Evaluating the Impact of Affirmative Action on Student Selection Outcomes: A Data Mining Approach Using SKD Test Performance at STMKG

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ABSTRACT

This study examines the impact of affirmative action on student selection outcomes at Sekolah Tinggi Meteorologi Klimatologi dan Geofisika (STMKG) in Indonesia, utilizing a data mining approach focused on SKD test performance. Affirmative action programs at STMKG aim to support applicants from marginalized regions, providing them with increased access to specialized academic opportunities. Using a dataset comprising TWK, TIU, TKP, and total SKD scores, this research compares the performance of affirmative action applicants against regular applicants, investigating differences in pass rates and score distributions. Exploratory data analysis reveals that regular applicants generally achieve higher mean scores across all test components. Statistical tests, including ANOVA, confirm significant differences in mean scores, particularly in TIU and total SKD scores. A Random Forest classification model was applied to predict selection outcomes, achieving an accuracy of 84.9%, although disparities in precision and recall indicate challenges in consistently classifying affirmative action applicants. Findings suggest that while affirmative action policies enhance access for underrepresented groups, additional support mechanisms may be required to bridge the performance gap. This research contributes valuable insights for policymakers and educational institutions seeking to refine affirmative action strategies, ensuring they promote both access and equity in competitive selection processes. Further studies could extend this analysis to include socio-economic factors and post-admission academic performance, offering a comprehensive evaluation of affirmative action's long-term impact on student success.

Keywords affirmative action, SKD test performance, student selection, data mining, STMKG

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Additional Information and Declarations can be found on page 72

Introduction

The fairness of student selection processes in higher education plays a critical role in shaping the academic environment and the societal impact of institutions. In specialized institutions such as the Sekolah Tinggi Meteorologi Klimatologi dan Geofisika (STMKG) in Indonesia, where students are trained for careers in national and public safety services, ensuring equitable access to education is essential. Fair selection practices allow institutions to evaluate candidates based on a transparent, merit-based system, ensuring that those with the necessary qualifications and potential are admitted, regardless of background. This supports diversity and inclusion and reinforces the legitimacy of the selection process [1]. Moreover, fairness in selection is integral to maintaining institutional integrity and public trust, particularly in sectors like meteorology and

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geophysics, which demand high levels of competency and responsibility.

In recent years, the emphasis on fairness has extended beyond merely evaluating test scores to recognizing systemic barriers that certain groups may face. Research has shown that the absence of fair selection processes can lead to biased outcomes, particularly against underrepresented groups, which may result in a lack of diversity in specialized fields [2]. For institutions like STMKG, where the stakes of student selection are high due to the specialized nature of the curriculum and its national importance, it is essential to adopt comprehensive and unbiased approaches to student admission. This underscores the need for transparent criteria and adaptive strategies that can account for applicants' varying socioeconomic, geographic, and educational backgrounds.

Data mining has emerged as a powerful tool in educational contexts, enabling institutions to analyze vast amounts of data and uncover patterns that inform decision-making processes [3]. Educational systems generate extensive datasets, including student test scores, demographic information, attendance records, etc. Analyzing these large datasets using data mining techniques allows institutions to identify key trends and relationships that might otherwise go unnoticed. For example, machine learning algorithms can predict student outcomes based on historical data, allowing educators to intervene when students risk failing proactively [4]. Moreover, data mining helps streamline administrative processes, optimize resource allocation, and improve strategic planning in educational institutions.

Numerous studies have highlighted the importance of data mining and machine learning techniques in analyzing and predicting outcomes across various fields, from educational performance to anomaly detection in financial transactions. Sustainable educational data mining has proven effective in identifying key factors and techniques that predict student performance, which is critical for assessing the impact of policies like affirmative action [5], [6]. Ensemble learning techniques, particularly in digital marketing, have demonstrated their predictive capabilities, offering a framework for student selection outcomes [7], [8]. Additionally, anomaly detection techniques, as used in blockchain transactions, can be applied to identify outliers or unusual trends within student performance datasets, helping institutions better understand variations in test scores [9], [10]. Moreover, studies on virtual property markets and virtual reality user experience provide insights into pattern identification and user engagement metrics, which can be adapted to examine and evaluate factors influencing student success and selection outcomes [11], [12]. Together, these studies underscore the potential of advanced data mining and machine learning techniques to enhance our understanding of student selection processes and inform policy improvements in educational institutions.

One key advantage of data mining in education is its ability to handle and analyze imbalanced datasets, which are common in student selection processes. The Synthetic Minority Oversampling Technique (SMOTE), for instance, addresses class imbalance by generating synthetic data for underrepresented classes, thereby improving the accuracy of predictive models [13]. By applying SMOTE in educational datasets, institutions can better understand the characteristics of minority or disadvantaged student groups, such as those admitted through affirmative action programs. This enables more equitable decision-making by clarifying how different student groups perform in selection processes and throughout their educational journey.

Data mining also enhances the ability to explore complex relationships between variables in educational data. Advanced techniques such as ensemble learning and neural networks have been particularly effective in identifying factors influencing student success, including performance in standardized tests, attendance patterns, and socioeconomic background [14]. These insights allow educational institutions to implement targeted interventions to improve retention and graduation rates. Furthermore, by leveraging data mining techniques, administrators and policymakers can make informed decisions that improve individual student outcomes and contribute to educational systems' overall effectiveness and inclusiveness [15]. Therefore, data mining is a critical asset in modern education, driving data-driven decision-making that fosters academic excellence and equity.

Affirmative action programs in Indonesia’s educational system are designed to address disparities in access to higher education, particularly for students from marginalized communities. These initiatives, which have been implemented in several government institutions, aim to provide equitable opportunities for historically underrepresented groups in academia. In the case of specialized institutions like the STMKG, affirmative action is pivotal in ensuring that students from regions such as Papua and other 3T (underdeveloped, frontier, and outermost) areas are given a fair chance to participate in competitive programs. Research highlights that such initiatives are key in fostering diversity and inclusion, which can improve the academic experience for all students.

At STMKG, affirmative action programs are designed to align with national policies promoting social equity. These programs ensure that students from disadvantaged backgrounds are not unfairly excluded due to systemic barriers, such as lower access to educational resources or geographical isolation. Through special admissions criteria and reserved slots for affirmative action candidates, STMKG helps bridge the gap between privileged and underprivileged groups. Additionally, affirmative action policies at STMKG align with broader national development goals by cultivating a more diverse student body, contributing to innovation, and improving societal outcomes. This approach enables STMKG to support Indonesia’s efforts to develop human resources from all regions and communities, further integrating underrepresented groups into vital sectors such as meteorology, climate, and geophysics.

Affirmative action’s effectiveness is seen in increased access to education and measurable outcomes such as higher graduation rates and improved academic performance among beneficiaries. Studies show that students admitted under affirmative action programs often perform well when given appropriate support, demonstrating the importance of such initiatives in equalizing opportunities. By using data-driven approaches, educational institutions like STMKG can continuously monitor and evaluate the success of their affirmative action policies, ensuring they are aligned with national standards while promoting equity in student selection. Thus, affirmative action remains a cornerstone of Indonesia's educational framework, particularly in specialized institutions where cultivating a diverse and skilled workforce is essential for national progress.

Exploring the Seleksi Kompetensi Dasar (SKD) test performance data is crucial for assessing the effectiveness of affirmative action in the student selection process at institutions like STMKG. Through detailed analysis of SKD scores, educational institutions can uncover important patterns and trends highlighting how different student groups—particularly those admitted through affirmative action—perform compared to their peers. By applying data mining techniques, such as classification algorithms and clustering, these institutions can evaluate whether affirmative action policies successfully improve the academic outcomes of underrepresented groups. This approach allows stakeholders better to understand the relationship between affirmative action and academic performance, providing empirical evidence for the policy's impact on ensuring educational access and fairness.

Furthermore, integrating machine learning and statistical analysis into SKD data exploration enables institutions to detect potential biases in the selection process that could disproportionately affect affirmative action beneficiaries. For example, ensemble learning methods can be applied to predict future academic success based on SKD scores, which offers insights into whether these students are equally prepared to succeed once admitted. Additionally, comparing the performance of affirmative action students with regular admissions students in the SKD offers a data-driven perspective on how well the selection criteria support equitable opportunities for all applicants. This ensures that affirmative action policies are focused on access and aligned with long-term student success.

The ongoing evaluation of SKD data plays a pivotal role in continuously improving the selection process to meet affirmative action programs' objectives better. By regularly analyzing this data, institutions can refine their selection models to promote fairness while maintaining high academic standards. Moreover, these insights help ensure that affirmative action programs contribute to the broader goals of social justice and equity in education, allowing underrepresented groups to thrive within specialized academic environments like STMKG. Therefore, leveraging SKD data is essential for making informed, evidence-based decisions that support the mission of affirmative action and foster an inclusive educational system.

This paper employs data mining techniques to investigate affirmative action's impact on student selection outcomes at STMKG. It specifically focuses on SKD test performance and pass/fail rates. The research seeks to understand how affirmative action influences the likelihood of success for underrepresented students in the SKD stage, particularly compared to regular applicants. Through the application of advanced data analysis tools, the study aims to provide empirical insights into whether affirmative action policies effectively contribute to creating equitable selection processes in specialized educational institutions like STMKG.

The study uses SKD test data to analyze the differences in test scores and pass rates between affirmative action beneficiaries and regular applicants. By applying machine learning models, such as Random Forest and K-Means clustering, the research identifies patterns in student performance that may highlight disparities or advantages linked to affirmative action policies. The study aims to evaluate overall test outcomes and examines which specific SKD components (such as TWK, TIU, and TKP) exhibit significant variations between the two groups. This investigation is intended to clarify how affirmative action impacts academic outcomes and whether it helps students from marginalized backgrounds succeed at the same rate as their peers.

In addition to analyzing test performance, this paper explores the effectiveness of affirmative action in terms of its alignment with national educational equity goals. The study evaluates whether affirmative action applicants are being adequately supported through the selection process and whether their performance justifies continued or enhanced affirmative measures. Through data mining, the paper aims to offer recommendations for refining affirmative action policies at STMKG to ensure they promote access and foster long-term success for underrepresented groups. The results of this research could potentially inform policy decisions that further integrate data-driven approaches to enhance fairness in student selection.

Literature Review

Educational Data Mining (EDM)

Data mining techniques in the field of education primarily focus on analyzing vast amounts of educational data to derive insights that can improve student learning outcomes and institutional decision-making. These techniques allow for the systematic extraction of patterns from complex datasets, enabling educational institutions to understand trends in student performance, enrollment, and retention. Commonly used data mining techniques include classification, which assigns students into categories such as pass/fail or at-risk/not at-risk, and clustering, which groups students based on similar characteristics, such as academic performance or engagement levels [13]. Other methods, such as association rule mining, can identify relationships between different variables, such as the link between attendance and academic achievement. These techniques are essential for developing targeted interventions aimed at improving student success.

In educational settings, machine learning algorithms, such as support vector machines (SVM) and neural networks, have accurately predicted key outcomes, including graduation rates, student retention, and academic performance [16]. These predictive models enable early identification of students at risk of academic failure, allowing institutions to implement timely interventions. Additionally, techniques like the Synthetic Minority Oversampling Technique (SMOTE) have been adopted to address class imbalance issues in educational data, ensuring more accurate classification of students from minority or underrepresented groups. The application of these data mining tools thus helps institutions improve predictive accuracy and promote fairness in educational outcomes by focusing on students who might otherwise be overlooked.

The impact of affirmative action on student admissions and performance has been extensively studied, with numerous researchers examining its effects on both access to education and academic outcomes. One key finding is that affirmative action policies have successfully increased diversity in higher education institutions by providing opportunities for underrepresented groups to gain access to previously difficult programs [13]. This increase in diversity is often linked to enhanced academic environments, where students from different backgrounds can interact and contribute unique perspectives to classroom discussions and group projects. In this context, affirmative action has expanded access and contributed to a more inclusive and vibrant academic atmosphere.

In educational research, data mining algorithms such as classification and clustering are commonly employed to analyze large datasets and enhance educational outcomes. Classification algorithms, including decision trees, support vector machines (SVM), and logistic regression, are widely used to predict student performance and outcomes. These algorithms help educators and administrators identify at-risk students early on by analyzing historical academic data and other relevant factors. For example, decision trees allow for categorizing students based on performance indicators, making it easier to predict whether a student is likely to pass or fail a course [13].

Clustering algorithms such as K-means and hierarchical clustering are also frequently utilized in educational contexts to group students based on shared characteristics, such as learning patterns, academic performance, or engagement levels. Clustering helps institutions understand the diversity within student populations by identifying distinct profiles or clusters that require different teaching approaches or resources. For instance, clustering can reveal student groups that excel in independent study compared to those who benefit from collaborative learning environments. This information allows for more personalized and adaptive educational experiences, which are crucial for addressing the varied learning needs of students in higher education.

In addition to classification and clustering, ensemble methods, which combine multiple algorithms to improve predictive performance, have gained prominence in educational research. These methods, such as Random Forest and Gradient Boosting, enhance the accuracy and robustness of predictive models by aggregating the strengths of individual algorithms. Studies have shown that ensemble techniques are particularly useful in addressing complex educational challenges, such as predicting student dropout rates and optimizing resource allocation for at-risk students. Overall, using these data mining techniques in educational research supports informed decision-making and contributes to developing more effective and equitable educational strategies.

Affirmative Action and Selection Outcomes

Affirmative action policies in higher education promote diversity and equal access to educational opportunities for historically marginalized groups. These policies often involve considering race, ethnicity, and gender in the admissions process to counterbalance systemic disadvantages faced by minorities and women. The primary objective is to create a more inclusive academic environment that supports social equity and enhances the overall educational experience for all students. Studies have demonstrated that institutions implementing affirmative action tend to have a more diverse student body, which fosters cross-cultural understanding and enriches classroom interactions. This diversity contributes to a dynamic learning environment where students benefit from varied perspectives and experiences.

Despite the positive outcomes, affirmative action remains a contentious issue in higher education policy. Critics argue that such policies may result in reverse discrimination, where candidates from majority groups, who may have higher qualifications based on traditional metrics, are disadvantaged in the selection process. These critics maintain that admissions should be based solely on merit, without consideration of an applicant's demographic background. In contrast, proponents argue that affirmative action is a necessary corrective to long-standing social inequalities and biases that have historically excluded certain groups from higher education opportunities. By leveling the playing field, affirmative action policies help ensure that underrepresented groups are afforded the same opportunities for academic success as their peers.

The impact of affirmative action on student performance has also been a topic of considerable research. Evidence suggests that students from underrepresented groups who are admitted through affirmative action tend to thrive in academic environments that are intentionally inclusive and supportive. These policies increase access and improve academic outcomes by fostering a sense of belonging and engagement among minority students. However, the debate surrounding fairness and meritocracy continues to challenge the broader implementation of these policies. In summary, while affirmative action aims to rectify historical injustices and promote diversity, it also raises important questions about how best to balance equity and merit in the admissions process. Affirmative action policies in higher education significantly influence both the selection processes and students' academic performance. These policies are designed to promote diversity by offering equitable opportunities to individuals from historically marginalized groups, particularly in competitive academic environments. Research has consistently shown that affirmative action increases the enrollment of underrepresented students, diversifying the academic population and enhancing the overall learning experience by integrating diverse perspectives. The presence of a more varied student body encourages collaborative learning, where different cultural and intellectual viewpoints contribute to a richer academic dialogue. This dynamic benefits the affirmative action beneficiaries and the entire student population.

However, the relationship between affirmative action and academic performance is complex and multifaceted. Some studies suggest that students admitted through affirmative action policies may face challenges, such as stereotype threat or feeling less prepared compared to their peers, which can impact their academic confidence and performance. These psychological factors can sometimes hinder academic success, particularly in highly competitive educational environments. On the other hand, other research has shown that students from marginalized groups often excel academically when provided with appropriate resources and support systems. Access to mentorship, tutoring, and community support can counterbalance any initial academic gaps, leading to improved outcomes and greater retention rates.

Furthermore, institutions implementing affirmative action policies are often better equipped to foster inclusive learning environments, positively affecting academic performance. A supportive and inclusive campus culture has been linked to higher retention and graduation rates, particularly for minority students. By creating a space where students feel valued and supported, affirmative action helps mitigate some of the challenges these students might face and promotes academic success. In summary, while affirmative action can introduce certain complexities to the selection process and academic outcomes, it is essential in improving access to higher education and ensuring that institutions remain diverse and inclusive. This highlights the importance of continuously evaluating and refining these policies to ensure their effectiveness in promoting both diversity and academic excellence.

Classification Accuracy formula

The classification accuracy formula calculates the proportion of correctly classified instances (true positives, TP, and true negatives, TN) out of the total instances considered, including false positives (FP) and false negatives (FN). Accuracy provides a straightforward way to assess how well a model distinguishes between different classes, which is particularly useful when analyzing large datasets, such as those used in student selection processes or educational assessments. The metric's simplicity makes it a common choice for evaluating classification models in various domains, including education, where it helps measure the effectiveness of algorithms used to predict outcomes like pass/fail rates.

However, accuracy alone may not always provide a complete picture, especially in cases of imbalanced datasets, where one class dominates the others. In such situations, a model might achieve high accuracy by simply predicting the majority class while ignoring the minority class. For instance, in educational research, if the dataset contains a significant imbalance between students who pass and those who fail, relying solely on accuracy could obscure the model's inability to properly classify students at risk of failing. As a result, additional metrics such as precision, recall, and the F1-score are often used in conjunction with accuracy to provide a more comprehensive evaluation of model performance.

The classification accuracy formula remains valuable in data mining applications, especially in scenarios like educational performance prediction. Its straightforward calculation allows for a quick assessment of model performance, but researchers are encouraged to consider other complementary metrics to ensure that their models are both accurate and equitable. Furthermore, techniques like ensemble learning or resampling methods, such as SMOTE, can be employed to improve classification accuracy in the presence of imbalanced data. These methods help ensure that models perform well in terms of overall accuracy and provide meaningful predictions across all classes in the dataset.

ANOVA To Compare Test Scores Across Different Group

The ANOVA (Analysis of Variance) formula is a powerful statistical method used to compare the means of three or more independent groups to determine if there are any statistically significant differences between them. This technique is widely used in educational research to analyze how different factors, such as teaching methods, instructional interventions, and student demographics, impact academic performance. The ANOVA test helps researchers identify whether the variance in student test scores is due to the treatment effect (between groups) or random variations within each group (within-group variance). By calculating the F-ratio, researchers assess if the differences observed across the groups are likely to have occurred by chance or are significant.

Several studies have used ANOVA to compare the effectiveness of different instructional strategies in the context of evaluating educational interventions. For example, research by [17] used ANOVA to evaluate the effectiveness of flipped classroom models, showing that students in flipped classrooms performed better on standardized tests than those in conventional classrooms. These findings underscore the value of ANOVA in helping educators and policymakers make informed decisions about teaching practices.

Beyond instructional methods, ANOVA has also been employed in educational data mining to compare the performance of machine learning algorithms used to predict student success. For instance, researchers like … utilized ANOVA to assess the accuracy of different predictive models, identifying which algorithms were most effective in forecasting student outcomes based on various features such as attendance, participation, and previous academic performance. This application of ANOVA in educational analytics highlights its versatility as a tool for comparing human-driven and algorithmic approaches to enhancing student success. Ultimately, ANOVA remains a crucial statistical method for drawing meaningful insights from complex educational data, ensuring that interventions and models are rigorously evaluated for their efficacy.

Several key statistical tests and evaluation metrics are employed to measure model performance in evaluating classification models, particularly within the context of student selection processes or educational assessments. Among the most widely used are precision, recall, F1-score, and the area under the curve (AUC). These metrics offer a more nuanced understanding of a model's accuracy beyond the traditional accuracy formula, helping to ensure that the model can correctly identify true positives while minimizing both false positives and false negatives. This is particularly relevant in educational research, where misclassification's implications can significantly impact student selection outcomes.

Precision is defined as the ratio of true positives (correctly predicted positive outcomes) to the sum of true positives and false positives. It measures the accuracy of the positive predictions made by the model, indicating how reliable the model is when it identifies an instance as belonging to the positive class. On the other hand, recall (or sensitivity) calculates the ratio of true positives to the sum of true positives and false negatives. This metric reflects the model's ability to identify all relevant positive instances, making it essential to identify every possible positive case. The F1-score, which is the harmonic mean of precision and recall, offers a balanced evaluation by considering both false positives and false negatives, making it particularly useful when dealing with imbalanced datasets, as often found in affirmative action or minority group studies.

In addition to these metrics, the AUC (Area Under the Curve) metric is frequently used to evaluate a model's performance across all possible classification thresholds. The AUC is particularly valuable when the goal is to assess the overall accuracy of a model in distinguishing between different classes, offering a single, comprehensive measure of performance. This is especially important in high-stakes contexts such as student admissions, where the consequences of false positives (admitting students who may not meet the required qualifications) or false negatives (rejecting qualified candidates) can have long-lasting impacts on individuals and institutions. Researchers have increasingly relied on these metrics to evaluate and improve classification models, ensuring that the algorithms used in data-driven decision-making processes are robust and equitable.

Research demonstrates that the use of these statistical metrics can significantly enhance model reliability and fairness. For example, studies by Mqadi et al. applied precision, recall, and the F1-score to evaluate the performance of various classification algorithms on imbalanced datasets, emphasizing the importance of these metrics in achieving a reliable and well-performing model. Similarly, Gameng's analysis of synthetic data generation methods highlighted the role of these evaluation metrics in improving model accuracy and fairness across different student groups [13]. Ultimately, by combining precision, recall, F1-score, and AUC, researchers are better equipped to develop models that perform well and align with broader goals of equity and fairness in educational contexts.

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in Figure 1 outlines the detailed steps of the research method.

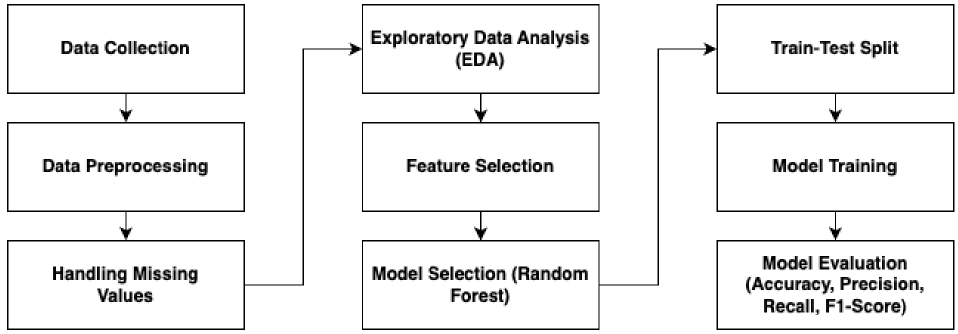

Figure 1 Research Method Flowchart

Data Description

The dataset used for this study originates from the 2024 Seleksi Kompetensi Dasar (SKD) admissions data for Sekolah Tinggi Meteorologi Klimatologi dan Geofisika (STMKG). This dataset includes detailed information on the performance of applicants in various SKD test sections, covering essential variables to analyze affirmative action policies in the selection process. Comprising 7,815 entries and 15 columns, the dataset contains a wide range of attributes related to applicant demographics, test performance, and selection outcomes. Key columns include `jenis.formasi`, which specifies whether an applicant belongs to an affirmative action group or the regular admissions pool; `skd.twk`, `skd.tiu`, and `skd.tkp`, which represent scores from different SKD sections; `skd.total`, which aggregates these section scores; and `skd.hasil`, which indicates each applicant’s selection result (pass or fail).

The columns in the dataset are varied in type, capturing both categorical and numerical information essential for a comprehensive analysis. For instance, `jenis.kelamin`, `pendidikan`, and `nama.prodi` provide categorical information on the gender, education background, and program choice of each applicant, while `skd.twk`, `skd.tiu`, and `skd.tkp` are float-type columns that record applicants' test scores. The columns `jenis.formasi` and `lokasi.formasi` specify the applicant's admission category, distinguishing between those from affirmative action regions such as Papua, NTT, and other underrepresented areas, and those from the regular applicant pool. This distinction is critical for examining how affirmative action applicants perform relative to their peers in the selection process.

To evaluate the effectiveness of affirmative action, data from affirmative action applicants, particularly those from regions such as Papua and NTT, were compared to data from regular applicants. The analysis focuses on SKD performance, considering both the individual section scores (`skd.twk`, `skd.tiu`, `skd.tkp`) and the overall `skd.total` score, to understand if there are notable differences in academic preparedness and selection outcomes between the groups. These comparisons aim to reveal patterns in test performance that could inform whether affirmative action policies are achieving their intended goals of promoting equal opportunity and increasing representation in specialized fields like meteorology and geophysics.

The dataset structure enables a robust exploration of potential disparities between affirmative action and regular applicants, using both descriptive and inferential statistical methods. By focusing on pass/fail rates captured in `skd.hasil`, the study investigates whether affirmative action applicants succeed at rates comparable to their regular applicant counterparts. Such comparisons provide insight into the potential benefits and challenges affirmative action applicants face in meeting the STMKG's competitive selection standards. This dataset, therefore, forms a comprehensive basis for analyzing affirmative action's impact on student selection outcomes, facilitating a data-driven approach to evaluating the policy's effectiveness in supporting underrepresented groups.

In conclusion, the STMKG dataset offers a rich source of information for examining affirmative action's impact on student selection outcomes through a detailed breakdown of test scores, demographics, and selection statuses. With variables capturing both performance metrics and applicant backgrounds, the dataset is well-suited to address the research question and support a thorough analysis of how affirmative action influences selection outcomes. This approach provides a balanced framework for understanding whether such policies level the playing field for applicants from underrepresented regions and contribute to a more inclusive academic environment at STMKG.

Exploratory Data Analysis (EDA)

The analysis began with calculating summary statistics to understand the distribution of SKD test scores among affirmative action and regular applicants. Descriptive statistics revealed notable differences in performance between the two groups across the SKD sections—TWK, TIU, TKP, and the total SKD score. For regular applicants, the mean TWK score was 69.59 (SD = 16.80), while affirmative action applicants had a mean TWK score of 63.94 (SD = 17.34). Similar differences were observed for the other sections, with regular applicants showing higher averages: TIU (mean = 90.80, SD = 29.00) compared to 76.35 (SD = 29.09) for affirmative action applicants, and TKP with a mean of 177.83 (SD = 14.53) versus 173.54 (SD = 19.29) for affirmative action applicants. Overall, regular applicants recorded a higher average total score of 338.23 (SD = 46.28), compared to 313.83 (SD = 51.46) for affirmative action applicants. These findings suggest that differences in test performance might exist between groups, warranting further analysis.

To visually explore the distribution of SKD scores between affirmative action and regular applicants, histograms and boxplots were created for each test section. The histograms illustrated distinct distribution patterns, with regular applicants generally scoring higher across the TWK, TIU, and TKP sections, suggesting a rightward shift compared to affirmative action applicants.

Histogram of SKD TWK Scores by Group (Figure 2) shows that majority of regular applicants ("TARUNA REGULER") are clustered between the 60–80 score range, showing a relatively balanced bell curve, with the peak of the distribution around 70-80. Affirmative action groups, such as "AFIRMASI OAP" and "AFIRMASI NUSA TENGGARA TIMUR," have significantly fewer participants and scores that are more spread out. Most scores in affirmative action groups are lower compared to regular applicants, with many falling under 60.

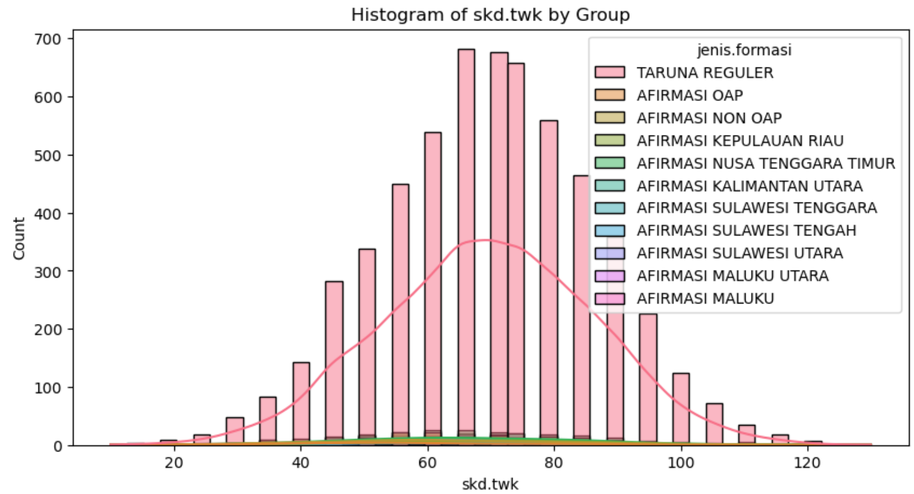

Figure 2 Histogram of SKD TWK Scores by Group

Histogram of SKD TIU Scores by Group (Figure 3) shows that, similar to TWK, the distribution for regular applicants peaks around 80-100, which indicates that the majority scored higher in this section. Affirmative action groups display lower scores, with the density distributed around the 60–80 range. There is a noticeable difference between the distributions, where regular applicants tend to perform better compared to affirmative action applicants.

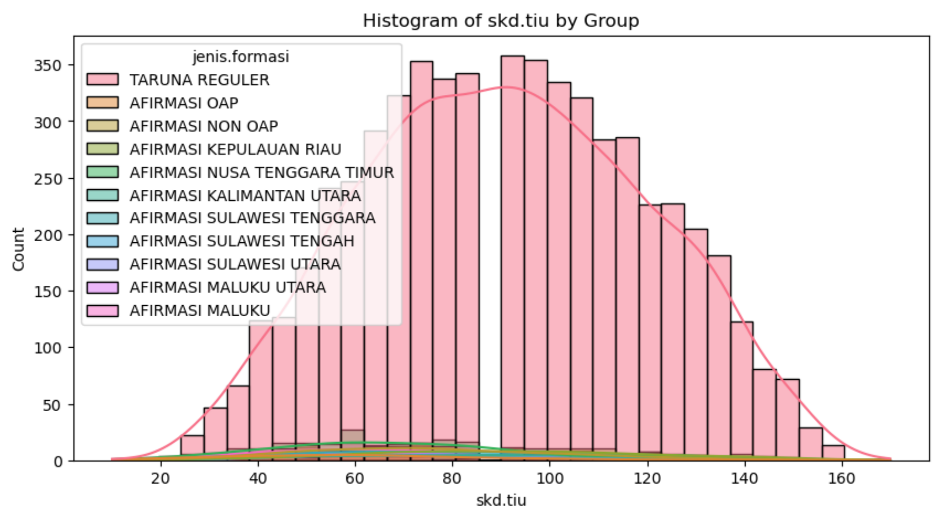

Figure 3 Histogram of SKD TIU Scores by Group

Histogram of SKD TKP Scores by Group (Figure 4) shows that for SKD TKP, regular applicants show a concentrated distribution between 170–190, with a clear peak around 180. Affirmative action applicants again show lower performance, with a broader distribution starting from around 130 to 190, but not peaking as high as regular applicants. Some affirmative action groups show even lower performance in this section, with noticeable spread below 150.

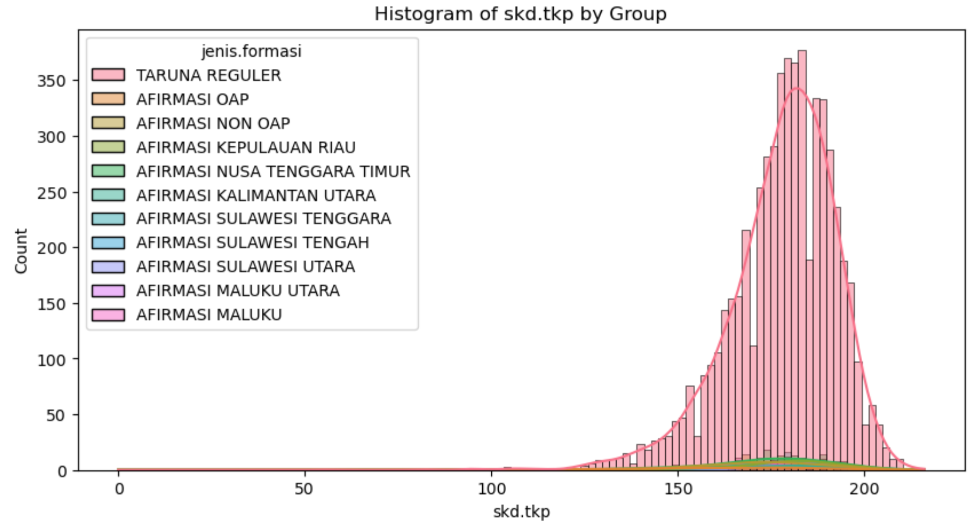

Figure 4 Histogram of SKD TKP Scores by Group

The histograms suggest that regular applicants tend to perform better across all three sections (TWK, TIU, TKP) compared to affirmative action groups. The affirmative action applicants have lower score distributions, which might indicate disparities in preparation or background that these programs are designed to address. The analysis indicates that affirmative action applicants may require additional support or resources to bridge this gap, especially as shown in the TKP section where the spread is wider and more skewed towards lower scores.

Figure 5 provided additional insights, revealing greater variability in the scores of affirmative action applicants. Outliers were more prominent in the affirmative action group, which could reflect varying levels of preparedness within this cohort. These visualizations offered a comprehensive understanding of score distributions, enabling an initial assessment of the potential impact of affirmative action policies on test performance.

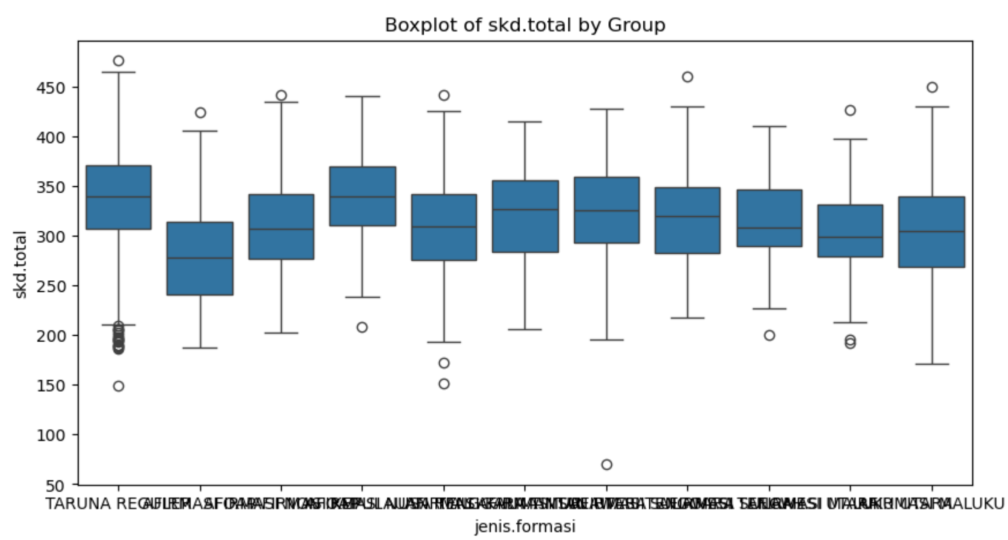

Figure 5 Boxplot of SKD Total Scores by Group

The dataset included missing values in some SKD test columns (TWK, TIU, and

TKP) that were addressed by filling these values with the median scores of the respective sections. This approach preserved the distributional characteristics of each group while maintaining the integrity of the dataset. Additionally, outlier values were detected, particularly in the TKP section for affirmative action applicants, and were handled using the Interquartile Range (IQR) method. Values falling outside 1.5 times the IQR were removed to reduce skewness in the data and minimize the impact of extreme values. This adjustment ensured a more representative analysis of central trends and group differences.

The exploratory data analysis provided foundational insights into the structure and distribution of SKD test scores among affirmative action and regular applicants. Summary statistics, visualizations, and careful handling of missing values and outliers enabled a robust assessment of group characteristics, offering a clearer view of how affirmative action policies might influence applicant performance in the STMKG selection process. These insights form the basis for further statistical testing to determine the significance of observed differences in SKD scores between the two groups. This visual representation highlights the differences between groups and sets the stage for deeper analysis on how affirmative action impacts overall selection outcomes.

Data Mining Techniques

To evaluate the impact of affirmative action on student selection outcomes at STMKG, several data mining techniques were applied to predict selection outcomes based on SKD test scores. A Random Forest classifier was utilized for classification tasks. Random Forest, an ensemble learning method, constructs multiple decision trees during training and outputs the mode of the classes for classification problems. In this study, the SKD test scores—TWK, TIU, TKP, and total scores—were used as input features, while the target variable was the selection outcome (`skd.hasil`, encoded as pass/fail). The Random Forest model was trained on 80% of the dataset, with the remaining 20% used for testing. This approach allowed for the evaluation of the predictive power of the SKD scores in determining which students passed or failed the selection process.

In addition to classification, KMeans clustering was employed to identify patterns within the SKD test scores. The dataset was grouped into two clusters based on TWK, TIU, TKP, and total scores. KMeans, a popular unsupervised learning algorithm, seeks to partition the data into clusters such that points within a cluster are more similar to each other than to points in other clusters. This method allowed for an exploratory analysis of whether students could be naturally grouped based on their performance, independent of affirmative action status. The results of the clustering were visualized using a scatterplot, highlighting how different score combinations form distinct clusters.

Furthermore, ANOVA (Analysis of Variance) was conducted to compare the mean scores of different groups—affirmative action and regular applicants—across the SKD test components. ANOVA, a statistical technique used to assess whether there are significant differences between group means, was applied to TWK, TIU, TKP, and total SKD scores. The results indicated significant differences between affirmative action and regular applicants for all components, with p-values far below 0.05, suggesting that the means of these groups differ substantially across the SKD score categories. The F-values for each test component reinforced the extent of these differences, particularly in

TIU and total SKD scores.

Evaluation Metrics

To evaluate the performance of the classification models, several key metrics were used, including accuracy, precision, recall, and F1-score. Accuracy measured the proportion of correct predictions made by the Random Forest classifier, while precision and recall provided insights into the model's ability to correctly identify true positives (i.e., applicants who passed) and minimize false positives and negatives. The F1-score, a harmonic mean of precision and recall, offered a balanced view of the model's performance, especially in cases where the dataset might be imbalanced between pass and fail categories. In this study, the Random Forest model achieved a high accuracy and a balanced F1-score, indicating its effectiveness in predicting selection outcomes based on SKD test scores.

Additionally, a confusion matrix was generated to evaluate the classifier’s performance in terms of true positives, true negatives, false positives, and false negatives. The confusion matrix highlighted the model’s strengths in correctly predicting both passing and failing outcomes, with relatively few misclassifications. This comprehensive evaluation allowed for a deeper understanding of how well the model generalized to unseen data and where potential improvements could be made.

Lastly, the ANOVA results were instrumental in statistically testing the differences in SKD scores between affirmative action and regular applicants. The F-statistic and associated p-values for TWK, TIU, TKP, and total SKD scores all suggested significant differences in means, with affirmative action applicants generally scoring lower than regular applicants. These results provided a statistical foundation for understanding how affirmative action impacts selection outcomes at STMKG.

Result and Discussion

Descriptive Statistics

The descriptive statistics for SKD test scores highlight distinct performance differences between affirmative action applicants and regular applicants. For the TWK component, regular applicants had a mean score of 69.59 (SD = 16.80), whereas affirmative action applicants scored slightly lower, with a mean of 63.94 (SD = 17.34). This trend continues across the other components: TIU scores show a more significant difference, with regular applicants scoring a mean of 90.80 (SD = 29.00) compared to 76.35 (SD = 29.09) for affirmative action candidates. For TKP, the gap narrows, with regular applicants scoring a mean of 177.83 (SD = 14.53), while affirmative action applicants averaged 173.54 (SD = 19.29). Finally, the total SKD scores reflect the overall trend, with regular applicants achieving a higher mean of 338.23 (SD = 46.28) compared to 313.83 (SD = 51.46) for affirmative action applicants.

These differences in mean scores suggest that, across all test components, affirmative action applicants generally scored lower than regular applicants. The higher standard deviation for affirmative action applicants in several test components, particularly TIU and TKP, also indicates greater variability in their performance. This variation could point to differences in academic preparation or access to resources among affirmative action candidates.

A comparison of pass and fail rates between affirmative action and regular applicants further underscores these performance differences. Among regular applicants, 2,762 passed the SKD test, while 3,741 failed. In contrast, 812 affirmative action applicants passed, while 500 failed. This results in a higher pass rate for affirmative action candidates (61.9%) compared to regular applicants (42.5%), likely due to the different passing thresholds established for these groups under the affirmative action policy.

When disaggregating the pass categories further, regular applicants mostly fell into the "P" (2,461) or "P/L" (301) categories, indicating passing with and without further eligibility for subsequent selection stages. On the other hand, affirmative action candidates who passed mostly fell into the "PA" and "PA/L" categories, with 406 in each category, reflecting their eligibility for further stages under affirmative action. A significant number of regular applicants failed the test with the "TL" code (3,034), while only 366 affirmative action applicants were classified as "TL," demonstrating the impact of affirmative action on improving pass rates for underrepresented groups.

These pass/fail statistics illustrate the tangible impact of affirmative action in raising the pass rates for underrepresented applicants, despite their overall lower mean test scores compared to regular applicants. The affirmative action program appears to be effective in helping candidates from disadvantaged regions and backgrounds achieve selection outcomes that would be difficult to attain based solely on standardized test performance.

Data Visualization

The data visualizations provide critical insights into the performance differences between affirmative action applicants and regular applicants based on SKD test scores. Boxplots comparing TWK, TIU, and TKP scores (Figure 6) between the two groups reveal notable disparities. Affirmative action applicants tend to score lower on average across these categories compared to regular applicants, with the distribution spread indicating a wider range of scores, especially in the TKP and TIU components. The median scores of regular applicants were consistently higher, highlighting the gap in test performance across the two groups.

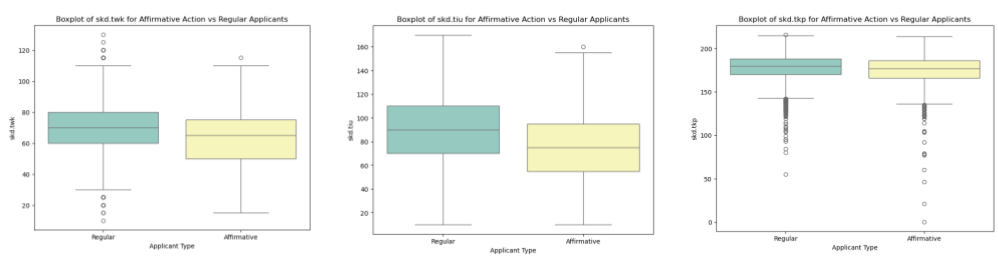

Figure 6 Boxplots of TWK, TIU and TKP Scores

Moreover, the bar charts illustrating the pass/fail rates (Figure 7) for both applicant groups offer a clear visual representation of selection outcomes. Regular applicants had a significantly higher pass rate compared to affirmative action applicants. This distinction is particularly evident in the substantial number of affirmative action applicants failing to meet the required SKD scores. For regular applicants, the pass rate far exceeds the fail rate, which contrasts starkly with the affirmative action group, where failures dominate.

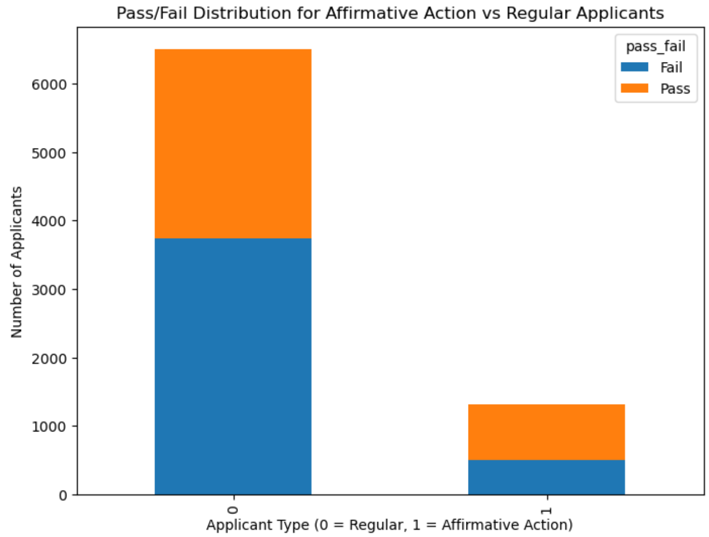

Figure 7 Pass/Fail Distribution

In addition, the visualized outcomes for different categories of results (Figure 8), such as "P/L" and "PA/L," further emphasize the differences in SKD performance between the two applicant types. The majority of regular applicants who passed were classified under the "P" category, while affirmative action candidates primarily fell into the "PA" and "PA/L" categories. This reflects the affirmative action measures in place, designed to accommodate underrepresented groups but also highlights the lower average scores within these groups.

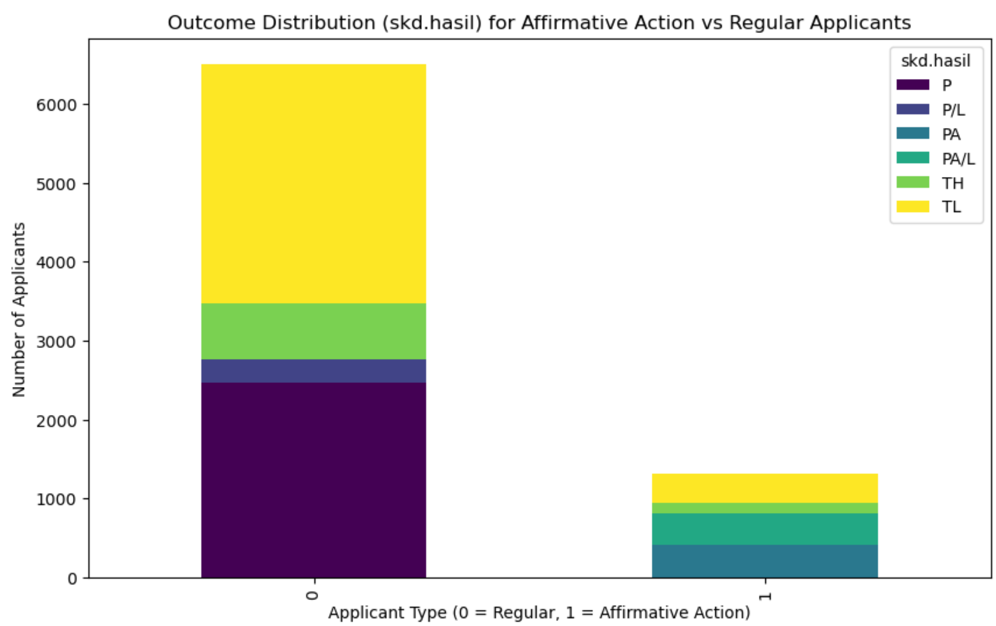

Figure 8 Outcome Distribution Distribution

Overall, these visualizations underscore the significant gap between affirmative action and regular applicants in terms of both test performance and pass rates.

While affirmative action measures provide opportunities for marginalized groups, the data suggest that a more focused intervention may be required to bridge the performance gap and ensure greater parity in selection outcomes.

Statistical Analysis

The results of the ANOVA tests conducted on SKD test scores (TWK, TIU, TKP, and total scores) reveal significant differences between affirmative action and regular applicants. For all test components, the P-values were effectively zero, suggesting that the observed differences in mean scores across the groups are statistically significant. The F-values for TWK, TIU, TKP, and total SKD scores were 109.59, 242.73, 75.61, and 261.49 respectively, indicating that the differences between the two groups are most pronounced in the TIU and total SKD scores. These results highlight the performance gap between affirmative action and regular applicants, with regular applicants consistently scoring higher on average.

In terms of classification results, a Random Forest classifier was employed to predict selection outcomes based on SKD test scores. The model achieved an accuracy of 84.90%, with precision and recall both around 65%, and an F1-score of 65.08%. These metrics reflect a moderate level of performance, indicating that while the classifier was relatively successful in predicting pass/fail outcomes, there is room for improvement in both precision and recall. The slightly lower F1-score suggests that the model encountered some difficulty in balancing false positives and false negatives, particularly in differentiating between borderline pass/fail cases.

The confusion matrix provides further insights into the classifier's performance. Among the correct predictions, 455 applicants were accurately classified as failing, and 66 were correctly classified as passing. However, misclassifications were also evident, especially in predicting borderline cases, such as those classified under the "P/L" category. A substantial number of affirmative action applicants who failed were misclassified as passing, reflecting potential challenges in accurately predicting outcomes for this group, particularly in cases where test scores were close to the passing threshold.

Overall, the ANOVA and classification results underscore the performance gap between affirmative action and regular applicants. While the Random Forest classifier performed reasonably well, the statistical differences observed in test scores suggest that further refinement of predictive models is needed to account for the complexities inherent in the affirmative action group, where performance variability may be higher.

Conclusion

This study reveals significant differences in SKD test performance between affirmative action and regular applicants at STMKG. Regular applicants consistently outperformed their affirmative action counterparts across all test components, including TWK, TIU, TKP, and total SKD scores. ANOVA results indicated statistically significant differences, with TIU and total SKD scores showing the largest performance gaps. The Random Forest classification model achieved moderate accuracy in predicting selection outcomes, highlighting areas where affirmative action applicants may struggle, particularly near the passing thresholds.

The findings have important implications for STMKG and similar institutions that implement affirmative action programs. The performance gap observed in SKD test scores suggests the need for enhanced preparatory programs or additional academic support for affirmative action applicants, ensuring they are better equipped to compete in the selection process. Institutions could also refine selection processes by incorporating holistic evaluation criteria, taking into account not only test scores but also other factors such as potential for academic growth and contribution to diversity. Additionally, these insights can help policymakers assess the effectiveness of affirmative action policies and adapt them to better support underrepresented groups.

Several limitations must be acknowledged in this study. The dataset was constrained by limited regional representation, and some missing data may have impacted the accuracy of the analysis. Moreover, the analysis focused solely on SKD test performance and did not account for other potentially influential factors, such as socio-economic status or prior educational experiences. Future research should explore these variables, as well as extend the analysis to assess the long-term academic performance of affirmative action students after admission. This would provide a more comprehensive understanding of how these programs influence student success beyond the initial selection stage.

Further research could benefit from expanding the dataset to include a broader range of regions, ensuring a more representative analysis of affirmative action outcomes. Additionally, extending the study to include post-admission performance data would allow for a deeper examination of how well affirmative action beneficiaries perform throughout their academic careers, compared to their peers. Future studies might also investigate the role of socio-economic factors, family background, and school quality to uncover other barriers that may affect the performance of underrepresented students during the selection process.

Declarations

Author Contributions

Conceptualization: L.K.O.; Methodology: L.K.O.; Software: L.K.O.; Validation: L.K.O.; Formal Analysis: L.K.O.; Investigation: L.K.O.; Resources: L.K.O.; Data Curation: L.K.O.; Writing Original Draft Preparation: L.K.O.; Writing Review and Editing: L.K.O.; Visualization: L.K.O.; The author have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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