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Explainable Ensemble Learning for Transparent and Efficient Zakat Scholarship Selection

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ABSTRACT

Education financial assistance funded by Zakat, Infaq, and Waqf holds significant potential to support sustainable higher education. However, the long-term sustainability of the Islamic Trust Fund Ar-Raniry's scholarship programs faces challenges. These challenges include the operational burden of a one-month manual process and concerns of subjectivity due to a lack of transparency in scholarship decisions. This study aimed to improve the efficiency, objectivity, and transparency of the selection process through the development of a Decision Support System (DSS). The study conducted a Decision-Oriented Diagnosis and Feasibility Study to better understand the decision-making process. The design of the DSS employed Unified Modeling Language (UML). A prototype was created using low-code/no-code development tools following the Rapid Application Development (RAD) methodology, while model development adhered to the Cross-Industry Standard Process for Data Mining (CRISP-DM). Previous studies have applied various machine learning models to scholarship selection, though a notable gap remains in the integration of Explainable Artificial Intelligence (XAI). This study found that the Soft Voting Ensemble of Naïve Bayes, K-Nearest Neighbors, and Support Vector Machine, combined with the Synthetic Minority Oversampling Technique (SMOTE), achieved an accuracy of 75.63% and a macro recall of 71.16% in holdout testing. Using Local Interpretable Model-Agnostic Explanations (LIME), the study identified Fee Level as the common factor affecting classification for the Eligible class—consistent with the criteria used in manual selection. The implementation resulted in integrated data and automated processes, thereby supporting the acceleration of an efficient, objective, and transparent scholarship selection process. An implementation strategy was also formulated, including parallel conversion, computer-based training, and ongoing system support and maintenance.

KEYWORDS *Decision Support System, Scholarship Selection, Machine Learning, Low-code/No-code, Explainable AI*

INTRODUCTION

Sustainable Development Goals (SDG) mandates high quality, inclusive, and equitable education for all (Transforming Our World: The 2030 Agenda for Sustainable Development, 2015). Daud and Wahid (2024) explained that financial circumstance is the main hurdle to achieve equitable education for which Zakat can alleviate. Likewise, Sriyanto et al. (2024) emphasized that Zakat, Infaq, and Waqf improve students' welfare through education financial assistance. Rohana et al. (2024) discussed a Waqf-based financing scheme called Waqf Al-Tadris, which was limited to religious schools but has expanded to financing higher education.

The management of education financial assistance funded by Zakat, Infaq, and Waqf fund faces numerous challenges such as limited human resources, procedural inefficiencies, allocation subjectivity, and misallocation of fund (Ismail et al., 2024; Mohaiyadin & Aman, 2021; Sabri et al., 2021). Zakat, Infaq, and Waqf institutions are looking at technologies to improve efficiency, objectivity, and transparency. Islamic Trust Fund (ITF) Ar-Raniry manages Zakat, Infaq, and Waqf to support three scholarship programs, namely Bantuan Biaya Pendidikan (BBP), Dana Darurat Pendidikan (DDP), and Ar-Raniry Scholarship. The managers of ITF Ar-Raniry aspire to improve their operations with optimal use of technology.

The current scholarship recipient's selection process is inefficient because of fragmented data collection and verification. The data are consolidated manually using spreadsheets for three days. Furthermore, the interview sessions are subjective with over reliance on assessment from faculty members and managers. Then, the interview sessions can last up to seven days. After that, the committee meeting was a bottleneck due to frequent delays. Further, the manual nature of the process leads to complaints regarding the transparency of the selection criteria. As a result, the overall selection process takes up to one month.

The sustainable operation of ITF Ar-Raniry depends on addressing inefficiencies, subjectivity, and transparency. An improvement to the decision-making process streamlines the workflow and ensures the long-term sustainability of the institution's scholarship programs. The institution risks operational bottlenecks and questions regarding fairness of its selection process without technological intervention. This study identified a solution through a literature review. The review involved 22 documents from Indonesia, Malaysia, and Southeast Asia on the topic of the scholarship recipient's selection process leveraging Algorithm, Predictive Model, Machine Learning (ML), and Explainable Artificial Intelligence (XAI).

Anggrawan et al. (2022) utilized Analytical Hierarchy Process (AHP) and Multi-Objective Optimization by Ratio Analysis (MOORA) to determine the rank of scholarship recipients. Pranoto et al. (2022) followed the same approach but replaced MOORA with Simple Additive Weighting (SAW). Mundzir et al. (2023) simplified the approach by using AHP to determine the rank. Aside from using AHP, past studies relied on managers to determine the criteria weight and then rank the recipients using SAW (Arsyah et al., 2021; Khasanah, Trias Handayanto, et al., 2020; Kumarahadi et al., 2020), Weighted Products (WP) (Khasanah, Trias Handayanto, et al., 2020), and Fuzzy Logic with Genetic Algorithm (Pratama et al., 2021).

Aside from Multi-Attribute Decision Making (MADM), two studies employed a decision-tree called C4.5 to classify scholarship recipients (Afrianto et al., 2020; Novita et al., 2021). Moreover, a study employed C4.5 with a tweak of Fuzzy Multi-Attribute Decision Making (Fuzzy MADM) (Haris et al., 2020). Uniquely, Kustiyahningsih et al. (2021) improved the C4.5 performance with pruning technique. On the other hand, Hendri et al. (2024) conducted a two-step recipients' selection with the use of K-Means before C4.5. The decision-tree approaches displayed classification accuracy up to 98% while also providing decision transparency through dendrogram (Afrianto et al., 2020; Haris et al., 2020; Hendri et al., 2024; Kustiyahningsih et al., 2021; Novita et al., 2021).

Febri and Sari (2023) conducted a study to classify scholarship recipients using Naïve Bayes (NB), while Rahman et al. (2021) compared NB with C4.5. Meanwhile, Kurniadi et al. (2022) applied Synthetic Minority Oversampling Technique (SMOTE) for K-Nearest Neighbor (KNN) to observe the impact on an imbalanced dataset. Sahid et al. (2022) employed the Brute Force technique to NB and KNN to identify the best classification criteria. Tempola et al. (2021) applied the Holdout technique for NB and KNN to ensure a stable model. Buslim et al. (2023) employed a combination of Support Vector Machine (SVM) and KNN to observe the impact of an ensemble model. Ahmad and Bakar (2020) compared Ensemble of decision-tree J48 and Apriori with Ensemble of complex models including Artificial Neural Network (ANN). Overall classification accuracy ranged from 50% to 100% (Buslim et al., 2023; Rahman et al., 2021).

The adoption of clustering model found in past studies leveraged Agglomerative Hierarchical Clustering (AHC) (Adiwijaya et al., 2023) and K-Means Clustering (Hendri et al., 2024; Khomarudin et al., 2021; Putra et al., 2021). The common treatment with clustering was aggregating the characteristics of each cluster (Adiwijaya et al., 2023; Hendri et al., 2024; Khomarudin et al., 2021; Putra et al., 2021). The aggregated characteristics allowed researchers to understand the common traits for the decision-making transparency (Adiwijaya et al., 2023; Hendri et al., 2024; Khomarudin et al., 2021; Putra et al., 2021).

Despite the prevalent use of machine learning models, past studies remained confined to experimental environments. First, experiment by Buslim et al. (2023) displayed a risk of overfitting with accuracy of 100%, while other experiments were prone to single-model bias (Afrianto et al., 2020; Febri & Sari, 2023; Haris et al., 2020; Kurniadi et al., 2022; Kustiyahningsih et al., 2021; Novita et al., 2021). Unlike studies by Buslim et al. (2023), Khasanah et al. (2020), Pranoto et al. (2022), Pratama et al. (2021), and Putra et al. (2021), most of the studies stopped at reporting high accuracy without the deployment and integration of models with institutional process.

Past experiments with Decision Tree and Clustering successfully paired classification results with the explainability aspect, whereas none of the other machine learning approaches addressed it. Therefore, this study intends to address this gap by designing, developing, and implementing a Decision Support System (DSS) that integrates Machine Learning with an Explainable Model. The main objective of this study is to improve efficiency, objectivity, and transparency in the selection process. Secondly, this study aims to formulate an implementation strategy that supports the institution's operations.

RESEARCH METHOD

This study is applied research using a case study to address practical problems at Islamic Trust Fund (ITF) Ar-Raniry. The study employed mixed-methods design, consisting of qualitative and quantitative methods. The qualitative aspect guided the system design, system development, and implementation strategy formulation. Meanwhile, the quantitative aspect focused on the classification model performance and explainability.

Firstly, this study started with a Decision Process Audit Plan to map existing workflow using a Data Flow Diagram (DFD). DFD helped identify gaps between the theoretical and actual decision-making processes. After a feasibility study with technical, financial, and organizational aspects, this study followed Rapid Application Development (RAD) methodology to integrate the database, model, and user interface (Dennis et al., 2015).

This study designed DSS with the help of Unified Modeling Language (UML) use case and activity diagrams (Dennis et al., 2015). The DSS model was developed with Python and Google Colab Integrated Development Environment (IDE), then the resulting model was deployed to Hugging Face (Hugging Face, 2025; Zhong et al., 2025). DSS database, interface, and communication between them was implemented using low-code/no-code platforms Softr.io and n8n, while testing was conducted at the unit, integration, and system levels (Dennis et al., 2015; El Kamouchi et al., 2023; Pawar et al., 2025; Wang & Wang, 2022). The implementation strategy followed Lewin's Unfreeze, Move, and Refreeze approach (Dennis et al., 2015).

Table 1. Classification Criteria

No	Name	Type	Description
1	Scholarship Program	Categorical	Chosen scholarship program
2	Scholarship Experience	Categorical	Past scholarship experience including from ITF Ar-Raniry
3	Father Condition	Categorical	Father is alive or deceased
4	Father Marital Status	Categorical	Father marital status
5	Father Occupation	Categorical	Father occupation
6	Mother Condition	Categorical	Mother is alive or deceased
7	Mother Marital Status	Categorical	Mother marital status
8	Mother Occupation	Categorical	Mother occupation
9	Academic Status	Categorical	Academic status upon application
10	Faculty	Categorical	Student's faculty
11	Study Program	Categorical	Student's study program
12	Year	Categorical	Length of study in year
13	GPA Level	Categorical	Latest GPA level
14	Fee Level	Categorical	Current tuition fee level
15	Sponsor	Categorical	Sponsor for tuition fee
16	Dependent	Categorical	Number of sponsor dependent

After completing the design for DSS, this study proceeded to model development following the Cross-Industry Standard Process for Data Mining (CRISP-DM). The population for the classification model consisted of Bantuan Biaya Pendidikan (BBP) and Dana Darurat Pendidikan (DDP) applications from the academic year of 2024 to 2025. BBP and DDP were chosen due to their similar student characteristics and selection processes.

A total of 800 applications with 16 criteria as described in Table 1 were acquired from the management of ITF Ar-Raniry. A total of 528 applications were ineligible (66%), leaving only 272 (34%) eligible applications. The data collected went through a cleaning process which was done manually by cross-checking missing data with various supporting documents. Further, the study utilized a label encoding process to translate the label for each criterion into a numerical values that are acceptable to machine learning models (Bellaj et al., 2024).

This study applied cost-sensitive learning to handle class imbalance. Cost-sensitive learning was achieved by adjusting the mechanics to consider the minority class. Besides, the study also implemented resampling techniques with the use of Random Over-Sampler (ROS) and Synthetic Minority Oversampling Technique (SMOTE) (Ghorbani & Ghousi, 2020; Kurniadi et al., 2022). Oversampling was applied to create duplicated or synthetic data from the minority class (Ghorbani & Ghousi, 2020; Kurniadi et al., 2022).

Python code generation was assisted by the Large Language Model (LLM) ChatGPT (Zhong et al., 2025). The modeling phase employed four classifiers: Naïve Bayes (NB), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and soft-voting ensemble of the three models. The dataset was split into 80% for training and 20% for testing (Almonteros & Matias, 2024). Model stability was ensured using Stratified 5-Fold Cross-Validation using 80% of the dataset (Almonteros & Matias, 2024). Meanwhile, the rest of the dataset was kept for holdout test (Almonteros & Matias, 2024).

Model performances were evaluated using Accuracy, Precision, Recall, F1-score, and Area under the Receiving Operating Characteristic Curve (AUC ROC) (Ahmad & Bakar, 2020; Buslim et al., 2023; Kurniadi et al., 2022). Accuracy is a measure of correct classification against the overall classification (Ahmad & Bakar, 2020; Buslim et al., 2023; Kurniadi et al., 2022). Meanwhile, precision is a measure of positive classification that is truly positive (Ahmad & Bakar, 2020; Buslim et al., 2023; Kurniadi et al., 2022). Then, recall is a measure of positive classification that was captured by the model (Ahmad & Bakar, 2020; Buslim et al., 2023; Kurniadi et al., 2022). Next, F1-score is a measure that balances the Precision and Recall score (Kurniadi et al., 2022). Lastly, AUC ROC is a measure of performance in distinguishing positive and negative classes (Kurniadi et al., 2022).

This study employed Local Interpretable Model-Agnostic Explanations (LIME) to address the explainability aspect. Ribeiro et al. (2016) explained that the expected characteristics of an explainable model comprise interpretability, local fidelity, and model-agnostic. Interpretability ensures that the explanation is easily understood by humans (Ribeiro et al., 2016). Local fidelity ensures that the explanation is locally accurate around the target data point (Ribeiro et al., 2016). Model-agnostic means the explainable model is independent of the model being explained (Ribeiro et al., 2016). The equation (1) below describes how LIME optimizes the relationship between the three desired characteristics.

$$\xi(x) = \arg\min_{g \in G} L\,(f, g, \pi_x) + \Omega(g) \quad (1)$$

$\xi(x)$ = The explanation for sample x
f = Original model being explained
g = The interpretable model
π_x = Proximity measure defining the locality around x
L = Loss function measuring local fidelity
$\Omega(g)$ = Complexity penalty to ensure interpretability

RESULT AND DISCUSSION

The Decision-Oriented Diagnosis produced a Data Flow Diagram (DFD) describing the as-is decision-making process. Figure 1 is a DFD illustrating the interplay among the actors, processes, and storage. The actors included students, faculty members, academic unit, Islamic Trust Fund (ITF) managers, and ITF leaderships. There were seven processes: (1) submission of application; (2) collection of students data; (3) integration of application and student data; (4) validation of application and student data; (5) nomination of recipients; (6) determination of recipients; and (7) publication of recipients. The repository consists of application data, students' data, integrated data, validation data, nomination data, and recipient data.

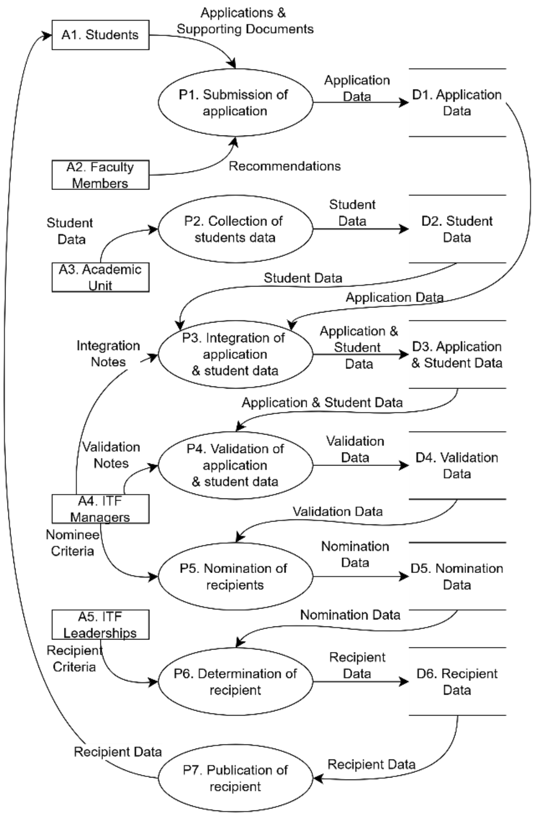

Figure 1. Data Flow Diagram

This study identified significant issues within the current decision-making process. First, irregular and poor application and student data are noticeable. Secondly, the data issue worsens with manual integration and unstandardized validation process. As a result, the data was fragmented, and the process of determining recipients was lengthy. These findings emphasized the need for improved efficiency, objectivity, and transparency.

After the diagnosis, this study conducted a Feasibility Study including technical, financial, and organizational aspects. From a technical perspective, the study noted that the institution has a good understanding of the decision-making process but lacks technical familiarity. Low-code/no-code platforms addressed the lack of technical familiarity with visual programming (El Kamouchi et al., 2023). From a financial perspective, low-code/no-code platforms provided free tier and self-hosted options to ensure rapid prototyping without the burden of upfront cost (El Kamouchi et al., 2023). From an organizational perspective, low-code/no-code platforms and Rapid Application Development (RAD) methodology secure the alignment of technology and business with quick iteration of prototypes (Dennis et al., 2015; El Kamouchi et al., 2023).

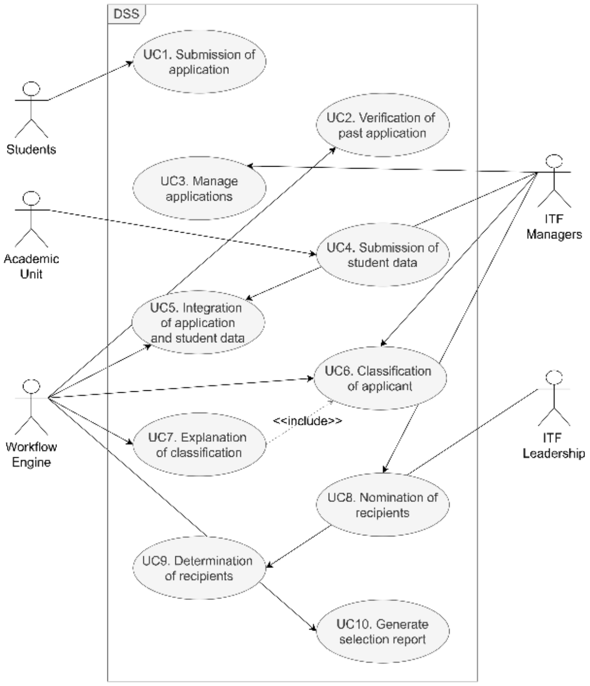

Figure 2. Use Case Diagram

The results of the Decision-Oriented Diagnosis and Feasibility Study drove the DSS design process. Figure 2 is a use case diagram to visualize the functional requirements of the DSS. There are ten use cases starting with the submission of applications that trigger verification of past applications. Then, the submission of student data by academic unit to ensure standardized data for automated integration. Further, the ITF managers can manage applications that may trigger different functionalities such as classification of applicants, explanation of classification, and the recipient nomination. Lastly, the ITF leadership has the authority to determine the recipient and generate the scholarship selection report.

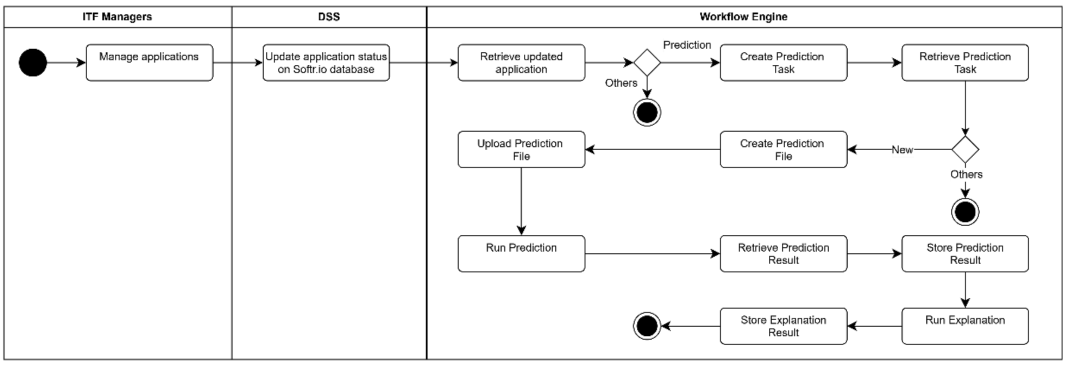

Figure 3. Activity Diagram

Aside from using a use case diagram, this study utilized an activity diagram to visualize the decision-making processes. A sample process was visualized in Figure 3 involving the application management for the purpose of classification and explanation. As shown in the diagram, when an ITF manager updates the status to

“Prediction”, a workflow is triggered to generate a prediction task and its associated file. This file is subsequently uploaded as an input to the classification model. After completing the classification, the result is stored to allow for identification of influencing factors using the explanation model.

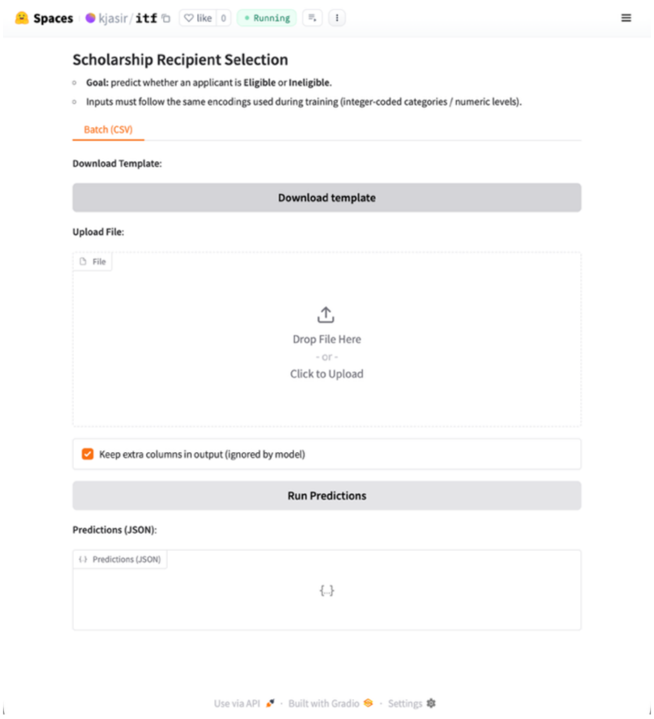

Figure 4. User Interface to Interact with Model

This study utilized Large-Language Model (LLM) ChatGPT to assist the development of the classification and explanation model with Google Colab for Integrated Development Environment (IDE) (Zhong et al., 2025). The model was developed using various libraries such as Pandas, Numpy, Imb-Learn, Scikit-Learn, and Gradio. Gradio is a library to generate a user interface and Application Programming Interface (API) so that it can be deployed easily to Hugging Face (Abid et al., 2019; Hugging Face, 2025). The API created allowed public access, hence integration with the DSS was possible. Figure 4 displayed the user interface generated in Hugging Face.

This study experimented with three base classifiers, namely K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naïve Bayes (NB), along with an ensemble integrating all three base classifiers. The also study applied Synthetic Minority Oversampling Technique (SMOTE) and Random Over-Sampler (ROS) to address the class imbalance. Furthermore, the study tailored hyperparameters for specific models, including Euclidean, Manhattan, and Hamming distance metrics for KNN, and cost-sensitive learning for NB and SVM. Effectively, this study covered 14 classification models whose results are listed in Table 2.

Table 2. Cross Validation Result

No	Model	Accuracy	Precision	Recall	F1	AUC
1	NB, KNN with Manhattan, & SVM (SMOTE)	73.75%	71.11%	70.75%	70.77%	73.45%
2	SVM Balanced	71.88%	69.09%	69.32%	69.01%	75.21%
3	SVM Balanced (ROS)	71.09%	68.04%	68.19%	68.00%	73.32%
4	SVM Balanced (SMOTE)	70.94%	67.90%	67.97%	67.85%	74.34%
5	NB (SMOTE)	70.78%	67.82%	67.86%	67.74%	71.89%
6	NB (ROS)	69.38%	66.67%	67.13%	66.70%	71.34%
7	NB Balanced	69.53%	66.68%	66.80%	66.58%	72.15%
8	NB Imbalanced	69.53%	66.32%	66.14%	66.13%	72.15%
9	KNN Manhattan (SMOTE)	68.44%	65.33%	65.62%	65.35%	68.38%
10	SVM Imbalanced	72.50%	70.01%	65.26%	66.08%	75.50%
11	KNN Manhattan (ROS)	66.41%	63.78%	64.52%	63.84%	66.36%
12	KNN Manhattan	70.31%	66.80%	63.82%	64.39%	68.65%
13	KNN Euclidean	70.00%	66.47%	63.46%	63.93%	67.83%
14	KNN Hamming	68.75%	64.70%	61.22%	61.51%	65.35%

The study found that among the three metrics for K-Nearest Neighbors (KNN), KNN with Manhattan is the best performing model in cross-validation. This model achieved a recall macro of 63.82%, a precision macro of 66.80%, a F1-score macro of 64.39%, and an accuracy of 70.31%. The application of resampling techniques improved the KNN model further with SMOTE coming up on top in recall macro of 65.62%, while ROS achieved recall macro of 64.52%. The effect of SMOTE to KNN is consistent with Kurniadi et al. (2022) findings. Yet, the best performing KNN model is still below the result of KNN with SMOTE from Kurniadi et al. (2022) with 90.12% accuracy.

Next, the cross-validation result for Support Vector Machine (SVM) with cost-sensitive learning has proven its high performance with recall macro of 69.32%, precision macro of 69.09%, F1-score macro of 69.01%, and accuracy of 71.88%. On the other hand, SVM with resampling techniques such as ROS and SMOTE have proven their significance since they improved the recall for the base SVM classifier from 65.26% to 68.19% and 67.97% respectively. Despite showing high performance, the highest Support Vector Machine result with cost-sensitive learning is still below the result from past study by Buslim et al. (2023) who managed to score SVM accuracy of 91%.

The cross-validation result for Naïve Bayes (NB) showed the effect of cost-sensitive learning, but the improvement was minimal with 0.66 percentage point (pp) increment for recall macro from 66.14% to 66.80%. Meanwhile, the resampling techniques have proven their superiority resulting in recall macro uplift to 67.86% with SMOTE and 67.13% with ROS. Naïve Bayes with SMOTE was the best performing NB model with a recall macro of 67.86%, a precision macro of 67.82%, an F1-score of 67.74%, and an accuracy of 70.78%. Despite showing positive uplift across the metrics, the result for Naïve Bayes with SMOTE is still below the result from past study by the Febri and Sari (2023) for NB classifier without resampling with accuracy of 86.84%.

This study combined the single base classifiers with soft voting and SMOTE encompassing K-Nearest Neighbors (KNN) with Manhattan distance, Support Vector Machine (SVM) with cost-sensitive learning, and Naïve Bayes (NB). In cross-validation, this model achieved significant performance gains across key metrics. In terms of accuracy, the ensemble model achieved 73.75%, which is three to five percentage points (pp) higher than the single base classifiers. Similarly, this model reached a macro recall of 70.75% with the same gains of 3pp to 5pp against the single base classifiers. This model has an uplift of 7.75pp from a base dummy classifier that predict the majority class. Moreover, this model displayed stability across the five folds with standard deviation ±3.91 points for accuracy and ±3.44 points for macro recall. Lastly, this result is consistent with findings from Buslim et al. (2023) who recorded improvement with the use of ensemble model.

The performance of the ensemble model with SMOTE improved further in holdout testing as shown in Table 3, reaching a macro recall of 71.16%, a macro precision of 72.80%, an F1-score macro of 71.79%, and accuracy of 75.63%. Despite, the Area under the Receiving Operating Characteristic Curve (AUC ROC) and minority class recall saw declines of 3.88 percentage points (pp) and 4.03pp respectively. The model generalizes effectively to unseen data, as evidenced by the improvement in macro F1-score by 1.02pp and accuracy by 1.88pp. The shift in minority class metrics indicated that, in the absence of oversampling, the model adopted a more conservative classification, prioritizing higher precision instead of recalling for minority class.

Table 3. Holdout Result

Class	Precision	Recall	F1	Accuracy	AUC ROC
0	79.65%	84.91%	82.20%	75.63%	69.57%
1	65.96%	57.41%	61.41%		
Macro	72.80%	71.16%	71.79%		

While the ensemble model achieved a respectable accuracy of 75.63%, the recall score for minority eligible class stood at 57.41%. This result indicated a risk of False Negative, with which truly needy students might be overlooked by the model. Ethically, this condition necessitates a Human-in-the-loop approach. Machine learning models were designed as a recommendation engine for the Decision Support System (DSS). Hence, all classificatoin results with low confidence must undergo manual review to ensure fair scholarship selection process.

Furthermore, this study applied Local Interpretable Model-Agnostic Explanations (LIME) to explain individual classification results (Alwarthan et al., 2022; Johora et al., 2025). Each classification result was attributed to five criteria affecting the result. The study adopted a generalized aggregation of local features as a proxy for global importance. This was a deliberate simplification to facilitate trend observation. This aggregation does not provide an exhaustive representation of the model's internal complexity and might introduce local-to-global distortion. The DSS itself retains the capacity for individual-level LIME reports to ensure granular accuracy in specific selection cases. Table 4 listed the top five criteria for each class.

Table 4. Explainable Model Result

No	Eligible		Ineligible	
	Criteria	**Count**	**Criteria**	**Count**
1	Fee Level	164	Father Marital Status	395
2	GPA Level	152	Mother Marital Status	375
3	Father Marital Status	151	GPA Level	282
4	Mother Marital Status	136	Dependent	242
5	Dependent	120	Year	237

The most common factor for the eligible class is the Fee Level that is tuition fee of at most Rp1,638,000. This factor is in line with the ITF managers' description that Fee Level is the first indicator of students' needs. GPA Level below 3.50 and number of dependents below three consistently ranked top on both classes. Parent marital status also appeared on both classes but the big different is that for eligible class the status included married, divorced, and divorced by death, while for ineligible class the status is only married. Uniquely, the students who are on track with their studies are classified as ineligible. This study showed the effectiveness of LIME to explain individual classification results akin to studies by Alwarthan et al. (2022) and Johora et al. (2025).

Effectively, the development of classification and explanation model addressed the subjectivity and transparency of the current scholarship selection process. The use of classification model ensured scholarship recipient selection based on quantified criteria, not only individual perception of the ITF managers. On top of that, the classification model is based on solid mathematical grounds which enforce transparency of decision-making processes. Further, the list of factors affecting classification reinforced transparency with a set of influential criteria.

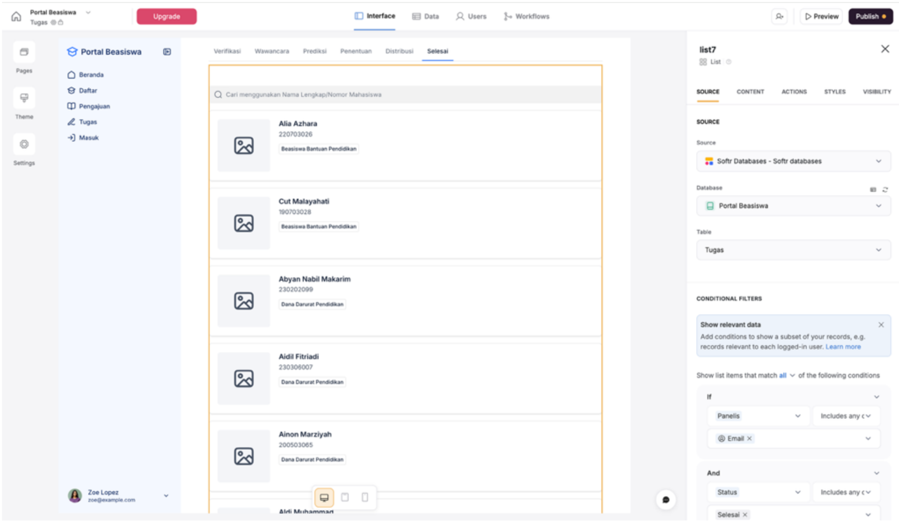

Figure 5. Softr.io IDE

Model is one part of the DSS, while two other components are database and user interface. The development of DSS employed a low-code/no-code platform called Softr.io (El Kamouchi et al., 2023). Softr.io provides an Integrated Development Environment (IDE) to visually create user interfaces and quickly deploy the interface to production (El Kamouchi et al., 2023; Softr, 2025b). This user interface dynamically follows the content stored in Softr.io database (El Kamouchi et al., 2023; Softr, 2025a). Figure 5 displayed how Softr.io provides seamless integration of user interface and database by using dropdown menu to choose which table to display (El Kamouchi et al., 2023; Softr, 2025b, 2025a).

Furthermore, the workflow to automate the business process was completed using an n8n workflow engine (Pawar et al., 2025). Like Softr.io, n8n provides an Integrated Development Environment (IDE) allowing users to visually add nodes and links them based on the business process (Pawar et al., 2025). This low-code/no-code tool provided various nodes including the nodes to manipulate data, interact with Softr.io databases, and request Application Programming Interface (API) (Pawar et al., 2025). Figure 6 illustrates a workflow for the classification and explanation process combining interaction between the Softr.io database and Hugging Face API.

With the completion of all three DSS components, this study conducted three levels of testing starting with black-box testing, integration testing, and system testing (Dennis et al., 2015). The study employed a black box testing within the n8n workflow to check if the node worked as expected, while the integration testing was carried out to check the overall workflow (Dennis et al., 2015). System testing was completed with the help of a Sharia Supervisory Board member to check the conformity of the DSS with the functionality defined previously as use cases. The testing results showed that all functionalities were included in the DSS.

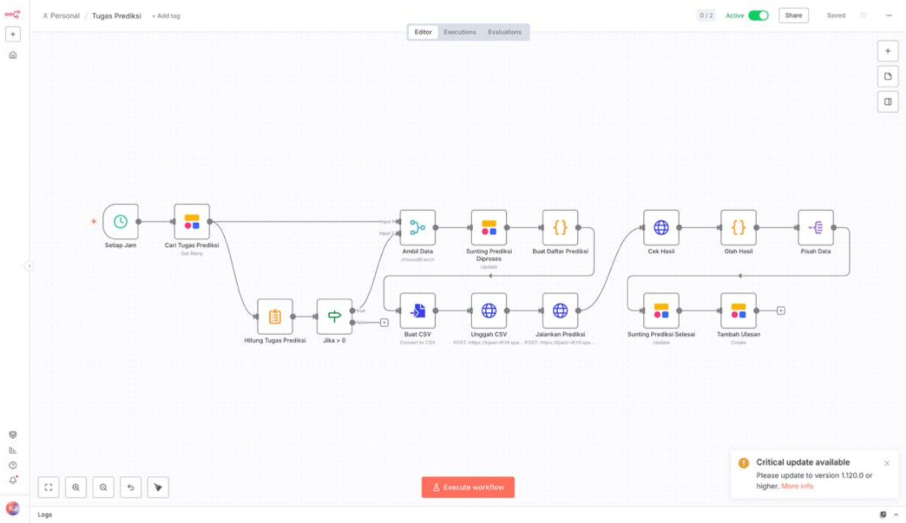

Figure 6. n8n IDE

The development of DSS and its respective workflow ensured the integration of data and automation of business processes. Consequently, the data is no longer fragmented and prone to human errors. Furthermore, ITF managers no longer need to sieve through documents just to identify duplicated and recurring applications. Lastly, the automated nomination of scholarship recipient expedites the selection process. The integrated data and automated process improved the overall efficiency allowing ITF Ar-Raniry to achieve its goal of optimizing technology to serve the scholarship selection process within two weeks.

With the completed DSS, the study shifted the focus to the implementation of DSS. The implementation of DSS consisted of a technical and organizational perspective (Dennis et al., 2015). From the technical perspective, the DSS can be deployed right away since Softr.io and n8n were cloud-based services which did not require technical setup. On the other hand, from an organizational perspective, the implementation strategy in this study comprised conversion and change management (Dennis et al., 2015). The implementation strategy was constructed with three phases including unfreeze, move, and refreeze (Dennis et al., 2015). The following points describe each phase.

1. Unfreeze

The unfreeze phase was meant to break down the current business process (Dennis et al., 2015). The Decision-Oriented Diagnosis and Feasibility Study were the key activities in which users participated to refine the requirements (Dennis et al., 2015). The unfreeze phase raised users' awareness of the DSS, hence laying the foundation for the implementation strategy (Dennis et al., 2015).

2. Move

The conversion for DSS was carried out following the parallel conversion to all users in one location (Dennis et al., 2015). The approach allowed the current process to run in parallel with data migration (Dennis et al., 2015). The change management process started with the revision of Standard Operating Procedure (SOP) and socialization to raise awareness of DSS benefits (Dennis et al., 2015).

The socialization follows the computer-based training approach allowing continuous education through documentation (Dennis et al., 2015).

3. Refreeze

The final phase ensured the post-implementation including the system support and maintenance (Dennis et al., 2015). On-demand training was the key activity to enable system support while educating users on the use of low-code/no-code platforms (Dennis et al., 2015). This approach can support sustainable use of the DSS by involving the users directly (Dennis et al., 2015).

CONCLUSION

This study found that the Decision-Oriented Diagnosis and Feasibility Study served as an effective foundation for the design, development, and implementation of the Decision Support System (DSS). This foundation provided the groundwork for designing the DSS using use case and activity diagrams. The development of classification and explanation models supported the initiative to improve the objectivity and transparency of the selection process through the application of quantitative models and explainable criteria. The model achieved an accuracy of 75.63% and identified students' Fee Level as the most common factor influencing eligibility decisions. The adoption of a low-code/no-code approach enabled rapid prototyping that directly involved end users without the need for software engineers. This approach facilitated the integration of data and process automation, thereby enhancing the efficiency of the selection process. The study also formulated an implementation strategy encompassing parallel conversion, system support, and system maintenance—anchoring the overall strategy to the sustainability of the low-code/no-code DSS for non-technical users. However, this study was conducted with several limitations, including its focus on a single institution, a dataset of only 800 applicants, and the absence of user acceptance evaluation. Therefore, it suggests future research involving multiple institutions, larger datasets, and a comprehensive evaluation of user acceptance.

REFERENCES

Abid, A., Abdalla, A., Abid, A., Khan, D., Alfozan, A., & Zou, J. (2019). *Gradio: Hassle-free sharing and testing of ML models in the wild* [Python]. https://doi.org/10.48550/arXiv.1906.02569

Adiwijaya, F. F., Zufar Fathurrahman, A., & Hardyanto, C. (2023). Application of Agglomerative Hierarchical Clustering (AHC) for Grouping Prospective Scholarship Recipients. *INCITEST - Proc. Int. Conf. Informatics Eng., Sci. Technol.* Scopus. INCITEST 2023 - Proceedings of the 2023 International Conference on Informatics Engineering, Science and Technology. https://doi.org/10.1109/INCITEST59455.2023.10395926

Afrianto, E., Suseno, J. E., & Warsito, B. (2020). Decision Tree Method with C4.5 Algorithm for Students Classification Who is Entitled to Receive

Indonesian Smart Card (KIP). *IOP Conference Series. Materials Science and Engineering*, *879*(1). https://doi.org/10.1088/1757-899X/879/1/012072

Ahmad, W. D., & Bakar, A. A. (2020). Ensemble machine learning model for higher learning scholarship award decisions. *International Journal of Advanced Computer Science and Applications*, *11*(5), 303–312. Scopus. https://doi.org/10.14569/IJACSA.2020.0110540

Almonteros, J. R., & Matias, J. B. (2024). Integration of Stratified KFold Cross Validation to Enhance Prediction Accuracy: A Comparison Study. *2024 5th International Conference on Data Analytics for Business and Industry (ICDABI)*, 81–85. https://doi.org/10.1109/ICDABI63787.2024.10800425

Alwarthan, S., Aslam, N., & Khan, I. U. (2022). An Explainable Model for Identifying At-Risk Student at Higher Education. *IEEE Access*, *10*, 107649–107668. https://doi.org/10.1109/ACCESS.2022.3211070

Arsyah, U. I., Jalinus, N., Syahril, Ambiyar, Arsyah, R. H., & Pratiwi, M. (2021). Analysis of the Simple Additive Weighting Method in Educational Aid Decision Making. *Turkish Journal of Computer and Mathematics Education*, *12*(14), 2389–2396.

Bellaj, M., Dahmane, A. B., Boudra, S., & Sefian, M. L. (2024). Educational Data Mining: Employing Machine Learning Techniques and Hyperparameter Optimization to Improve Students' Academic Performance. *International Journal of Online and Biomedical Engineering (iJOE)*, *20*(03), 55–74. https://doi.org/10.3991/ijoe.v20i03.46287

Buslim, N., Zulfiandri, & Lee, K. (2023). Ensemble learning techniques to improve the accuracy of predictive model performance in the scholarship selection process. *Journal of Applied Data Sciences*, *4*(3), Article 3. https://doi.org/10.47738/jads.v4i3.112

Dennis, A., Wixom, B., & Tegarden, D. (2015). *Systems Analysis and Design: An Object-Oriented Approach with UML*. John Wiley & Sons.

El Kamouchi, H., Kissi, M., & El Beggar, O. (2023). Low-code/No-code Development: A systematic literature review. *2023 14th International Conference on Intelligent Systems: Theories and Applications (SITA)*, 1–8. https://doi.org/10.1109/SITA60746.2023.10373712

Febri, F. M., & Sari, D. P. (2023). Determination of Bank Indonesia Scholarship Recipients Using Naïve Bayes Classifier. *Barekeng*, *17*(3), 1595–1604. Scopus. https://doi.org/10.30598/barekengvol17iss3pp1595-1604

Ghorbani, R., & Ghousi, R. (2020). Comparing Different Resampling Methods in Predicting Students' Performance Using Machine Learning Techniques. *IEEE Access*, *8*, 67899–67911. https://doi.org/10.1109/ACCESS.2020.2986809

Haris, N. A., Nidhom, M., Ariyanto, A. S. S., Asgar, H., & Kusrini. (2020). KIP Recipient Decision Making For Students Affected by Covid_19 Pendemi Using Fuzzy MADM Method. *2020 3rd International Conference on*

Information and Communications Technology (ICOIACT), 61–65. https://doi.org/10.1109/icoiact50329.2020.9332049

Hendri, H., Andrianof, H., Robianto, R., Awal, H., Putra, O. A., Wijaya, R., Gusman, A. P., Hafizh, M., & Pondrinal, M. (2024). A hybrid data mining for predicting scholarship recipient students by combining K-means and C4.5 methods. *Indonesian Journal of Electrical Engineering and Computer Science*, *33*(3), Article 3. https://doi.org/10.11591/ijeecs.v33.i3.pp1726-1735

Hugging Face. (2025). *Terms of Service*. https://huggingface.co/terms-of-service

Ismail, M. H., Razak, T. R., Noor, N. M., & Aziz, A. A. (2024). Evaluating Machine Learning Algorithms for Predicting Financial Aid Eligibility: A Comparative Study of Random Forest, Gradient Boosting and Neural Network. *2024 18th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, 1–6. https://doi.org/10.1109/imcom60618.2024.10418450

Johora, F. T., Hasan, M. N., Rajbongshi, A., Ashrafuzzaman, M., & Akter, F. (2025). An explainable AI-based approach for predicting undergraduate students academic performance. *Array*, *26*, 100384. https://doi.org/10.1016/j.array.2025.100384

Khasanah, F. N., Handayanto, R. T., Herlawati, Thamrin, D., Prasojo, P., & Hutahaean, E. S. H. (2020). Decision Support System For Student Scholarship Recipients Using Simple Additive Weighting Method with Sensitivity Analysis. *2020 Fifth International Conference on Informatics and Computing (ICIC)*, 1–6. https://doi.org/10.1109/icic50835.2020.9288617

Khasanah, F. N., Trias Handayanto, R., Herlawati, H., Thamrin, D., Prasojo, P., & Hutahaean, E. S. H. (2020). Decision support system for student scholarship recipients using simple additive weighting method with sensitivity analysis. *Int. Conf. Informatics Comput., ICIC*. Scopus. 2020 5th International Conference on Informatics and Computing, ICIC 2020. https://doi.org/10.1109/ICIC50835.2020.9288617

Khomarudin, A. N., Zakir, S., Novita, R., Endrawati, Mat, M. Z. bin A., & Maiyana, E. (2021). K-Mean Clustering Algorithm in Grouping Prospective Scholarship Recipients. *Journal of Physics: Conference Series*, *1779*(1), 012007. https://doi.org/10.1088/1742-6596/1779/1/012007

Kumarahadi, Y. K., Apriliyanto, E., & Yulianto, D. (2020). Decision Support System for Determining the Provision of Single Tuition Relief Using KNN and SAW Methods. *Int. Conf. Cyber IT Serv. Manag., CITSM*. Scopus. 2020 8th International Conference on Cyber and IT Service Management, CITSM 2020. https://doi.org/10.1109/CITSM50537.2020.9268886

Kurniadi, D., Nuraeni, F., Abania, N., Fitriani, L., Mulyani, A., & Agustin, Y. H. (2022). Scholarship Recipients Prediction Model using k-Nearest Neighbor Algorithm and Synthetic Minority Over-sampling Technique. *2022 12th*

International Conference on System Engineering and Technology (ICSET), 89–94. https://doi.org/10.1109/icset57543.2022.10010947

Kustiyahningsih, Y., Khotimah, B. K., Anamisa, D. R., Yusuf, M., Rahayu, T., & Purnama, J. (2021). Decision Tree C 4.5 Algorithm for Classification of Poor Family Scholarship Recipients. *IOP Conference Series. Materials Science and Engineering*, *1125*(1). Publicly Available Content Database (2535616654). https://doi.org/10.1088/1757-899X/1125/1/012048

Mohaiyadin, N. M. H. J., & Aman, A. (2021). Understanding the Issues of Waqf at Public University: Preliminary Findings. *International Journal of Islamic Thought*, *20*, 95–108. Publicly Available Content Database (2922156627). https://doi.org/10.24035/ijit.20.2021.214

Mundzir, Zulkarnain, R., Hardi, R., Risnanto, S., Dwijayanti, R., & Matulessy, D. P. (2023). Innovating Scholarship Design: A Comprehensive Approach Using Fuzzy Logic. *2023 17th International Conference on Telecommunication Systems, Services, and Applications (TSSA)*, 1–5. https://doi.org/10.1109/tssa59948.2023.10366973

Novita, R., Zakir, S., Khomarudin, A. N., Maiyana, E., & Hasyim, H. (2021). Use of the C4.5 Algorithm in Determining Scholarship Recipients. *Journal of Physics: Conference Series*, *1779*(1), 012009. https://doi.org/10.1088/1742-6596/1779/1/012009

Pawar, N., Deshpande, S., Hajare, A., Wagh, S., Wakode, S., Thorat, A., & Dulange, V. (2025). Workflow Engines for Task Automation: Taxonomy and Analysis. *2025 International Conference on Emerging Trends in Industry 4.0 Technologies (ICETI4T)*, 1–6. https://doi.org/10.1109/ICETI4T63625.2025.11132233

Pranoto, G. T., Pebrianti, D., Darwis, M., & Krishnasari, E. D. (2022). Selection of Education Assistance Recipients Based on AHP and SAW. *Int. Semin. Intell. Technol. Appl.: Adv. Innov. Electr. Syst. Humanit., ISITIA - Proceeding*, 163–168. Scopus. https://doi.org/10.1109/ISITIA56226.2022.9855329

Pranoto, G. T., Pebrianti, D., Darwis, M., Yaddarabullah, & Krishnasari, E. D. (2022). Selection of Education Assistance Recipients Based on AHP and SAW. *2022 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 163–168. https://doi.org/10.1109/isitia56226.2022.9855329

Pratama, Y., Pasaribu, M., Nababan, J., Sihombing, D., & Gultom, D. (2021). Selection of Scholarship Recipient by Implementing Genetic Algorithm and Fuzzy Logic. In Rahim R., Mesran null, Supriyanto null, Watrianthos R., & Hutahean J. (Eds.), *J. Phys. Conf. Ser.* (Vol. 1933, Issue 1). IOP Publishing Ltd. Scopus. https://doi.org/10.1088/1742-6596/1933/1/012069

Putra, A. A. N. K., Nasucha, M., & Hermawan, H. (2021). K-Means Clustering Algorithm in Web-Based Applications for Grouping Data on Scholarship

Selection Results. *2021 International Symposium on Electronics and Smart Devices (ISESD)*, 1–6. https://doi.org/10.1109/isesd53023.2021.9501716

Rahman, S. N., Suparmi, Jamhur, A. I., Elva, Y., Surmayanti, & Rianti, E. (2021). Comparison of the Effectiveness of C.45 Algorithm with Naive Bayes Algorithm in Determining Scholarship Recipients. *2021 International Conference on Computer Science and Engineering (IC2SE)*, 1–5. https://doi.org/10.1109/ic2se52832.2021.9791995

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). “Why Should I Trust You?”: Explaining the Predictions of Any Classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’16*, 1135–1144. https://doi.org/10.1145/2939672.2939778

Rohana, N. A. M., Rameli, M. F. P., Surtahman, A. W., Razak, A. Q. A., Halim, F. H., & Amin, S. M. (2024). Waqf for Education in Malaysia: Historical Implementation, Types, and Significance. *Global Business and Management Research*, *16*(2s), 135–150.

Sabri, N. H., Azmi, R., Taha, R., Mustafa, R., Ismail, F., Harun, S. K., Mohamad, A. M., Mohamad, M. Z., & Jasmi, S. N. (2021). *My Ihsan: Improving Students’ Financial Aid System for a Bright Future*. https://doi.org/10.24507/icicelb.12.10.891

Sahid, D. S. S., Widyasari, Y. D. L., & Purwanto. (2022). Implementation Brute Force-KNN Method for Scholarship Program Selection. *2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 643–647. https://doi.org/10.1109/isriti56927.2022.10052944

Softr. (2025a). *Build databases to power your apps*. https://www.softr.io/databases

Softr. (2025b). *Create stunning user interfaces without devs or designers*. Softr.Io Website. https://www.softr.io/product/interface-builder

Wang, H., & Wang, S. (2022). Teaching Tip: Improving Student Performance by Introducing a No-Code Approach: A Course Unit of Decision Support Systems. *Journal of Information Systems Education*, *33*(2), 127–134.

Zhong, C., Oruongo, J., & Kim, J. B. J. B. (2025). LLM-Powered Low-Code/No-Code Data Analytics in Education and Workforce Development. *Computer*, *58*(3), 49–59. https://doi.org/10.1109/MC.2024.3516614