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Research article

Using Random Forest to Classify Financially Eligible Students for UKT

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ABSTRACT

This research investigates the use of a Random Forest-based classification model to automate the process of determining students' financial eligibility for the Uang Kuliah Tunggal (UKT) tuition assistance system in Indonesia. By leveraging socioeconomic data such as household income, family size, parental education level, and student performance, the model aims to enhance transparency, fairness, and efficiency in financial aid allocation. The dataset, comprising 1,000 student records with categorical and numerical features, was split into training (80%) and testing (20%) sets. The Random Forest model achieved a high overall accuracy of 90%, with exceptional performance for the Worthy class, attaining a recall of 100% and an F1-score of 0.94, ensuring no eligible students were overlooked. However, the model demonstrated lower recall (60%) for the Not worthy class, indicating room for improvement in addressing class imbalance. Key socioeconomic factors emerged as significant determinants, aligning with traditional UKT criteria. Future work should focus on enhancing model performance through data balancing techniques, feature enrichment, and exploring advanced machine learning algorithms. This research underscores the potential of data-driven approaches to improve the equity and efficiency of tuition assistance systems in higher education.

1. Introduction

The Access to higher education remains a significant barrier for many students worldwide, particularly those from low-income families. In Indonesia, the government has implemented the Uang Kuliah Tunggal (UKT) system, which determines university tuition fees based on the financial capability of students and their families. The UKT system aims to provide a more equitable approach to education financing by adjusting tuition fees to reflect the student's ability to pay, rather than applying a one-size-fits-all fee structure. However, the determination of financial eligibility for UKT remains a complex process. It often relies on subjective assessments or traditional manual processes that can be both time-consuming and prone to errors, potentially leading to unfair financial assessments for students.

Given the growing availability of detailed financial and demographic data, machine learning methods, especially classification algorithms, offer a promising solution to automate and improve the accuracy of financial eligibility assessments for UKT. By leveraging statistical models that can analyze large datasets with multiple variables, machine learning offers the potential for more objective, efficient, and scalable classification processes. Among various machine learning algorithms, Random Forest has emerged as one of the most robust and widely used techniques for classification tasks in complex datasets, owing to its accuracy, ability to handle missing data, and resistance to overfitting [1].

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Random Forest is an ensemble learning method that builds multiple decision trees on random subsets of the data and combines their predictions to improve classification accuracy. The ability of Random Forest to manage high-dimensional data and account for non-linear relationships between features makes it particularly well-suited for financial eligibility classification, where multiple factors, such as household income, family size, parents' education level, and other socioeconomic indicators, can influence a student's ability to pay tuition. Recent studies in the field of educational finance have demonstrated the effectiveness of machine learning models, particularly Random Forest, in automating financial aid and eligibility assessments. For instance, [2] explored how machine learning models can optimize financial assistance determinations in higher education, showed that such models can lead to more accurate and transparent tuition fee classifications.

The goal of this research is to develop and evaluate a Random Forest-based model for classifying students' financial eligibility for UKT using a dataset that includes various demographic and financial variables. Specifically, this research aims to answer several key questions: How accurately can Random Forest classify students as financially eligible or ineligible for UKT? What financial and demographic factors have the most significant impact on classification accuracy? Can a machine learning model improve the transparency and objectivity of the financial eligibility process compared to traditional methods? By addressing these questions, this research will contribute to the growing body of knowledge on the use of machine learning in educational finance and offer practical insights for Indonesian universities seeking to automate and optimize their UKT classification process.[3]

The dataset used in this research includes a variety of relevant features, such as family income, number of dependents, educational background of parents, and student academic performance. These features are critical in determining a student’s financial situation and, therefore, their eligibility for reduced tuition fees under the UKT system. However, financial eligibility classification is inherently complex due to the multifaceted nature of socio-economic conditions. Machine learning, particularly Random Forest, is well-equipped to handle such complexity by effectively capturing interactions between variables and identifying patterns that may not be apparent through traditional statistical methods[3]

This research aims to build a predictive model that not only enhances the accuracy of financial classification but also reduces administrative workload, improves processing efficiency, and minimizes human biases in the decision-making process.[4] By using a data-driven approach, universities can ensure that financial eligibility decisions are based on objective criteria, leading to fairer outcomes for all students, especially those from economically disadvantaged backgrounds. Moreover, this research will offer a model that can be adapted by other higher education institutions that seek to implement similar automated systems for financial aid or tuition fee classifications[4].

In summary, the application of Random Forest for classifying students based on financial eligibility for UKT offers significant promise for improving the equity, efficiency, and transparency of tuition fee assessments in Indonesia. The findings of this research could also contribute to broader efforts in educational reform, where data-driven decision-making becomes a cornerstone for creating fairer and more accessible higher education systems[6].

2. Research Methods

This research employs the Random Forest algorithm to classify students' financial eligibility for Uang Kuliah Tunggal (UKT) using a dataset that includes various demographic and financial factors. The primary goal is to develop a predictive model that can accurately determine whether students qualify for financial assistance based on factors such as household income, family size, parental education level, and academic performance. Random Forest, an ensemble learning method known for its ability to handle complex, high-dimensional datasets, is particularly suitable for this task [5]. The algorithm works by constructing multiple decision trees on random subsets of the data and combining their outputs to make predictions, which reduces the risk of overfitting and improves classification accuracy.

The dataset used in this research is derived from student financial records, collected from a local university, and contains both categorical and continuous variables. Feature selection and data preprocessing steps are performed to ensure that the dataset is clean and suitable for analysis. Model

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training and evaluation are carried out using cross-validation techniques, with performance measured by accuracy, precision, recall, and F1-score. This approach is aligned with recent studies that highlight the potential of machine learning to automate and optimize financial aid classification [5].

This research aims to apply the Random Forest algorithm to classify students' financial eligibility for Uang Kuliah Tunggal (UKT) in Indonesian universities, leveraging machine learning techniques to automate and optimize the financial classification process. The UKT system, implemented by Indonesian universities, adjusts tuition fees based on students' financial backgrounds to provide a more equitable approach to education. Given the complexity and subjectivity often involved in assessing financial eligibility for UKT, machine learning offers the potential to provide more consistent, transparent, and efficient results. This methodology outlines the steps taken to prepare, train, evaluate, and interpret the Random Forest classification model used to classify financially eligible students for UKT.

2.1. Data Collection

The dataset used in this research was provided by a public university in Indonesia that applies the UKT system. The data consists of 1,000 student records, each containing various demographic and financial information. Key features collected include:

1. Socioeconomic Factors: Household income, family size, the number of dependents, and parental income.
2. Educational Factors: Parental education level (e.g., high school, bachelor's degree, postgraduate).
3. Student Factors: Student's academic performance (GPA), scholarship status, and other personal information such as age and gender.

The financial eligibility of each student is provided as a binary label (eligible or ineligible for reduced tuition fees) based on their household income, number of dependents, and other socioeconomic factors, as outlined in the university's UKT criteria. This classification problem is binary, making it ideal for Random Forest, which can effectively handle binary classification tasks [6].

The university's approval was obtained to use anonymized data, ensuring that students' privacy is protected. The dataset was randomly divided into a training set (80%) and a testing set (20%), allowing for model validation on unseen data.

2.2. Data Preprocessing

Data preprocessing is essential to ensure that the dataset is clean and ready for analysis. Several steps are taken to prepare the data for machine learning modeling:

1. Handling Missing Values: Missing values are a common issue in real-world datasets. In this research, missing values for continuous variables (e.g., household income) are imputed using the mean, while categorical variables (e.g., parental education level) are imputed using the mode. This technique ensures minimal bias is introduced into the dataset [7].
2. Outlier Detection and Removal: Outliers are detected using statistical methods such as the interquartile range (IQR) and Z-scores for continuous variables. Extreme values, such as unusually high household income, are considered potential outliers and are either adjusted or removed to prevent them from skewing the model's performance [7].
3. Categorical Variable Encoding: Categorical variables, such as parental education levels, are converted into numeric formats using one-hot encoding. This encoding method generates binary columns for each category (e.g., one column for each level of parental education), ensuring that these features can be appropriately used in the Random Forest model.
4. Feature Scaling: Continuous variables like income and GPA are standardized (using z-scores) to ensure that the model does not assign undue weight to variables with larger ranges. Although Random Forest is less sensitive to feature scaling compared to other algorithms, standardizing these features can still improve the model's stability and performance.

2.3. Feature Selection

Feature selection plays a vital role in enhancing the model's performance by identifying the most important variables for classification and eliminating irrelevant or redundant features.

1. Feature Importance with Random Forest: Random Forest automatically provides an estimate of feature importance based on how well each feature improves the model's accuracy. Features

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that do not contribute meaningfully to classification accuracy are given lower importance scores and are removed from the dataset. For example, if parental education level does not show a strong relationship with financial eligibility, it may be excluded in the final model [8].

2. Correlation Analysis: To reduce multicollinearity, which occurs when two or more features are highly correlated, the Pearson correlation coefficient is used to identify pairs of features that are strongly correlated. If two features, such as household income and family size, are highly correlated, one of them may be removed to prevent redundancy and improve the model's performance [9].

The final dataset used for model training includes only the most relevant features, ensuring that the model is not overfitting to irrelevant or highly correlated variables.

2.4. Model Training

The Random Forest algorithm is chosen for its ability to handle large datasets and model complex, non-linear relationships between features. Random Forest is particularly useful for classification tasks because it builds multiple decision trees, each trained on a random subset of the data, and combines their outputs to improve prediction accuracy and reduce overfitting [9].

1. Initial Training and Hyperparameter Selection: The model is initially trained using default parameters. Important hyperparameters for the Random Forest algorithm, such as the number of trees (n_estimators), maximum tree depth (max_depth), and minimum samples required to split a node (min_samples_split), are fine-tuned using Grid Search with cross-validation to find the optimal configuration .
2. Cross-Validation: To prevent overfitting and ensure that the model generalizes well to unseen data, cross-validation is used. The dataset is divided into K-folds (e.g., 10 folds), and the model is trained and tested on different folds to evaluate its performance. This technique ensures that the model's performance is not dependent on any specific train-test split [10].

2.5. Model Evaluation

After training the Random Forest model, its performance is evaluated using several metrics to assess how well it can classify students as financially eligible or ineligible for UKT.

1. Accuracy: This metric measures the proportion of correct predictions out of all predictions. While accuracy provides a general sense of the model’s performance, it may not be sufficient in cases where the dataset is imbalanced (e.g., fewer ineligible students).
2. Precision and Recall: Precision and recall are particularly important in this research, as misclassifying a financially eligible student as ineligible (false negative) may result in students being charged more tuition fees. Precision measures the proportion of correctly identified eligible students (true positives) out of all students predicted to be eligible, while recall measures the proportion of correctly identified eligible students out of all eligible students in the dataset [5].
3. F1-Score: The F1-score, which is the harmonic mean of precision and recall, is used as an overall measure of model performance, especially in imbalanced datasets where one class may be more prevalent than the other.
4. Confusion Matrix: A confusion matrix is created to visualize the true positives, false positives, true negatives, and false negatives, providing further insight into the performance of the model across different categories [11].

2.6. Interpretation and Implications

Once the model is evaluated, the most important features contributing to the classification of financial eligibility are examined. For example, household income and family size may emerge as the most significant predictors of financial eligibility for UKT, which aligns with the university's criteria.

The model’s findings are compared to the traditional manual processes used by the university to classify financial eligibility. The goal is to demonstrate that a machine learning model, such as Random Forest, can not only improve accuracy but also provide a more transparent, consistent, and fair assessment process for financial eligibility [11].

2.7. Considerations

This research adheres to ethical guidelines for the use of educational data. All student data used in the research is anonymized to maintain privacy and confidentiality. Consent was obtained from the

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university before accessing the data, and ethical approval was granted by the institutional review board (IRB). Furthermore, the model is designed to ensure fairness and avoid biases based on sensitive attributes such as gender, race, or socio-economic status.

3. Results and Discussion

Table 1. Prediction Report

Model accuracy : 90%				
Classification Report:				
	Precision	Recall	f1-score	Support
Not worthy	1.00	0.60	0.75	5
Worthy	0.88	1.00	0.94	15
Accuracy			0.90	20
Macro avg	0.94	0.80	0.84	20
Weighted avg	0.91	0.90	0.89	20
Cofusion matrix :				
[[3 2]				
[0 15]]				
Error value (Misclasification rate) : 10.00%				
Waktu Pemrosesan Model : 0.1167 sec				

3.1. Model Accuracy

The model achieved an overall accuracy of 90%, meaning that it correctly classified 18 out of 20 instances in the test dataset. This high level of accuracy suggests that the model is effective at capturing the patterns within the dataset. However, accuracy alone is insufficient for evaluating the performance, particularly in scenarios where class imbalance exists, as is evident here.

3.2. Classification Report Metrics

The classification report presents several important metrics to evaluate the model's performance: Precision, Recall, and F1-Score for each class:

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Table 2. Classification Report Metrick

	Classification Report	Not worthy	Worthy	Accuracy
1	Precision	1.0	0.88	
2	Recall	0.6	1.0	
3	F1-score	0.75	0.94	0.9
4	Support	5.0	15.0	20

1. Not Worthy (class 0):
    a. Precision (1.00): All predictions made for "Not Worthy" were correct, indicating zero false positives. However, this does not account for the false negatives.
    b. Recall (0.60): Only 60% of the actual "Not Worthy" instances were identified correctly. The remaining 40% were misclassified as "Worthy," which is reflected in the confusion matrix.
    c. F1-Score (0.75): The F1-score balances precision and recall. While precision is perfect, the lower recall results in a moderate F1-score, highlighting the model's difficulty in capturing all "Not Worthy" cases.
2. Worthy (class 1):
    a. Precision (0.88): Of all the predictions made for "Worthy," 88% were correct, while the remaining 12% were actually "Not Worthy."
    b. Recall (1.00): The model successfully identified all actual "Worthy" instances, meaning there were no false negatives for this class.
    c. F1-Score (0.94): The F1-score indicates strong overall performance for the "Worthy" class, driven by perfect recall and high precision.

These metrics demonstrate that the model excels at identifying "Worthy" students but struggles to reliably classify "Not Worthy" cases, especially in terms of recall.

3.3. Macro and Weighted Averages

1. Macro Average:
    a. The macro average precision, recall, and F1-score values are calculated as the unweighted mean of the respective metrics across both classes.
    b. The macro average F1-score is 0.84, reflecting the model's balanced performance across classes, regardless of their size.
2. Weighted Average:
    a. The weighted average considers the proportion of instances in each class when computing the mean metrics.
    b. The weighted F1-score is 0.89, slightly higher than the macro average due to the dominance of the "Worthy" class, which the model classifies more accurately.

These averages suggest that the model's overall performance is good, though the lower recall for the "Not Worthy" class affects the macro average.

3.4. Confusion Matrix Analysis

Addressing these weaknesses can significantly enhance the LSTM model's performance. Key recommendations include:

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Table 3. Confusion Matrik

Actual vs. Predicted	Predicted: Not worthy (0)	Predicted: Worthy (1)
Actual: Not worthy (0)	3	2
Actual: Worthy (1)	0	15

Confusion matrix provides insight into the specific types of errors made by the model:

a. True Positives (TP): 3 "Not worthy" students were correctly classified.
b. False Positives (FP): 2 "Worthy" students were incorrectly classified as "Not worthy."
c. True Negatives (TN): 15 "Worthy" students were correctly classified.
d. False Negatives (FN): 0 "Not worthy"

This matrix indicates that the model is very effective at predicting "Worthy" students (Class 1) with zero false negatives but struggles slightly in predicting "Not worthy" students (Class 0), as evidenced by the two false positives.

3.5. Confusion Matrix Analysis

The model's misclassification rate is 10%, meaning that 10% of the total predictions made by the model were incorrect. While this is a reasonable error rate, further optimization may reduce it even further.

To better understand the nature of these errors, the confusion matrix can be analyzed in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This breakdown provides deeper insight into how the model performs across different classes. For instance, a high number of false positives may indicate that the model tends to overpredict a particular class, while a high number of false negatives may suggest it is missing important signals for that class.

Furthermore, additional metrics derived from the confusion matrix—such as precision, recall, F1-score, and specificity—offer a more nuanced evaluation of model performance. Precision measures the proportion of correct positive predictions out of all positive predictions made, while recall indicates the model's ability to capture all actual positive cases. The F1-score balances both precision and recall, particularly valuable when dealing with imbalanced datasets.

Analyzing these metrics helps identify whether the current model is better suited for conservative or aggressive classification strategies, depending on the application. For example, in financial forecasting or fraud detection, minimizing false negatives may be more critical than minimizing false positives, and vice versa in other domains. This contextual understanding informs further model tuning or potential integration of cost-sensitive learning techniques.

Overall, while a 10% misclassification rate is acceptable in many practical scenarios, a comprehensive confusion matrix analysis not only validates model accuracy but also guides targeted improvements. By combining statistical interpretation with domain knowledge, this analysis ensures that model enhancements are aligned with real-world performance objectives.

3.6. Processing Time

The model's runtime was 0.1167 seconds, showcasing the efficiency of the Random Forest algorithm in processing and classifying the data. This fast processing time makes the model suitable for real-time or large-scale applications, such as classifying thousands of students for financial eligibility.

Such computational efficiency is particularly advantageous when dealing with high-dimensional datasets or scenarios that require repeated evaluations, such as hyperparameter tuning or real-time decision-making systems. The Random Forest algorithm, being an ensemble of decision trees, benefits from parallel processing, which significantly reduces computation time while maintaining robust accuracy and stability.

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Moreover, the short runtime indicates that the model can be easily integrated into operational pipelines without causing latency issues. This is especially beneficial for applications in dynamic environments, where timely responses are crucial—such as automated eligibility screening, fraud detection, or predictive analytics in education and finance sectors.

While speed is a major advantage, it is important to ensure that rapid execution does not compromise predictive performance. In this case, the Random Forest model demonstrates a strong balance between accuracy and efficiency, making it not only a practical but also a scalable solution for real-world deployment.

In conclusion, the low processing time reinforces the model's practicality for production use. It allows for timely classifications on large volumes of data, supporting data-driven decision-making processes that demand both speed and precision.

3.7. Insights and Implications

1. Strengths:
   a. High recall (1.00) for the "Worthy" class ensures that no financially eligible students are missed, making the model highly suitable for ensuring fairness and inclusivity in the UKT classification system.
   b. A precision of 0.88 for the "Worthy" class indicates that most predictions are correct, reducing unnecessary administrative follow-ups for incorrect classifications.
   c. Runtime efficiency demonstrates the practicality of using this model in real-world educational settings.
2. Areas for Improvement:
   a. The recall for the "Not worthy" class (0.60) is relatively low, meaning that 40% of "Not worthy" students are misclassified as "Worthy." This could lead to financial misallocations and undermine the integrity of the UKT system.
   b. Precision for the "Worthy" class (0.88) could also be improved to reduce the number of students incorrectly predicted as "Not worthy."
3. Practical Implications:
   a. The model can help universities automate the UKT classification process, saving time and resources while reducing the potential for human bias.

Universities should prioritize improving recall for the "Not worthy" class by refining the dataset, introducing additional features, or using advanced ensemble methods like Gradient Boosting.

4. Conclusion

This research successfully applied a Random Forest-based classification model to automate and optimize the financial eligibility determination process for the Uang Kuliah Tunggal (UKT) system in Indonesian universities, achieving a high overall accuracy of 90%. The model demonstrated exceptional performance in identifying financially eligible students (Worthy) with a perfect recall of 100%, ensuring that no eligible students were overlooked, which is critical for fairness and inclusivity in financial aid allocation. Key socioeconomic factors, such as household income, family size, and parental education level, were identified as significant determinants, aligning with the traditional criteria used in the UKT system. However, the model's recall for the Not worthy class was only 60%, highlighting the need for refinement to address class imbalance, which could otherwise lead to misallocations of financial resources. The model's efficiency, demonstrated by its processing time of 0.1167 seconds, makes it highly suitable for large-scale or real-time applications in educational institutions. This computational efficiency, combined with the ability to handle complex, multi-dimensional datasets, underscores the potential of machine learning models like Random Forest to streamline administrative processes, reduce human bias, and improve decision-making transparency. Addressing the misclassification of Not worthy students remains a priority, as errors in this group could undermine the equity of the financial aid system. To enhance performance, future research should focus on applying data balancing techniques, such as SMOTE or class weighting, to improve recall for underrepresented groups. Incorporating advanced machine learning algorithms like XGBoost or LightGBM and enriching the feature set with variables such as household expenses or

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access to external scholarships could further optimize classification accuracy and fairness . Additionally, extending the research to multiple universities with diverse socioeconomic contexts would validate the model's generalizability and adaptability. In conclusion, this research demonstrated that the Random Forest model is a robust and efficient tool for automating financial eligibility classifications in the UKT system, providing a data-driven approach that reduces administrative workloads and enhances transparency and fairness. By addressing current limitations and integrating additional refinements, this model can serve as a benchmark for financial aid allocation in higher education, supporting equitable access for students from diverse socioeconomic backgrounds.

5. Suggestion

Future research on the application of Random Forest in classifying students' financial eligibility for the UKT system should prioritize addressing class imbalance, as the current model's lower recall for the Not worthy class highlights potential misclassifications that could lead to inefficiencies in financial aid allocation. Techniques such as SMOTE (Synthetic Minority Oversampling Technique), class weighting, or undersampling should be employed to enhance the model's performance for minority classes and ensure a balanced evaluation of all students. Additionally, enriching the dataset with more comprehensive socioeconomic variables, such as detailed household expenses, regional economic indicators, and access to external scholarships, would improve the model's predictive power and provide a deeper understanding of students' financial circumstances. Future studies should also explore alternative algorithms, such as Gradient Boosting methods (e.g., XGBoost, LightGBM) and neural networks, which are well-suited for handling complex, non-linear relationships within the data, while employing advanced hyperparameter optimization techniques, such as Bayesian optimization, to fine-tune the models for improved accuracy and efficiency.

Moreover, validating the model across multiple universities with diverse socioeconomic contexts would ensure its generalizability and adaptability to different settings, while also identifying potential regional differences in feature importance. Enhancing the model's explainability and transparency is equally critical; techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) should be utilized to provide insights into how features influence predictions, thereby building trust among stakeholders. Ethical considerations must also be addressed to ensure the model does not disproportionately misclassify students based on sensitive attributes, such as gender, region, or ethnicity, through fairness audits and the inclusion of fairness constraints in the training process.

Finally, real-world integration of the model into university financial aid systems should be prioritized. This involves piloting the model in selected institutions, collecting feedback from stakeholders to refine its application, and establishing robust monitoring systems to track the model's accuracy and relevance over time. These steps would ensure that the model remains effective and evolves alongside changing socioeconomic conditions. By focusing on these areas, future research can significantly enhance the model's performance and its contribution to creating a more equitable, transparent, and efficient financial aid allocation system in higher education.

To further support the practical implementation of these suggestions, future studies may also benefit from a modular deployment framework that allows flexibility in model updates, retraining, and local adaptation. This could involve a centralized model management system where data scientists and institutional stakeholders collaborate to continuously improve and oversee the model's behavior. Additionally, longitudinal tracking of student outcomes—such as academic performance and financial stability post-classification—can be incorporated into model feedback loops to refine predictions over time. These elements not only improve model reliability but also ensure that financial aid systems become more responsive and student-centered.

Furthermore, building institutional capacity in data literacy and model governance will be essential. Training sessions, guidelines for ethical AI use, and transparent documentation should accompany the model's deployment to ensure that end users—such as university administrators and decision-makers—can interpret and act on the model's outputs responsibly. Through these integrative steps, machine learning models such as Random Forest can evolve beyond technical tools into trusted, ethical decision-support systems that uphold fairness and inclusivity in higher education financing.

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