strategies and placement guidelines. These factors include long-term workforce planning, financial constraints, digital transformation initiatives, and socio-cultural considerations. Effective staff placement must align with these policies to ensure that employees are distributed efficiently across departments while maintaining organizational stability.

Another critical component of SPM is placement criteria and factors, which provide structured decision-making guidelines. These criteria ensure fair and merit-based allocations by considering job-specific skills, employee experience, location preferences, and past performance metrics. By defining these criteria, organizations can minimize placement mismatches and improve workforce efficiency.

Based on the study and observations conducted, the researcher has identified 20 attributes that correspond to SPM through personal, position, and placement type factors. Table 2 shows the description of personnel attributes, table 3 shows the description of staffing position attributes, table 4 presents description of placement type attributes and table 5 shows the description of human factors attributes,.

TABLE 2. Description of Personnel Attributes

Attribute	Attribute Name	Details
Gender	D1	Male / female
Marital status	D2	0: No information, 1: Not married, 2: married, 3: widowed, 4: Widowed, 5: widowee 9: other
Type of school	D3	Primary, secondary, full boarding, religious, vocational, art, sports
Position	D4	According to the number of posts: 54 types of posts
Type of position	D5	1: Administrative position, 2: non-administrative position
Original option	D6	Option code
Dominant option	D7	Dominant Option Codes: 76 types of Options
Contractual bond	D8	Yes / no
Period of service in the state	D9	Date of placement in the state
Period of service in the district	D10	Date of settlement in the district
Teaching subject experience	D11	Subject code
Long tenure	D12	Year / month
Long apart	D13	Month

TABLE 3. Description of Staffing Position Attributes

Attribute	Attribute Name	Details
Staffing requirements according to staffing norms	J14	Information on the status of staffing requirements
Staffing requirements according to option	J15	Information on the status of staffing requirements
Staffing requirements according to position	J16	Information on the status of staffing requirements
Application state	J17	State name / code applied
Application PPD	J18	District name / code applied

TABLE 4. Description of Placement Type Attributes

Attribute	Attribute Name	Details
Type of School	E19	List Of Type of School 1.
Dominant Teaching Option	E20	List of Job

TABLE 5: Description of Human Factors Attributes

Attribute	Attribute Name	Details
Chronic pain case	H21	1: Yes, 0: No)
Chronic pain case: self	H22	1: Yes, 0: No)
Chronic pain case: spouse	H23	1: Yes, 0: No)
Chronic pain case: Children	H24	1: Yes, 0: No)
Personal safety threats	H25	1: Yes, 0: No)
Personal safety threats: death threats		1: Yes, 0: No)
Personal safety threats: injury threats		1: Yes, 0: No)
Follow spouse	H26	1: Yes, 0: No)
Follow spouse: instruction		1: Yes, 0: No)
Follow spouse: according to spouse in the state / PPD / school applied for		1: Yes, 0: No)
Follow spouse: joint application	H27	1: Yes, 0: No)

ITPS is an adaptation of the SPM, specifically designed for educational workforce distribution. While the general principles of SPM apply to various industries, teacher placement involves unique challenges that require specialized decision-making frameworks. The ITPS addresses subject specialization, geographical disparities, staffing shortages, and teacher job satisfaction. Ensuring that teachers are placed in schools where they can maximize their expertise is crucial for educational quality and student learning outcomes.

METHODOLOGY

1. DATA PREPARATION - ACCORDING EXISTING TEACHER PLACEMENT SELECTION

The first step was data collection, where teacher application records were retrieved from eGTukar. This dataset included teacher demographic information, placement preferences, work experience, subject specialization, and humanitarian factors affecting transfers, such as medical conditions or spouse relocation requests. Given that teacher transfers occur twice a year, the dataset provided a comprehensive view of teacher mobility patterns.

Therefore, having a structured knowledge base is essential for the efficiency of teacher placement management. A centralized and systematic database will help to prevent mismatched assignments by making placement decisions more objective and accurate thus preventing constant teacher transfers. Through data analytics and artificial intelligence (AI), MOE can, for example, analyze the relevant experience and subject expertise of each teacher and recommend him or her the best school and location.

In addition, knowledge accumulation contributes to higher teacher satisfaction and motivation. MOE can avoid placing teachers in locations far from home, where infrastructure is lacking, or where the appointments are unsuitable for the teachers by analyzing these factors. A: This minimizes the stress of those more far away placements, increasing satisfaction with jobs and better teaching.Data Description refers to the collection, classification, and analysis of information related to teachers and school requirements. This data is used to understand trends, patterns, and challenges in the teacher placement process.

Key Components of Data Description:

1. Teacher Information
   The teacher's profile includes essential details such as their name, age, gender, and current service status, alongside their academic qualifications and areas of specialization. Additionally, it encompasses their teaching experience and performance records, providing a comprehensive overview of their professional background and expertise in the educational field.

2. Placement Information
   The placement information outlines the school's location, indicating whether it is situated in an urban or rural area. It also details the number of existing teachers categorized by subject and highlights the demand for teachers across different disciplines within each school.

3. Job Demand & Vacancies
   The job demand and vacancies section identifies the subjects that are experiencing a shortage of teachers, as well as the number of educators who are requesting transfers or resignations from their current positions.

4. Trend Analysis & Future Projections
   The trend analysis and future projections section includes data on the anticipated number of teachers who are expected to retire within the next 5 to 10 years, as well as an evaluation of past teacher placement patterns and their effectiveness. This information is crucial for understanding future staffing needs and addressing potential shortages in the education sector.

Placement Database is a database system that digitally stores and manages all information related to teacher placements. This system helps the MOE make placement decisions based on accurate and up-to-date data. Figure 3 shows the ERD diagram for the Placement Database System.

1. The Placement Database is designed to streamline the process of matching teachers with schools in need. It has several important functions. Here are some of these important functionalities:
2. Teacher Registration and Data Storage: With this feature, teachers can create personal profiles. These profiles list their qualifications, work experience and other pertinent information about them; all organized in one place where those who need it most easily retrieve it.
3. School Needs Mapping: This function analyzes and identifies schools that are experiencing teacher shortages, particularly in specific subjects, so one can see where teachers most needed.
4. Placement Recommendation System: Through advanced algorithms, this system matches the profiles of registered teachers with suitable placement opportunities based upon their qualifications and the needs of schools.

5. Application for Online Teacher Transfers: This program lets teachers apply for transfers to different schools on the internet. They can specify where they'd like to go, and what criteria should comprise the decision.
6. Cumulatively, the Placement Database improves efficiency in sending qualified teachers where schools need their services, while at the same time simplifying the application process for teachers seeking new opportunities.

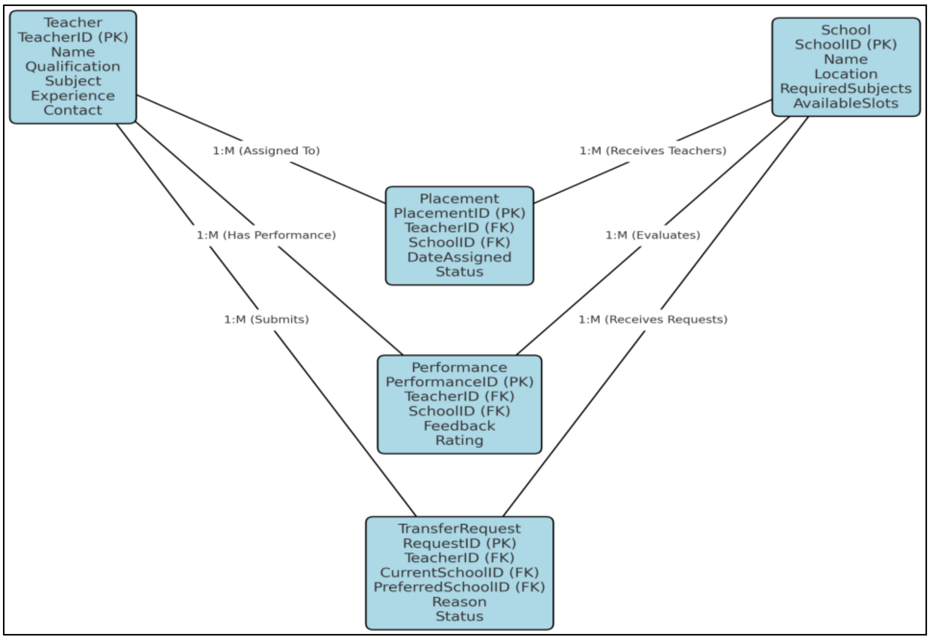

FIGURE 3. Diagram for the Placement Database System.

Data Integration

The data integration process involves merging datasets from multiple sources. These include databases such as eOperasi, eGTukar and SGMy and all the rest of the messy handwritten injury data out there: data consistency is of paramount importance in this kind of work as it can be used against you as easily as any other information. This is achieved through manual file combination techniques using Microsoft Excel, Access, and SQL to consolidate teacher data from various states into a single, unified file. To maintain uniformity, the process includes standardizing column names, data formats, and data types followed by thorough data cleaning and adjustment to enhance quality. Finally, the cleaned and integrated data is stored in a suitable storage system or database (such as Oracle) for future access and analysis.

Knowledge accumulation in teacher placement is a key part of effective operation in Malaysia's education system. Continuously collecting and utilizing data, MOE ensures fair teacher distribution, proper teacher specialization matches with subjects and an overall improvement of teacher placement efficiency. This approach works not just for teachers but also for students, the entire education industry and as such contributes to a future education system that is more organized, well-founded on facts and high-quality.

The data collection and preparation phase in this stage is to satisfy the requirements for developing and validating the ITPS. A questionnaire survey is used to measure user satisfaction with the current placement process, while expert interviews provide background on such issues as criteria for placements and operational difficulties. The collected data is then prepared for analysis using classification-based data mining techniques. Predictive analytics is used to implement the proposed ITPS, identifying patterns and trends from past teacher placements. Machine learning algorithms are applied so as to recommend optimal teacher placements based on predefined attributes. Combination of data mining techniques ensures that placement decisions are data-driven, which brings about both decreasing mismatches and inefficiency in manpower distribution.

Data preprocessing is a crucial step to enhance data quality before analysis. Below are the main techniques used:

1. Handling Missing Values
   Missing values can affect the performance of machine learning models. In this dataset, one column contains missing values, There are 1,742 missing values in the attribute 'Recommendation_ITPS. The approach used involved filling the missing values in "Recommendation_ITPS" with "NOT_RECOMMENDED" since it is categorical data.

2. Handling Outliers
   Outliers are extreme values that can impact analysis results. The number of outliers detected using the Interquartile Range (IQR) method is as follows. Table 6 shows the Number of Outliers

TABLE 6. Number of Outliers

Column	Number of Outliers
Service_Duration	290
Humanity_Weight	163
Experience	0

The handling method involved applying Winsorization to "Service_Duration" and "Humanity_Weight" by replacing extreme values with upper and lower limits, while no action was needed for "Experience" as no outliers were detected.

The IQR method is used to identify and remove outliers based on the interquartile range.

Formula used:

$$IQR = Q3 - Q1$$
$$\text{Lower Bound} = Q1 - 1.5 \times IQR$$
$$\text{Upper Bound} = Q3 + 1.5 \times IQR$$

Where:

- Q1 (First Quartile) = the value below which 25% of the data falls
- Q3 (Third Quartile) = the value below which 75% of the data falls
- IQR = the difference between Q3 and Q1

Processing options:

- Remove values outside the Lower Bound and Upper Bound.
- Replace outliers with the Q1 or Q3 value.

3. Normalization

Normalization helps ensure that data is on a consistent scale, especially for machine earning.

Handling method:

- Min-Max Scaling is used to scale data into the range **[0,1]**.
- It is applied on numeric columns such as " Service_Duration ", "Humanity_Weight", dan " Experience ".

Formula used:

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin}$$

- Xnorm = Normalized value
- X = Original value
- Xmin = Minimum value in the dataset
- Xmax = Maximum value in the dataset

Function: Scales data into the range [0,1] or another specified range. Advantages: **Usefu**l when data does not follow a normal distribution. Disadvantages**:** Highly sensitive to outliers because it depends on the maximum and minimum values.

2. MINING THE TEACHER PLACE SELECTION (TPS) DATA

The data mining process for the TPS follows a structured approach, including data collection, preprocessing, classification, and validation. The dataset was obtained from eGTukar, which records teacher transfer applications under the MOE. The purpose of this phase is to extract meaningful patterns to optimize teacher placement.

The method employed in this research is cross-validation, which is used to determine the most effective technique for predicting teacher placements based on historical data. To optimize processing, irrelevant data was removed, and the dataset was split into 90% training data and 10% test data for model evaluation. 10-fold cross-validation was applied to improve the model's robustness. The classification algorithms tested included J48, Decision Tree, Naïve Bayes, Random Forest, and Kstar. These models were compared to determine the most effective technique for predicting teacher placements based on historical data.

In this study, the researcher used 4,484 records of inter-state transfer and placement applications for the year 2020 as study data. These records represent placement transfer applications for the teaching staff group. Table 7 shows 20 Attributes were selected from factor Personel Attributes, Staffing Position and Placement Type

TABLE 7. Description of Personel Attributes

Factor	Attribute Name	Attribute
Personel Attributes	D1	Gender
	D2	Marital status
	D3	Type of school
	D4	Position
	D5	Type of position
	D6	Original option

Factor	Attribute Name	Attribute
	D7	Dominant option
	D8	Contractual bond
	D9	Period of service in the state
	D10	Period of service in the district
	D11	Teaching subject experience
	D12	Long tenure
	D13	Long apart
Staffing Position	J14	Staffing requirements according to staffing norms
	J15	Staffing requirements according to option
	J16	Staffing requirements according to position
	J17	Application state
	J18	Application PPD
Placement Type	E19	Type of School
	E20	Dominant Teaching Option

For classification, a 10-fold cross-validation approach was used. Accuracy (on the interval [0, 1]) was computed per random dataset (R) and averaged over the 10 classification models per random dataset. Here you train the models on the number of training data (L) and testing data (U). Total normalized precision was calculated in the same way for all the experiments to assess model performance. This stage was developed on Weka software version 3.8.6 (http://www.cs.waikato.ac.nz/ml/weka/) and used to classify five classification algorithms, which identified the algorithm that presented the best accuracy. To evaluate accuracy a cross-validation method which is a statistical method that splits the data into two parts one for the training of model and the another one for validation was used (Lei, 2020). Table 8: Cross-validation strategy produced from J48 technique We applied the same process to test each algorithm J48, Decision Tree, Naïve Bayes, Random Forest and Kstar

TABLE 8. Classification Accuracy of J48

Bil	**% Split**	***Correctly Classified Instances***	***Incorrectly Classified Instances***
1	**10 90**	**71.20 %**	**28.80 %**
2	20 80	70.00 %	30.00 %
3	30 70	71.10 %	28.90 %
4	40 60	70.36 %	29.64 %
5	50 50	70.18 %	29.82 %
6	60 40	70.47 %	29.53 %
7	70 30	70.42 %	29.58 %
8	80 90	70.13 %	29.87 %
9	90 10	70.31 %	29.69 %

The model accuracy analysis from this experiment is summarized in Table 9. The results from the full-attribute experiment show that the J48 algorithm consistently outperformed other classification algorithms across all three placement datasets. Furthermore, the analysis indicates that the number of data points influences model accuracy, as seen when comparing follow-up data to initial data except for the J48 classification technique, which experienced a slight decline in accuracy. Additionally, models containing outliers exhibited a minor decrease in accuracy, emphasizing the impact of outliers on model performance.

TABLE 9. Model Accuracy for Full Attributes

Bil	% Split		*Correctly Classified Instances*	*Incorrectly Classified Instances*
J48	**10**	**90**	**71.20 %**	**28.80 %**
K-Star	90	10	68.98 %	31.02 %
RF	30	70	68.90 %	31.10 %
Decision Table	20	80	68.30 %	31.70 %
NaiveBayes	10	90	67.29 %	32.71

Data Mining for Intelligent Teacher Placement Selection (ITPS)

The second phase of data mining utilizes the same dataset as the previous phase but incorporates additional attributes related to human factors. These attributes provide deeper insights into the decision-making process by considering elements such as employee well-being, job satisfaction, and other socio-psychological aspects that may influence staff placement and transfers. Table 10 shows 7 Attributes were selected from Human factor.

TABLE 10. Description of Human Factor Attributes

Factor	Attribute Name	Attribute
Humannity Attributes	H21	Chronic pain case
	H22	Chronic pain case: self
	H23	Chronic pain case: spouse
	H24	Chronic pain case: Children
	H25	Personal safety threats
		Personal safety threats: death threats
		Personal safety threats: injury threats
	H26	Follow spouse
		Follow spouse: instruction
		Follow spouse: according to spouse in the state / PPD / school applied for
	H27	Follow spouse: joint application

In this phase, classification was performed using the **10-fold cross-validation** method, consistent with the approach applied in the initial phase. This technique systematically partitions the dataset into **ten subsets**, where each subset serves as a **test set once**, while the remaining **nine subsets** function as the **training set**. This process is iterated **ten times** to enhance the reliability and robustness of the classification outcomes.
To evaluate model performance, multiple machine learning algorithms were employed, including J48, Decision Tree, Naïve Bayes, Random Forest, and KStar. Each algorithm was utilized to extract patterns from the dataset and assess its predictive capability in determining staff placement decisions.

Table 11 presents the results of the full-attribute experiment conducted in the second phase. The findings indicate that the **J48 algorithm** achieved relatively higher accuracy compared to other classification algorithms across all three placement datasets used. The accuracy analysis for the full-attribute model further reveals that the number of data points significantly influences model performance.

TABLE 11: Model Accuracy for Full Attributes

Bil	% Split		*Correctly Classified Instances*	*Incorrectly Classified Instances*
J48	**10**	**90**	**95.74 %**	**4.26 %**
K-Star	90	10	94.24 %	5.76 %
RF	30	70	92.99 %	7.01 %
Decision Table	20	80	94.69 %	5.31 %
NaiveBayes	10	90	94.10 %	5.90 %

Overall, the results of accuracy are improved for the model second phase. The analysis phase of the Intelligent Teacher Placement System (ITPS) receives data about the accuracy of models and the kind of classification techniques that can be used and about predictive performance. It makes sure that the selected classification algorithms quarter reliable and accurate predictions for teacher placement whilst improving workforce allocation efficiency.

Analysis of model accuracy from the two experiments

The accuracy analysis from both experiments is summarized in Table 12. Among the classification algorithms evaluated, the J48 algorithm demonstrated the highest and most consistent accuracy across both experimental phases. Figure 4 presents a comparative analysis of the classification results obtained in Phase 1 and Phase 2.

TABLE 12. Model Accuracy for Full Attributes From two Experiment

Algoritma	*Face 1 (20 Atribut)*	*Fasa 2 (27 Atribut)*
J48	**71.20 %**	**95.74 %**
K-Star	68.98 %	94.24 %
RF	68.90 %	92.99 %
Decision Table	68.30 %	94.69 %
NaiveBayes	67.29 %	94.10 %

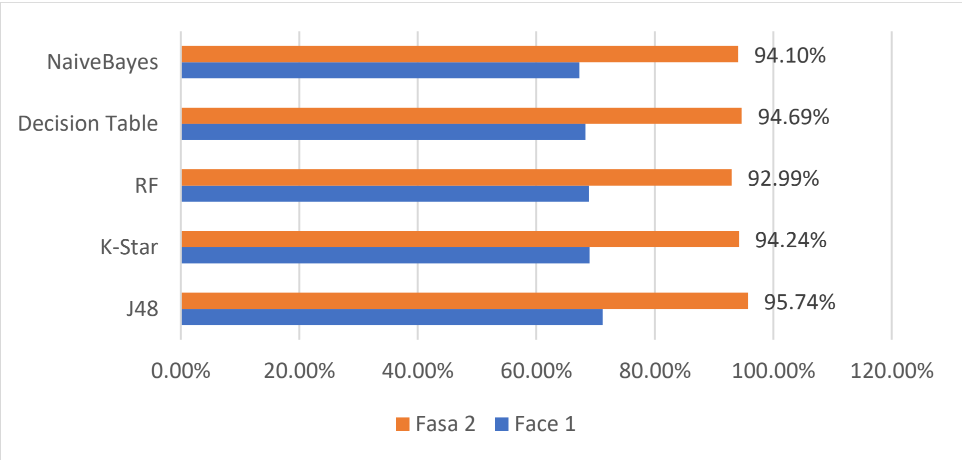

FIGURE 4. Comparison graph of the results from two experiments.

Advanced classification methods are utilized in the Intelligent Teacher Placement System (ITPS) to ensure the best possible allocation of teachers, allowing the system to make better placement decisions for teachers in Malaysia and minimizing human error in the overall school management process. Such a data-driven approach is transparent, objective and aligned with workforce distribution needs.

Moreover, human factor characteristics enrich the decision-making framework. The model takes into account the professional qualifications of applicants as well as personal or family-related circumstances, ensuring a more equitable and holistic approach to teacher placement.

Classification Rules & J48 Decision Tree (Pruned Tree)

The classification rules derived from the J48 algorithm serve as a decision-support mechanism for organizations in determining lecturer assignments based on predefined criteria. These rules provide a systematic and data-driven approach to staff placement, ensuring alignment with key factors such as qualifications, experience, and human factors. By integrating these classification rules, organizations can enhance the efficiency and accuracy of lecturer placement while optimizing workforce distribution. Figure 5 and Figure 6 illustrate an example of a Decision Tree generated by the J48 algorithm.

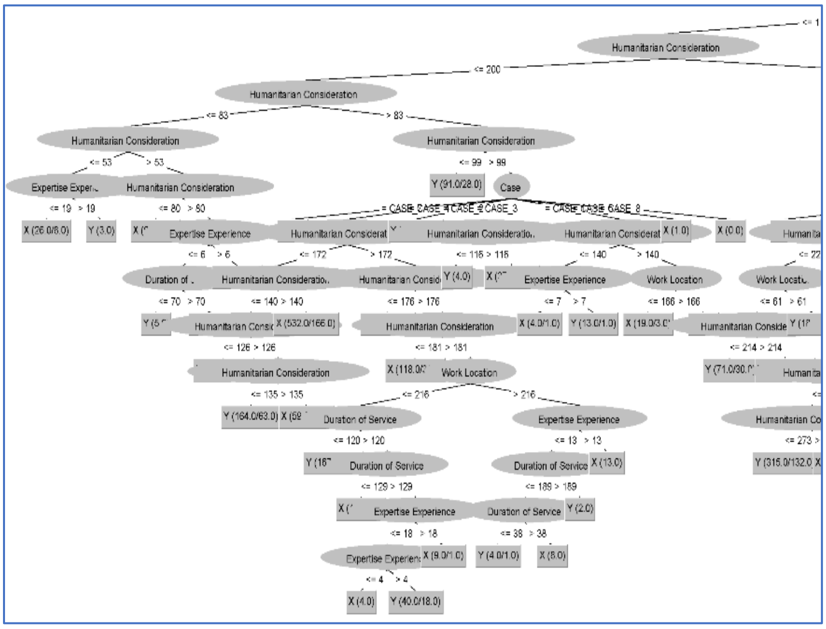

FIGURE 5: example of a Decision Tree.

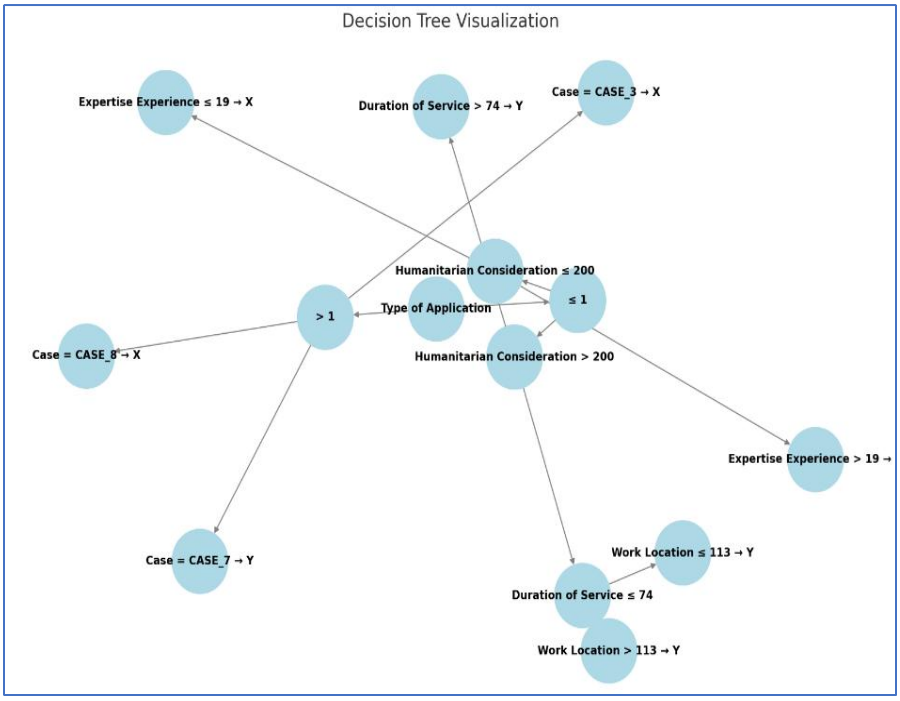

FIGURE 6: Decision Tree Visualization.

The decision tree consists of a set of **if-then** rules that classify data based on different attribute conditions. Here's how the rules can be interpreted. Table 13 show a decision rules for classification

TABLE 13 : decision rules for classification

Condition	Decision (X/Y)
Type of Application ≤ 1 AND Humanitarian Consideration ≤ 200 AND Expertise Experience ≤ 19	**X (26.0/8.0)**
Type of Application ≤ 1 AND Humanitarian Consideration ≤ 200 AND Expertise Experience > 19	**Y (3.0)**
Type of Application ≤ 1 AND Humanitarian Consideration > 200 AND Duration of Service ≤ 74 AND Work Location ≤ 113	**Y (39.0/3.0)**
Type of Application ≤ 1 AND Humanitarian Consideration > 200 AND Duration of Service ≤ 74 AND Work Location > 113	**Y (294.0/22.0)**
Type of Application ≤ 1 AND Humanitarian Consideration > 200 AND Duration of Service > 74	**Y (294.0/22.0)**
Type of Application > 1 AND Case = CASE_7	**Y (851.0)**
Type of Application > 1 AND Case = CASE_4	**Y (0.0)**
Type of Application > 1 AND Case = CASE_2	**Y (0.0)**
Type of Application > 1 AND Case = CASE_3	**X (1.0)**
Type of Application > 1 AND Case = CASE_1	**Y (0.0)**
Type of Application > 1 AND Case = CASE_5	**Y (0.0)**
Type of Application > 1 AND Case = CASE_8	**X (15.0)**
Type of Application ≤ 1 AND Humanitarian Consideration ≤ 200 AND Expertise Experience ≤ 19	**X (26.0/8.0)**
Type of Application ≤ 1 AND Humanitarian Consideration ≤ 200 AND Expertise Experience > 19	**Y (3.0)**

3. MODEL EVALUATION

The development of the Teacher Placement Prototype System is a crucial phase to assess the effectiveness of ITPS. To evaluate the feasibility of TPM, the prototype was developed to process and analyze teacher placement data, ensuring that predictions align with actual workforce needs. The prototype integrates data-driven decision-making processes.
This prototype aims to test and validate the accuracy of teacher placement predictions by applying classification techniques from data mining. The system is designed to simulate real-world teacher placement scenarios and provide a structured framework for analyzing and optimizing placement decisions. Figure 7 shows the main components in the design development of the Teacher Placement Decision Support System (TP-DSS).

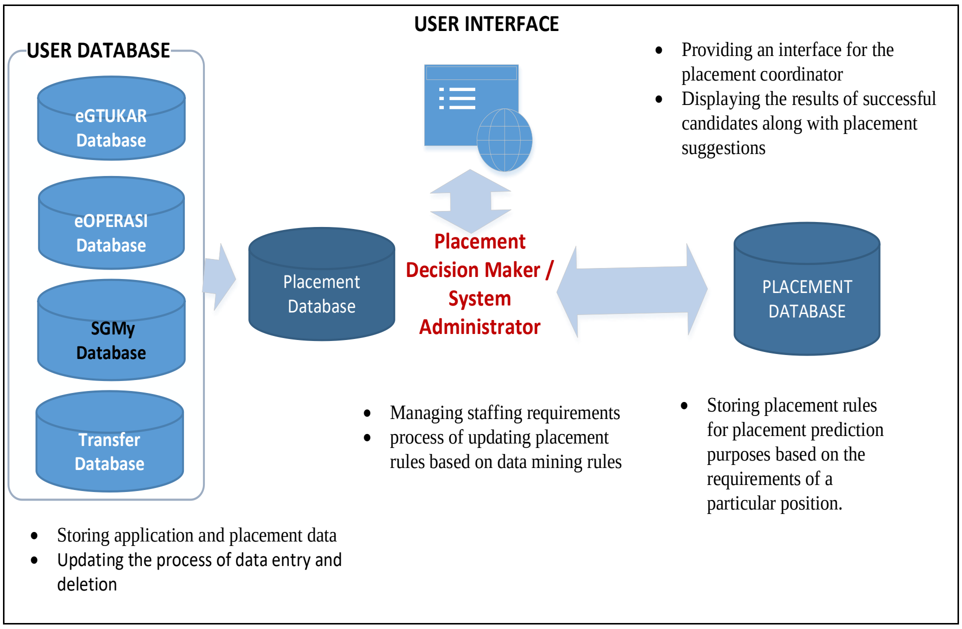

FIGURE 7. Main components in the design development of the TP-DSS

The prototype was built to support automated teacher placement predictions based on historical data. The system applies classification algorithms to analyze placement criteria such as employment status, subject specialization, geographical preference, and service history. The accuracy of the model was evaluated by comparing predicted placements with actual historical placements recorded in the *eGTukar* system. By doing so, the prototype ensures that the placement recommendations are based on data-driven insights rather than manual selection processes.

Testing the prototype involved analyzing classification performance using a separate dataset to ensure unbiased placement recommendations. The J48 algorithm generates classification rules that serve as guidelines in the decision-making process within the Teachears Placement Decision Support System (TP-DSS). These rules form the basis for the placement algorithm in TP-DSS, ensuring that every decision is made based on a systematic and structured data analysis.

The effectiveness of the placement model was evaluated using 2,562 new application records from candidates in the second session of 2020. Placement model evaluation was conducted using a significance test (t-test) to determine if a particular classification

technique is statistically significant compared to others. Previous studies suggest that decision tree classifiers often produce highly accurate models. In this study, analysis found that J48 decision tree classifier achieved slightly higher accuracy percentages than other classifiers. To confirm this observation for placement data, a paired t-test was performed.
The t-test is used to determine whether there is a significant difference between the means of two data groups. In this analysis, we conducted a t-test on the TPC and ITPS columns in the given dataset. Table 14 shows the descriptive statistics for the TPC and ITPS and Table 15 show t-Test result.

TABLE 14. Descriptive statistics for the TPC and ITPS

Statistic	**TPC**	**ITPS**
Sample size (n)	2562	2562
Mean	0.609	0.617
Standard deviation	0.488	0.486
Minimum	0.000	0.000
Maximum	1.000	1.000

Table 15. t-Test Results

Test Statistic	**Value**
t-value	-0.631
p-value	0.528

Based on the t-test results, the obtained p-value is 0.528, which is greater than the significance level of 0.05. This means that there is no statistically significant difference between the means of TPC and ITPS. Therefore, the null hypothesis stating that both means are equal cannot be rejected. Based on this analysis, there is no statistical evidence to suggest a significant difference between the TPC and ITSM values in this dataset. If necessary, further analysis using other statistical methods can be conducted to gain deeper insights.
Based on 2,562 new teacher placement applications from the second session of 2020, the ITPS model approved 1,582 placements, compared to 1,560 in the actual decisions. This results in a difference of 22 candidates who were not placed using TPC but were approved under ITPS. ITPS recommended a successful placement for these 22 candidates based on several justifications, including:

Key Findings of the ITPS Candidates Qualifications for TPC First, the data shows that TPC-elgible candidates had a substantially longer average service duration (88.28 months vs. 64.41 months for non-selected candidates). This means that TPC may not reward candidates with a longer employment history. The average humanitarian weightage for approval of ITPS cases is also 68.67 as opposed to 61.27 for rejection of TPC cases, suggesting that increasing humanitarian weightage may improve the chances of approval under TPC. Another notable outcome is the effect of expertise experience: while the best-practice cases (ITPS) were selected, the average for TPC-approved cases was 251.04 months of expertise experience, while the average for rejected cases was 620.04 months of experience. This implies that it is possible that TPC likes candidates who has moderate cv rather than extreme sorts. Taken together, these findings imply that TPC evaluation criteria may favor service duration and humanitarian considerations over raw expertise.

Overall, the analysis indicates that candidates who have served for longer periods and have made substantial humanitarian contributions are more likely to be selected for both ITPS and TPC programs. Strikingly, almost everyone with very high expertise did not gain TPC approval, indicating that expertise isn't the only item item upon which those offering approval do their figured out spending. For the improvement of the selection process for ITPS and TPC, it is highly recommended to consider candidates who have more experience with substantive humanitarian contributions and not just their technical expertise. This would help achieve more comprehensive and ideal selections that take into consideration the essence of these programs and their goals.

RESULTS & DISCUSSION

The study focuses on the transfer and placement database for 2020, specifically analyzing teacher placements within requested districts to uncover insights within the dataset. Staff placements at MOE are among the most critical processes in HRM, particularly for handling applications and assignments across the country. MOE is one of the organizations with a high number of employees.

The study successfully develops a ITPS using data mining techniques to enhance the efficiency and fairness of teacher allocation. By analyzing historical placement data and applying classification techniques, the model identifies key factors influencing teacher assignments, reducing mismatches and improving workforce distribution. ITPS ensures that teachers are placed based on subject specialization, school needs, and workforce demand, making the process more structured and data-driven.

A major contribution of this study is the classification-based approach to teacher placement. By systematically defining placement attributes and processes, the model improves prediction accuracy and refines decision-making. The research evaluates multiple classification techniques on real placement data year 2020, selecting the most effective algorithm for optimizing teacher assignments. The results highlight the potential of data mining in workforce management, particularly in forecasting staffing needs and improving placement policies.

A t-test was conducted to compare the model's decision (ITPS) with the actual decision (TPC) to determine whether the difference in means between the two was statistically significant or merely coincidental. In this analysis, ITPS predicted 1,582 successful placements, whereas the TPC showed 1,560 successful placements. A paired t-test was used, as both datasets originated from the same sample.

Future research should enhance ITPS by integrating workforce forecasting, financial planning, and training development. Expanding machine learning techniques, such as fuzzy logic and genetic algorithms, may further refine placement predictions. The model's automated implementation could link a knowledge transformation engine to a knowledge database for better efficiency. Improving the system prototype will also ensure its practical application in real-world teacher placement scenarios.

This study successfully achieves its objective of developing a structured ITPS using data mining, contributing to more systematic and data-driven teacher allocation within the MOE. The model serves as a foundation for optimizing workforce distribution in education and can be adapted for broader human resource management applications.

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CONCLUSION

This paper proposes a data mining methods-based Integrated Teacher Placement System (ITPS), demonstrating an important contribution to the teacher placement process. Using systematic analysis of the 2020 transfer and placement database, the study addresses the guiding restrictions for the efficiency and fairness of the assignment process in MOE. Finally, classifying techniques successfully can aid in prediction accuracy and enhance decision-making, leading to higher success rates in placements.

Results of the paired t-test suggest that traditional placement methods were outperformed by the ITPS, highlighting its potential to minimize mismatches in skills and maximize workforce usage relative to both subject specialty and school needs. This methodical, data designed process provides a robust basis for performing future builds, such as consolidating workforce forecasting and machine learning purposes.

In addition, the automated implementation of the model will enable a more efficient process of teacher placement, making it adaptive to real-life constraints. At the same it does also gives insight for practitioners working further into human resources management so as to keep few things into a note during such practices. Future investigations should further refine the ITPS and feature creative methodologies to promote its practical applicability and optimal use in producing a desirable educational workforce.

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