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Enhancing Teaching and Learning through Data-driven Optimization of Servicing Code Demand and Lecturer Allocation using WEKA Analysis

Nur Atiqah Rochin Demong[1*], Murni Zarina Mohamed Razali[2], Juliana Noor Kamaruddin[3], Sazwan Shamsuddin[4], Nor Ain Awang[5], Norjuliatie Kamarudin[6], Noor Faradilla Wan Othman[7]

[1234567]*Faculty of Business and Management, Universiti Teknologi MARA, 42300 Puncak Alam, Selangor, Malaysia*

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ABSTRACT

The increasing demand for servicing codes across faculties has created a growing need for data-driven decision supports in optimizing lecturer allocation and cost efficiency. This study applies machine learning techniques using the WEKA analytical tool to explore, cluster and classify servicing code applications using a dataset gathered from multiple faculties, and campuses within the Faculty of Business and Management in a selected public university in Malaysia. The dataset of 297 instances comprised attributes such as Course Code, Course Name, Course Type, Faculty, Program, Campus, Total Number of Students Enrolled and Approval Status. The main objective of this study is to identify the demand patterns and optimizing the lecturer's contribution by maintaining a class sizes of maximum number of students in each class is 30 and a teaching load of up to 20 credit hours per lecturer. An Expectation-Maximization (EM) clustering model revealed five distinct clusters representing varied course demand concentrations and faculty distributions, with Cluster 1 (30%) showing the highest cumulative demand across university courses. Complementary K-Means clustering grouped the data into two major clusters, indicating that a clear differentiation between economic-based and entrepreneurship-based courses in terms of student enrolment volume and approval distribution. Attribute selection through Information Gain Attrite Evaluation model highlighted Program Code, Course Code and Type of Course as the strongest predictors of course approval and demand levels. Furthermore, classification using the Random Forest algorithm depicted that a 95.3% accuracy (k=0.768), confirming robust predictive capability in identifying course approval status and demand trends. These results identifying course approval status and demand trends. These re suggest that machine learning driven approaches can effectively support academic administrations in making informed staffing decisions, balancing full time and part time lecturer assignments, and optimizing cost structures without compromising teaching quality. Theoretically, this study contributes to the emerging literature on data-driven academic resource management and the application of artificial intelligence in higher education operations. Practically, it offers a replicable analytical framework for institutions seeking to forecast servicing code demand and align lecturer allocation strategies with real time dynamics and cost optimization goals.

1. Introduction

In recent years, higher education institutions have faced increasing pressure to optimize their teaching resources while maintaining quality and cost efficiency. This challenge is particularly evident in large multi campus universities where servicing codes or courses offered by a particular faculty but taught across different faculties and have become the essential in supporting interdisciplinary learning and curriculum integration. The Faculty of Business and Management is one of the most popular faculty that offers servicing codes to other faculties due to the nature of subject matter and curriculum standards and structure to fulfil the requirements of quality assurance by the ministry of higher education. This faculty regularly receives numerous servicing code applications from various faculties and branch campuses with different total number of students enrolled by different program types and academic requirements. The management of this request normally done manually and often results in inefficiencies such as imbalanced lecturer workloads, overlapping course schedules and increased operational costs.

Traditional approaches to resource planning rely heavily on manual estimation or historical data without using predictive or analytical findings (Akinboboye et al., 2022). According to Okoli et al. (2022), this manual technique makes it difficult to forecast future and demand accurately or to determine the optimal number of lecturers required to meet teaching loading requirements. Moreover, variations in class size, course credit hours, and the ratio of part time and fulltime lecturers' allocation make the decision-making process difficult (Pennino, 2023). These challenges highlight the need for a systematic, data-driven approach to analyze servicing code demand and optimize academic manpower allocation. Thus, this study employs machine learning techniques using the WEKA analytical tool to model and analyze servicing code data collected from multiple faculties and branches. The dataset includes attributes such as Course code, Course Name, Course Type either Elective or University Code), Faculty Name, Faculty Branch and Campus, Program, Total Number of Students and Approval Status. Main objective of this study is to identify patterns of high servicing code demand among faculties or programs in the selected public university. Next, to predict the level of demand from different faculties and programs and to determine which factors contribute to the high demand of the servicing code. Based on this output, it will help to derive the optimal lecturer requirement to be offered as part time or fulltime lecturer to tackle the demands. Moreover, the result from the analysis also helps to predicts the number of lecturers requirements based on the total number of demands with the limitation of class size and credit hours of the courses offered.

By applying clustering, classification and attribute selection tech, this research provides empirical evidence on how data mining can be utilized for educational resource optimization. Specifically, clustering (K-Mean and Expectation Maximization (EM)) was used to identify natural groupings of courses based on the demand and faculty characteristics while classification (Random Forest algorithm) helps predict approval status and demand levels for new or future servicing code requests. Next, Information Gain Attribute Evaluation were selected for attribute selection techniques to determine the most influential factors contributing to the servicing code demand. Together, these analyses support the formulation of optimized staffing model that balances the number of fulltime and part-time lecturers while minimizing cost and maintaining teaching quality.

Theoretically, this study contributes to the growing body of knowledge in educational data mining, decision support systems and academic resource management by integrating data analytics into strategic planning processes. It extends the application of machine learning in higher education beyond student performance prediction toward operational and administrative optimization. Practically, the findings provide valuable findings for the top management in forecasting demand, scheduling teaching load and planning for recruitment effectively. This research highlights how data-driven methods can transform traditional academic administration into a more intelligent, efficient and evidence-based system ensuring that institutional resources are fully utilized and optimal resources while sustaining the quality and accessibility of education.

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2. Literature Review

2.1 Servicing Code and Cross-Faculty Management

Servicing codes, also known as service courses or cross faculty offerings are course offered by one faculty to students from other faculties or programs. They are common in multidisciplinary institutions where foundational subject such as Business Management, Entrepreneurship or Economics are required across various programs. According to Kumar and Limbachiya (2023), servicing codes ensure interdisciplinary integration and resource sharing, but they also introduce complexities in scheduling, teaching allocation, and administrative coordination. Managing servicing code requests across multiple faculties often involves reconciling variation in student enrolment, campus locations, and course credit structures (Okur et al., 2024).

The increasing volume of servicing code applications particularly from non-business faculties has led to challenges in maintaining consistent class sizes, lecturer availability and teaching quality (Okoli et al., 2022). Kenny and Fluck (2022) emphasize that without analytical forecasting, the faculty will face a problem of over allocation of lecturers or academicians that leads to inefficiencies and increased costs. These operational inefficiencies highlight the need for a systematic analytical approach that can model servicing code demand and inform staffing decisions based on data rather than manual judgment (Nabeel, 2024).

2.2 Academic Resource Planning and Optimization

Academic resource management involves balancing teaching loads, class sized, and available human resources to achieve both pedagogical and financial efficiency (Liu, 2025). Previously, workload distribution and lecturer allocation were determined through historical data departmental planning meetings (Olwal, 2023). However, this manual approach often lacks predictive accuracy and does not count for dynamic factors such as student enrolment fluctuations, part time lecturer availability and inter campus demand variance.

Studies by Makki et al. (2022) and Andrian et al. (2024) have applied optimization models and decision support systems to address manpower planning in education. These studies show that integrating data analytics can reduce lecturer workload differences and ensure cost effective staffing. The key performance indicators in such optimization include the ratio of lecturers to students, the number of credit hours per lecturer, and total cost of staffing. In the context where servicing code demand varies across semesters and faculties, resource planning must also consider equity, flexibility and sustainability in human resource distribution. By adopting a data driven approach, institution can model not only current demand but also forecast future lecturer needs based on historical enrolment trends, course approval rates and program expansion plans.

2.3 Data Mining and Machine Learning Applications in Higher Education

The adoption of data mining and machine learning techniques in higher education has expanded beyond student performance prediction to include administrative and operational domains. WEKA (Waikato Environment for Knowledge Analysis) has become a popular open-source tool for such applications due to its accessibility and comprehensive machine learning algorithms (Abdulkareem, 2025).

Previous studies demonstrate how WEKA can be used to analyze large educational datasets for classification, clustering and forecasting. Shilbayeh and Abonamah (2021) used WEKA to classify student

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enrolment patterns, while Wu (2022) applied clustering algorithms to group courses by popularity and resource demand. These works support the potential of WEKA as a decision support mechanism in higher education management. In resource planning contexts, machine learning models such as Random Forest have shown strong predictive capabilities in identifying key factors affecting workload distribution and course approval success (Uppal et al., 2024).

In this study, WEKA's clustering (K-Means, EM), classification using Random Forest and attribute selection using Information Gain Attribute Evaluation model have been selected to uncover the hidden pattern in servicing code data. These techniques not only reveal the underlying demand structure but also provide a foundation for optimization lecturer allocation and cost management.

2.4 Research Gap

While a growing number of literatures exists on education analytics and institutional planning, few studies have specifically examined servicing code demand analysis as a data driven decision problem. Most early works focus on academic performance or student retention prediction, leaving a gap in operational optimization research within higher education fields (Fahd et al., 2022). Moreover, existing studies often overlook the integration of multiple variables such as course type, program, faculty, credit hours and student numbers in a unified predictive model. This study addresses the gap by proposing an integrated WEKA based analytical framework that combine clustering, classification and optimization. The novelty lies in linking servicing code demand analysis directly to lecturer resource optimization in balancing the full time and part time staffing requirements by having the limitations of cost and workload constraints. This study extends the application of data mining into the domain of academic manpower planning and contributes to both theoretical and practical advancements in higher education management.

3. Methodology

3.1 Research Design

This study adopts a quantitative, data driven research design grounded in machine learning analysis. The approach focuses on identifying servicing code demand patterns and optimizing lecturer allocations across faculties and branch campuses. The design is descriptive and analytical in nature, integrating both exploratory to identify the demand structure and predictive to estimate the lecturer requirements components. The WEKA analytical tools were employed that applies several machine learning techniques namely clustering, classification and attribute selection to analyze the 297 instances of a dataset gathered based on application from various faculties and programs. The outcomes of these analyses inform an optimization model that determines the ideal number of lecturers either full time or part time required to maintain operation efficiency while ensuring teaching quality and cost effectiveness.

3.2 Data Description and Collection

Data were collected form servicing code application records submitted by various faculties to the Faculty of Business and Management for the academic session. Each record represents a single course request and contains the following information as depicted in the Table 1.

Table 1. Dataset description.

Attribute	**Description**	**Data type**
Course Code	Unique identifier for each servicing code	Text

Course Name	Name or title of course offered which align with the course code	Text
Credit hours	Number of teaching hours aligned with the course code	Integer
Course Type	Indicates whether the course is an elective or university core subject	Text
Faculty	The requesting faculty or department	Text
Branch /Campus	Physical location of the program	Text
Program	The academic program making the request	Text
Total Number of students	Enrolment size for the servicing course	Integer (Range): Below 33, 34 – 64, More than 64
Approval Status	Indicates whether the application is approved or pending	Text

3. 3 Data Preprocessing

Prior to analysis, the data went through several process. First, the dataset collected need to be cleaned by removing invalid and duplicate data. Next, normalization process has been conducted to ensure the standardization of attribute data type to ensure consistent scaling. Then, the data conversion of categorical attributes for total number of students that originally using numbers as input have been changed to nominal data type to allows for attributes ranking using select attributes function via discretization function in WEKA tool.

3.4 Analytical Techniques and Validation

For clustering analysis, the K-Mean and EM clustering was applied to identify the natural groupings and patterns in servicing code demand. K-Means algorithm was selected to grouped courses into clusters based on attributes such as Total Students, Course Type and Branch. While, EM clustering provided the probabilistic groupings, offering deeper findings into overlapping demand patterns across the faculties. These clustering results revealed high demand and low demand course segments, enabling administrators to visualize where lecturer resources should be prioritized.

Meanwhile, the classification analysis was selected to predict future servicing code approvals and demand categories. Random Forest algorithm was utilized due to its robustness and high accuracy in handling mixed data types. The model was trained using 10-fold cross validation, and performance was evaluated based on accuracy, kappa statistics, precision and recall metrics. The classification results indicate which factors most strongly predict course approval success and high enrolment levels. Besides, Information Gain Attribute Evaluation model was performed to identify the most influential variables affecting service code demand. This step ranked the attributes according to their contribution to predicting demand intensity and approval outcomes. Attributes such as Program, Course Code, and Course Type were found to be the strongest determinants in the model.

4 Findings and Discussion

The analysis main objective is to identify the demand trends form servicing code applications across faculties and identify the key determinants of course approval. Several machine learning techniques namely

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clustering, classification and attribute selection were applied to the servicing code dataset and analyzed using WEKA software.

4.1 Visualize All

As shown in Figure 1, the class attribute for this analysis is the approval status depicted in blue color represent Approved and red color represent Not Approved. Main objective is to identify pattern of which course, faculty and campus related factors influence whether a servicing code request is approved. All attributes describe in Table 1 approval pattern visualized in this Figure 1. It shows that certain course codes and names have very high approval represented in blue color with count of 62 and 50 showing some specific subjects or servicing codes are repeatedly approved due to consistent demand, core requirements and availability of qualified lecturers. The approval rate is not evenly distributed meaning that certain subjects are considered more essential or suitable for cross faculty servicing. For credit hours, it is not a major discriminating factor since almost all subjects are standardized to 3 credit hour subjects. Course type shows a dominant blue bar (n-264) and a smaller red-blue combination (n-33). This indicates that most approved subjects are university code or compulsory courses while elective courses have more rejection represented with red color. Core or university courses are prioritized for servicing due to broader student demand. For Program Code, programs with repeated or overlapping syllabus requests likely get approval priority due to large student cohorts or shared curriculum. Total student count also a strong dominant of approval status depicted with two major clusters specifically one large (201) and one smaller (92). Larger classes are more likely to be approved for servicing since they justify lecturer allocation. For approval, majority of servicing requests were approved with 258 instances highlight servicing code application have been approved while 39 instances not approved shows strong class imbalance. This suggests a supportive cross-faculty teaching environment. Future analysis shoud consider this imbalance.

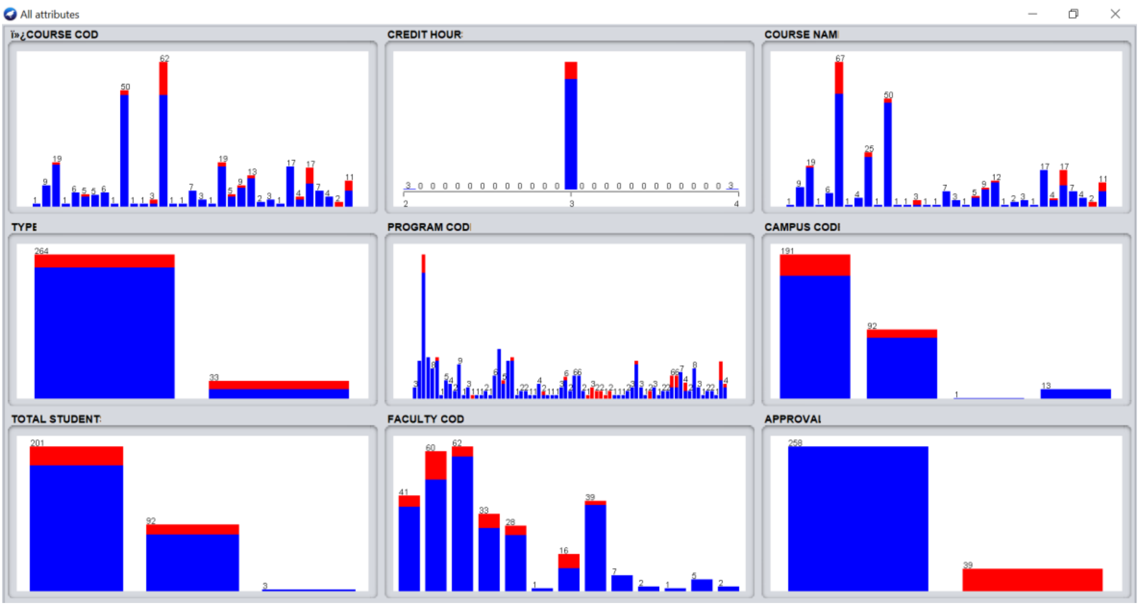

Figure 1. Visualize all attributes showing patterns of approval status.

4.2 Clustering Analysis: Demand Patterns across Faculties

The clustering results using K-Means and EM (Expectation-Maximization) algorithms revealed distinct demand segments among faculties as shown in Table 2 and Table 3 respectively.

Table 2. Summary of K-Means Clustering Results.

Cluster	Instances Percentage	Total Instances	Dominant Course Type	Branch Concentration
Cluster 0	32%	94	University Code (Economic)	Central (B)
Cluster 1	68%	203	University Code (Technology Entrepreneurship)	Central (B)

As shown in Table 2, the algorithm of k-Means generates two clusters for the total instances of 297 servicing code applications. Cluster 0 mainly represents Economics related courses while Cluster 1 represents Technology Entrepreneurship related courses which explain clear thematic separation of social science-based servicing code of entrepreneurial or technical servicing code. Both clusters belong to university servicing codes rather than electives in which both are part of the shared curriculum structure or standard qualification and requirements of the program offered. Cluster 0 courses serve smaller student group representing ideal 30 students per class. These courses need consolidation or shared classes across branches to optimize lecturer deployment. Without combing classes, they may require more lecturers per student ration that involve higher cost per student that leads to inefficiencies. Cluster 1 have larger student counts that exceeding the optimal 30 student target represent the core high demand servicing codes that already operate at or near optimal capacity. This course may justify additional part time lecturer loading if demand increases to ensure each lecturer stays withing the 20 hours credit limit of teaching load. Both clusters mainly consist of approved requests, suggesting approval decision are consistent across both subject domains.

Table 3. Summary of EM Results – Approval Trends Across Clusters

Cluster	Total Instances	% of Data	Approved	Not Approved	Dominant Course
0	83	28%	69.98	5.83	Foundation Management or general business courses/Economics
1	81	27%	74.42	16.17	Entrepreneurship
2	46	15%	73.19	5.93	Marketing
3	33	11%	6.07	13.07	Small specialized programs
4	54	18%	39.35	3.00	Technology/Interdisciplinary

Based on Table 3, Expectation- Maximization (EM) algorithm generated 5 clusters based on the 297 total instances. Essentially, EM grouped the data automatically based on probabilistic similarity of course code, type, faculty and student totals and not a fixed distanced metric like K-Means. Cluster 0 have the highest approval rate depicted strong performing cluster. Cluster 1 also offers high approval rates but with higher failure rates that contribute to the variability. Cluster 2 shows stable cluster with small percentage of instances but consistent. However, Cluster 3 have the highest Not Approved tendency showing underperforming cluster and Cluster 4 present moderate performance but small Approved sample base. Based on these results, it can be summarized that Clusters 0, 1 and 2 are successful course clusters which majority of the applications was approved. While Cluster 3 stand out as the problematic with low approval cluster or high percentage of Not Approved ration despite smaller size. Next, Cluster 4 seems moderate and low sample density but consistent with the Approved status, possibly elective or niche courses. Moreover, Clusters 0,1 and 2 correspond to large, standardized courses such as Technology Entrepreneurship, Economics and Management. Cluster 3 are tied to low enrolment or cross disciplinary possibly electives with more subjective assessment or less standardized support.

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4.3 Attribute Selection: Determinants of Course Approval and Demand

Attribute Selection using Information Gain Ranking identified the most influential factors contributing to service code approval demand variation. Table 4 shows the attribute importance ranking.

Table 4. Attribute importance ranking.

Rank	Attribute	Information Gain Value
1	Program Code	0.31032
2	Course Code	0.14142
3	Course Type	0.13899
4	Faculty	0.05992
5	Branch/Campus	0.04777
6	Total Number of Students	0.00226
7	Credit Hours	0.00000

The Information Gain values measure how much each attribute reduces uncertainty in predicting approval status of servicing code requests. Ranked 1 is the program code which dominate the analysis and labelled as dominant determinant. It shows that program with strategic or compulsory subjects have a higher chance of approval. Ranked second is the Course Code depicted that courses that are universally accepted due to their role in the curriculum or accreditation requirements. This mean that the course requested is the core knowledge which are institutional requirements. Furthermore, ranked three is the Course Type showing university subjects are more likely approved than elective code. This highlights institutional alignment toward cross faculty education and shared curriculum goals. For credit hours that ranked last show no variance or no impacts to the approval status. In summary, the Information Gain attribute selection revealed that Program Code, Course Code, and Course type are the strongest determinants of servicing code approval.

4.4 Classification using Random Forest Algorithm

The Random Forest classifier was applied to evaluate the predictive capability of servicing code approval outcomes based on the selected attributes namely Program Code, Course Code, Code Type, Faculty Code, Campus Code, Credit Hours and Total Students. The model achieved an impressive 95.29% classification accuracy as shown in Figure 2. This indicates that a high level of consistency in predicting whether an application for a servicing code would be approved (LULUS) or not approved (XLULUS). The Kappa statistics of 0.7681 demonstrates substantial agreement between the predicted and actual classifications, confirming the robustness of reliability of the model beyond chance. The low error rates depicted by the value of Mean Absolute Error with the value of 0.0818 and Root Mean Square Error (RMSE) equal to 0.1831 further validate the model's predictive strengths and stability. For the Approved (LULUS) class, the model achieved a True Positive Rate of 99.2 percent and a precision of 95.5 percent, meaning the majority of approved applications were accurately identified. For the Not Approved (XLULUS) class, despite a smaller data proportion, the model still achieved precision of 93.1 percent and Recall of 69.2 percent reflecting good sensitivity in detecting rejected applications. The Receiver Operating Characteristic (ROC) area of 0.93 across both classes indicates excellent discriminative ability, with the classifier highly capable of differentiating between approval and non-approval outcomes.

Classifier output

```
=== Summary ===

Correctly Classified Instances         283               95.2862 %
Incorrectly Classified Instances        14                4.7138 %
Kappa statistic                          0.7681
Mean absolute error                      0.0818
Root mean squared error                  0.1831
Relative absolute error                 35.5626 %
Root relative squared error             54.2101 %
Total Number of Instances              297

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.992    0.308    0.955      0.992    0.973      0.779    0.983     0.997     LULUS
                 0.692    0.008    0.931      0.692    0.794      0.779    0.983     0.912     XLULUS
Weighted Avg.    0.953    0.268    0.952      0.953    0.950      0.779    0.983     0.986

=== Confusion Matrix ===

   a   b   <-- classified as
 256   2 |   a = LULUS
  12  27 |   b = XLULUS
```

Figure 2. Classification Result using Random Forest Algorithm.

The confusion matrix further confirms these strengths representing by 297 total instances where 256 were correctly predicted as Approved (LULUS) and 27 as Not Approved (XLULUS), with only minimal misclassification with 14 total cases. This model can be integrated as a decision support tool to pre-screen or recommend servicing code approvals, potentially reducing administrative workload and increasing transparency in academic resource allocation. The results also provide a foundation for developing a predictive approval system that flags potential issues or misalignments before submission, ensuring compliance and efficiency in inter faculty teaching management.

5 Theoretical and Practical Implications

5.1 Theoretical Implications

This study makes several fundamental contributions to the existing theoretical frameworks within the educational management, human resources, and decision support systems. This research serves as bridge conceptual gaps and guidance to establish novel interventions and connections that enrich the understanding of resource allocation in the complex academic environments. Machine learning algorithms via WEKA analysis have been applied for educational management to handle the academic resource planning and course servicing theory. By analyzing the historical data on servicing code demand and student enrolment patterns help to predict resource allocation in pedagogical learning. This integration offers a new approach to understand and management the dynamic requirements between education demand, available teaching capacity, and providing solutions for strategic academic planning that was previously reliant on perception or historical pattern.

Furthermore, this study significantly extends existing human resource optimization models by thoroughly adapting them to the complex academic context. Conventional human resource management often prioritize efficiency and cost effectiveness in industrial settings. This study integrates critical academic specific constraints namely lecturer's workload or contact hours, preparation time, assessment marking and research commitments in which all these tasks contribute to the potential burnout, and it will impact work life balance. This study offers more comprehensive theoretical lens for academic human resource management and extends the human resource optimization in higher learning education or education industry. This research also contributes to the theory of decision support systems within higher education. It provides a concrete and analytical framework for data utilization including historical servicing code applications data that were systematically processed and analyzed using big data tools such as WEKA that was employed in this study to analyze the data and make predictions to inform and validate the staffing decisions.

5.2 Practical Implications

One of the most important and significant practical implications of this study is the empowerment of the top management of the faculty to make decisions on staffing for teaching load and human resources management. Top management of the faculty can predict the total number of demands for service code requirements based on the historical data to cater last minutes requests or uncertain requirements related to this study. This study employs WEKA tools that provide analytical capabilities through techniques like classification and regression as well as forecasting the precise demand for servicing code from various programs and branches. This allows for proactive and efficient planning of lecturer allocations for selected semester or even in full academic year. Top management can strategically assign lecturers with loading that can optimize the total number of part-time and full-time lecturers that should be hired to meet the demands of the servicing code requests. The current process of determining servicing code demand and subsequently allocating lecturers is often a challenging process which involves numerous emails, meetings, and manual adjustments, leading to significant administrative bottlenecks and potential errors. The WEKA driven system reduces this administrative burden drastically by providing predictive insights into which branches or programs will need more servicing code that allowing administrative staff to focus on other tasks rather than the scheduling process and management. Besides, the data driven approach applied in this study contributes to optimized cost efficiency by allocating the optimal number of part time and full-time staff that preventing the insufficient of full-time staff and met the demand of servicing codes requirements. The forecasting demand can avoid over staffing or under staffing that prevent financial limitations and ensure the optimal allocation of resources. Furthermore, this study also contributes to the education system to ensure academic quality assurance in which the classes of servicing code demand will run smoothly. This data-driven approach ensure optimal learning environments is maintained and minimize risk of class delay or unattended by respective lecturers that should be tackle before the semester starts. This study offers data decision that support quality and encourage pedagogical achievement fostering excellent education experiences for students and a more sustainable operating model for the education industry.

6. Conclusion

This study demonstrates the potential of data analytics and machine learning techniques in optimizing the management of servicing code applications across faculties. WEKA software has been selected to conduct the clustering, attribute selection and predictive modelling analysis. The analyses revealed that servicing code demand can be effectively segmented into clusters characterized by course type, faculty origin and student enrolment volume. Course such as Technology Entrepreneurship and Economics were found to be among the most frequently requested and approved indicating their cross disciplinary relevance and institutional importance and requirements.

The Information Gain ranking further revealed that Program Code, Course Code and Course Type are the most significant attributes influencing course approval outcomes, surpassing factors such as total student count or campus location. This suggests that servicing code approval is primarily driven by academic program requirements and curriculum alignment rather than logistical or demographic factors. The clustering and attribute analyses together highlight the need for data such as lecturers loading can be distributed based on actual demand, course specialization and optimal class size thresholds.

From a managerial perspective, the findings offer a structured decision support framework for optimizing lecturer deployment while maintaining cost efficiency. By setting a class size cap of 30 students per class and a maximum of teaching load of 20 credit hours for part time lecturers, institutions can effectively balance resource utilization between full time and part time lecturers. Furthermore, courses with consistently low enrolment may be combined across campuses or programs to minimize redundancy and improve cost effectiveness. This study provides an evidence-based framework for decision-making on servicing code requirements. It also demonstrates the practical use of WEKA as a transparent and accessible tool for institutional analytics. Meanwhile, it supports policy formulation for manpower optimization across multi-campus or multi-faculty structures. Besides, this study offers a scalable model that other faculties or institutions can replicate to manage teaching demand more effectively.

In conclusion, the integration of data analytics into academic resource planning presents a transformative opportunity for higher education institutions. Future research may extend this work by incorporating predictive simulations for lecturer workload balancing, exploring longitudinal data to tack changing demand patterns, and integration cost benefit analysis to further refine the optimization model.

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