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Analyzing the Impact of Academic and Financial Factors on the Employment Prosperity of Engineering Graduates: A Case Study from Universitas Negeri Yogyakarta

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Abstract

The rapid technological advancements and evolving job markets present a pressing need to understand how academic experiences shape the career outcomes of engineering graduates. This understanding is crucial for educational institutions aiming to align their curricula with industry demands and for graduates seeking to maximize their career prospects. Notably, the role of financial support, academic performance, and early career experiences in influencing graduate prosperity remains underexplored. This study aims to analyze the correlation between finance support, GPA, study period, job waiting times, salary details, and the prosperity of graduates from the Faculty of Engineering at Universitas Negeri Yogyakarta. The prosperity of graduates is defined as earning wages equal to or exceeding the Indonesian minimum average wage. Using data from a tracer study questionnaire, the research employed logistic regression and correlation analysis to investigate these relationships. The data underwent several stages of filtering, resulting in a refined dataset of 70 records for analysis. This study used SPSS software for statistical analysis, focusing on descriptive statistics, correlation, and logistic regression models. The results highlighted significant predictors of graduate prosperity, including GPA and types of financial support, while illustrating the limited predictive power of early career experiences on long-term earnings. The study also indicated that extended study periods do not necessarily correlate with higher wages. In conclusion, the study underscores the importance of targeted educational strategies and student support systems that are responsive to the dynamics of the job market, enhancing the readiness and prosperity of engineering graduates.

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INTRODUCTION

The landscape of engineering education is rapidly transforming due to technological advancements and evolving job market demands. As industries continuously adapt to new technologies, there is a critical need for educational institutions to ensure that their curricula effectively prepare graduates for these changes [1]–[4]. Understanding how various academic factors such as financial support and performance metrics affect graduates' career outcomes is vital for optimizing educational strategies and enhancing student success in the professional world [5]–[8].

In response to these needs, this study examines the correlations between academic experiences—specifically financial support, GPA, study period, job waiting times, and salary details—and the prosperity of graduates from the Faculty of Engineering at Universitas Negeri Yogyakarta. In this context, prosperity is quantified as graduates earning wages equal to or exceeding the Indonesian average minimum wage [9]–[11]. The research identifies significant predictors of graduate prosperity by utilizing logistic regression and correlation analysis on data refined from a tracer study questionnaire. These include GPA and the type of financial support, which play substantial roles in influencing graduates' earning capacities shortly after entering the job market [12]–[15].

However, existing literature and studies often overlook how these factors interact collectively to impact career outcomes, particularly within the Indonesian context. This study aims to fill that gap by providing a comprehensive analysis of how educational experiences correlate with the professional success of engineering graduates [16]–[20]. By focusing on a specific case at Universitas Negeri Yogyakarta, it offers detailed insights into the dynamics between education and employment outcomes in a localized setting [21]–[26].

The research questions guiding this study are: 1) What is the relationship between the source of financial support for students and their academic performance as measured by GPA? 2) How do academic achievements and early career experiences, such as GPA and the waiting time for the first job, influence their salary levels in initial employment? 3) Can a logistic regression model effectively predict graduate prosperity based on a combination of academic variables, job characteristics, and initial salary details?

Overall, this study provides a detailed exploration of how educational factors influence the career prosperity of engineering graduates. By addressing the research questions posed, the study seeks to provide actionable insights that can help educational institutions tailor their programs to meet the job market's needs better, thereby enhancing their graduates' economic success and satisfaction. This research contributes to a broader understanding of educational impacts on career outcomes, paving the way for future studies and policy considerations focusing on the alignment between academic preparation and professional achievement.

METHODS

This study employed a quantitative approach to investigate the relationships between various academic and employment variables and their impact on the prosperity of graduates from the Faculty of Engineering at Universitas Negeri Yogyakarta. The data for this research was sourced from a tracer study questionnaire administered to all department graduates, specifically targeting those from the Department of Electronics and Informatics Engineering Education.

Data Source and Sampling

The initial dataset for this study contained responses from 1669 graduates. This large number of responses was necessary to comprehensively examine the factors influencing the career paths of recent engineering graduates from Universitas Negeri Yogyakarta. Refining the dataset only to include specific programs within the engineering faculty was essential to ensure that the analysis was focused and relevant. Therefore, the dataset was carefully filtered to include only graduates from three particular study programs chosen because of their significant representation and diverse educational focuses within the faculty.

The study focused on graduates from the Bachelor of Education in Informatics Engineering, the Bachelor of Education in Electronics Engineering, and the Bachelor of Engineering in Information Technology. These programs were selected because they offer a unique approach to engineering education, focusing on different skills and teaching methods expected to influence the graduates' success in the job market differently. By focusing on these programs, the study aims to understand how different types of engineering education prepare students for their careers. This approach helps to control for differences in curriculum that could impact the study's findings, allowing for a more precise analysis of how specific educational experiences contribute to career outcomes in engineering.

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Data Reduction

A systematic data reduction process was employed to refine the dataset for detailed analysis, ensuring that only the most relevant and high-quality data were included. This process was crucial for maintaining the integrity of the study's findings. Initially, the dataset included 1669 entries, which were substantial but included various variables that needed to be streamlined to focus on the study's specific aims. The first step in the data reduction process involved narrowing down the dataset to 272 entries. This was achieved by selecting only those entries corresponding to graduates from the three targeted study programs: Bachelor of Education in Informatics Engineering, Bachelor of Education in Electronics Engineering, and Bachelor of Engineering in Information Technology. This initial reduction was essential to ensure that the subsequent analyses would be pertinent to the study's focus on specific educational programs.

Following the initial filtering, the dataset was further refined through several stages to ensure the completeness and accuracy of the data relevant to the study's goals. In the second stage, the dataset was maintained at 272 entries by removing any records that lacked information on financial support, which was a key variable for the study. The third reduction reduced the number of entries to 234 by discarding those without any job information, streamlining the focus to graduates who had entered the workforce. The fourth stage of reduction involved excluding records with incorrect or incomplete data regarding the main salary, bringing the dataset down to 224 entries. The dataset was then significantly reduced to 70 entries by removing those without GPA information, which is crucial for analyzing academic performance. Finally, the dataset count remained at 70 after eliminating entries lacking study period data, which was necessary to understand the duration of the educational impact. Through these reduction stages, the final dataset comprised 70 comprehensive records, each providing complete and relevant data for an in-depth analysis of the relationship between academic experiences and career outcomes.

Variables

In this study, we analyzed several variables to understand how different academic and professional factors affect the career success of engineering graduates, as summarized in Table 1. These variables included ID (A), a unique number for each graduate; Study Program (B), which specifies the engineering program the graduate completed; Graduation Month (C); and Graduation Year (D), which tells us when the graduate finished their studies. We also looked at Finance Support (E) to see how different funding sources impact student outcomes. Waiting Time (F) measures how many months graduates took to land their first job, providing insight into their transition from school to work. We included First Job (G) and Permanent Job (H) to learn about graduates' initial and ongoing jobs. Main Salary (I), Overtime Salary (J), and Other Salary (K) were analyzed to understand the financial benefits associated with different jobs. GPA (L) was used to gauge academic success, and Study Period (M) helped us see how long each student spent in their program. Each variable was chosen to help us piece together a complete picture of what factors lead to graduate success in the job market.

Data Analysis

The data analysis for this study was carried out using SPSS software, a powerful tool for statistical analysis and data management. Initially, descriptive statistics were calculated to give an overview of the data distribution. This step involved summarizing the dataset's distribution's central tendency, dispersion, and shape. By examining measures such as mean, median, mode, standard deviation, and range, we could understand the general characteristics of the data and ensure its suitability for further analysis. Descriptive statistics are crucial as they provide a foundation for making informed decisions about which analytical techniques are appropriate, depending on the data's nature and the study's objectives.

Following the initial statistical summaries, correlation analysis was performed to investigate the relationships among critical variables: financial support, GPA, study period, waiting time until the first job, and various salary metrics. This analysis helped identify which factors are significantly related and how these relationships could influence graduate outcomes. For instance, understanding the correlation between GPA and salary variables could reveal the academic factors most associated with higher earnings post-graduation. Subsequently, logistic regression was utilized to predict the likelihood of graduates achieving prosperity, which is defined for this study as earning a wage equal to or greater than the Indonesian average minimum wage. Logistic regression is suitable for this purpose because it deals with binary outcomes—in this case, whether graduates achieve prosperity—and estimates the probability of occurrence by modelling the data on a logistic curve. This method allowed us to assess the impact of various predictors on graduate prosperity, providing insights into which educational and early career factors are most predictive of successful employment outcomes.

Table 1. Variable Summary: Key identifiers and descriptions used

Code	Variable	Description
A	ID	Unique identifier for each graduate
B	Study Program	Specific Engineering program completed
C	Graduation Month	The month when the graduate finished their studies
D	Graduation Year	The year when the graduate finished their studies
E	Finance Support	The type of financial support the graduate received
F	Waiting Time	Months until the graduate secured their first job
G	First Job	Title of the first job after graduation
H	Permanent Job	Title of stable, long-term job
I	Main Salary	Primary salary from permanent job
J	Overtime Salary	Salary earned from working extra hours
K	Other Salary	Additional earnings outside the main job
L	GPA	Grade Point Average on a 4.0 scale
M	Study Period	Total time spent in the study program

RESULT AND DISCUSSION

Descriptive Analysis of Graduate Academic Achievements and Employment Outcomes

In this section, we explore the academic and professional journeys of 70 graduates through descriptive analysis of their academic performances, study periods, and subsequent job placements, including waiting times and salary details.

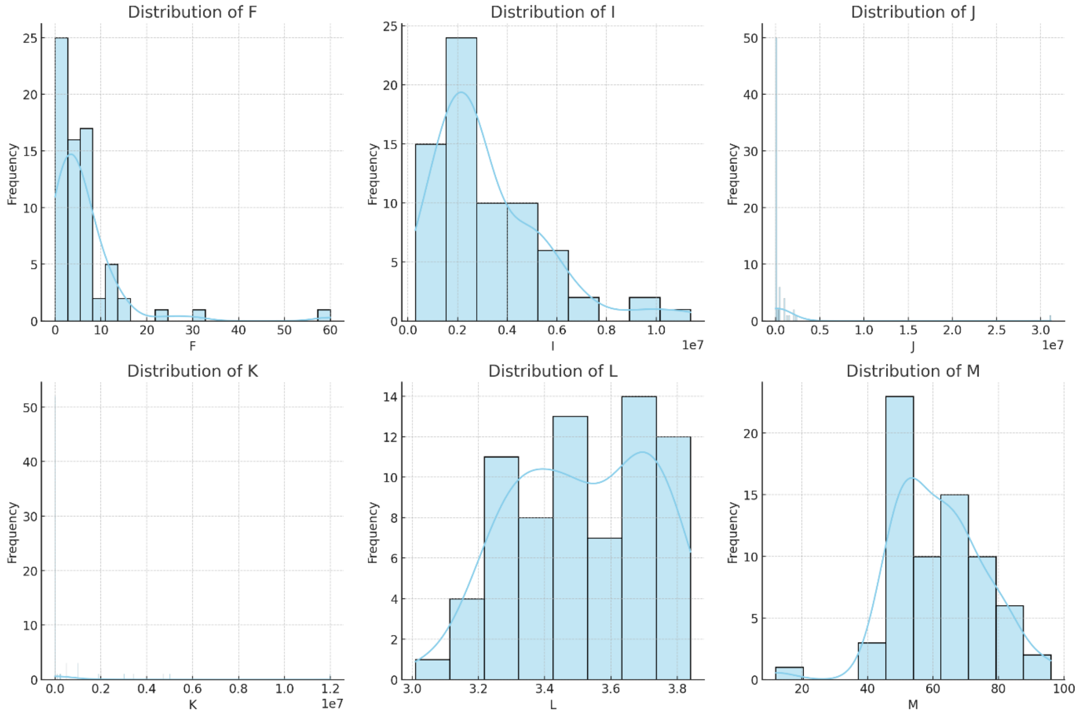

Figure 1. Distribution of Key Variables: This figure illustrates the frequency distributions for waiting time until first job (F), main salary (I), overtime salary (J), other salaries (K), GPA (L), and study period among graduates (M).

As visually presented in Figure 1, the academic performance of graduates, measured by Grade Point Average (GPA) on a 4-point scale, exhibited an average of 3.52. This indicates generally high academic achievement, with GPAs ranging from 3.01 to 3.84. This consistent level of performance suggests that most students were successful in their academic endeavors.

Regarding the duration of their studies, the average study period was approximately 61.87 months, ranging from 12 months to an extended 96 months. This variability indicates that while most students completed their educational programs within the expected timeframe, some took considerably longer due to various personal or academic challenges.

Transitioning from the academic environment to the professional world, the analysis reveals significant insights into the employment outcomes of graduates. The waiting time until the first job was secured varied widely among the graduates, averaging about six months, as described in Table 2. The range was from immediate employment (0 months) to a maximum of 60 months. This indicates that factors such as job market conditions, industry demands, and individual career choices play crucial roles in the employment timelines of graduates.

Regarding compensation, as presented in Table 2, graduates reported their earnings in three categories: main salary, overtime salary, and other salaries. The average main salary was IDR 3,191,786, ranging significantly from IDR 300,000 to IDR 11,380,000. This spread highlights the diverse economic sectors and roles that graduates enter, which can significantly influence their compensation packages.

Furthermore, in Table 2, overtime salary data underscored the variability in work conditions and compensation, with an average overtime pay of IDR 691,571. Graduates reported a wide range of overtime earnings from none to IDR 31,130,000, reflecting the diverse contractual and work-hour arrangements across different sectors.

Additionally, other salaries, which encompass earnings outside of the primary job, averaged IDR 558,814, extending to IDR 12,000,000, as mentioned in Table 2. These details suggest that some graduates engage in entrepreneurial or freelance activities, providing supplementary income alongside their main jobs.

Table 2. Descriptive statistics of waiting time for first job, main salary, overtime salary, other salaries, GPA, and study period.

Variable	N	Mean	Std. Dev.	Min	25%	50%	75%	Max
Waiting Time (F)	70	6.04	8.38	0.00	1.00	4.00	6.75	60.00
Main Salary (I)		3,191,786	2,227,090	300,000	1,762,500	2,500,000	4,575,000	11,380,000
Overtime Salary (J)		691,571	3,727,241	0	0	0	275,000	31,130,000
Other Salary (K)		558,814	1,725,453	0	0	0	37,500	12,000,000
GPA (L)		3.52	0.21	3.01	3.33	3.51	3.70	3.84
Study Period (M)		61.87	14.00	12.00	51.96	60.48	70.53	96.00

This comprehensive overview, from academic performance to job market integration, offers valuable insights for educational institutions and students. It underscores the importance of aligning academic and career support services with the realities of the job market. Such alignment is crucial for setting realistic expectations and preparing students effectively for their post-graduation careers. These findings also highlight the need for targeted interventions to bridge the gap between academic success and satisfactory employment outcomes.

Correlation Analysis of Academic Variables and Their Impact on Employment Outcomes

This section explores the intricate relationships between academic factors and their subsequent impacts on job market outcomes among graduates. Our analysis focused on understanding how financial support, GPA, study period, and waiting times for the first job correlate with various salary components.

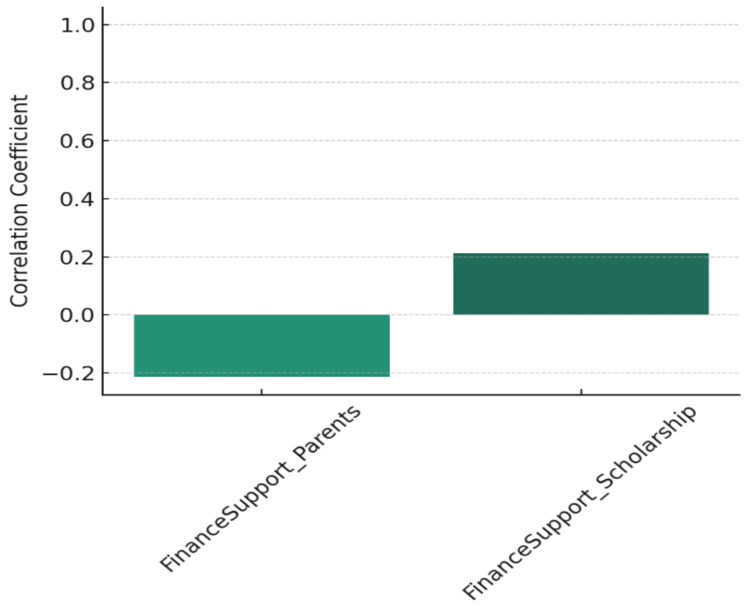

Figure 2. Correlation Coefficients between Types of Finance Support and GPA

As presented in Figure 2, the relationship between finance support and GPA was initially investigated. The findings indicated a slight positive correlation between receiving a scholarship and higher GPA scores (r = 0.213), contrasting with a negative correlation for those supported by parents (r = -0.213). This suggests that scholarships, possibly due to their contingent nature on maintaining specific academic standards, may incentivize students to achieve higher grades.

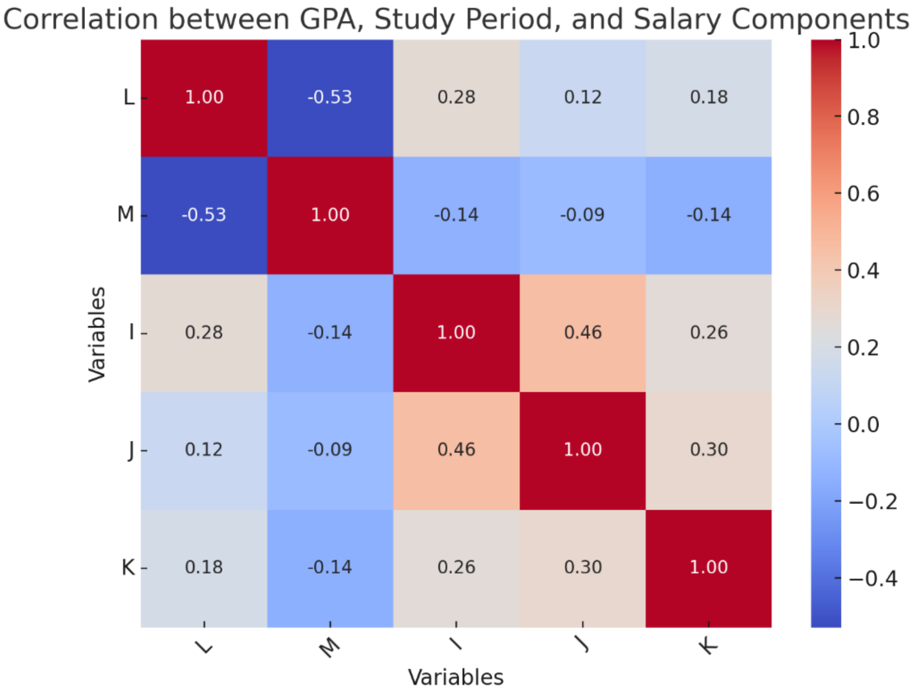

Figure 3. Correlation Heatmap of GPA, Study Period, and Salary Components

Moving on to the influence of GPA and study period on salary components (Figure 3), it was observed that GPA positively correlates with the main salary (r = 0.275892), indicating that higher academic achievements tend to enhance earning potential. However, the study period demonstrated negative correlations with all salary components, suggesting that longer durations in education might not necessarily translate into better salary outcomes. This could be due to various factors, including delays in gaining practical experience while extending academic pursuits.

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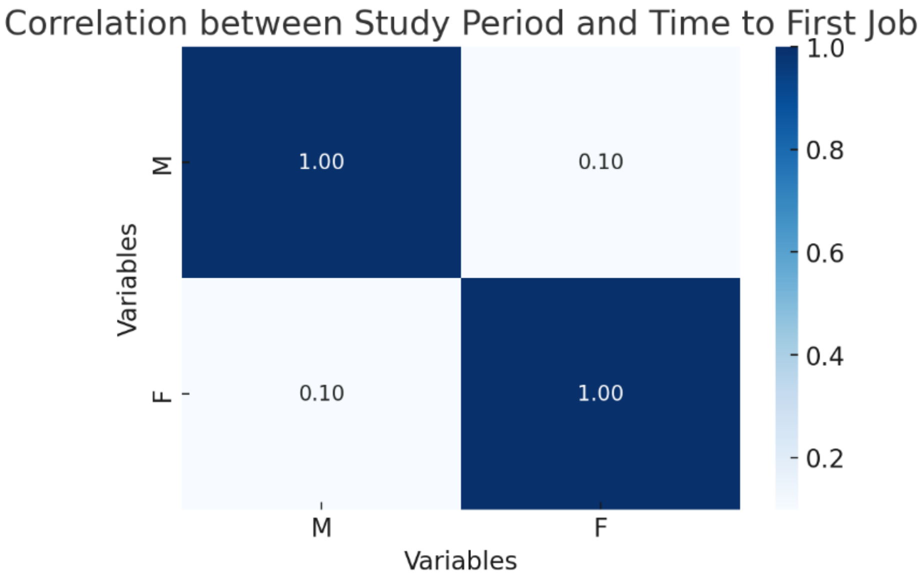

Figure 4. Correlation Heatmap of Study Period and Time to First Job

The analysis also highlighted the minimal impact of study periods on the waiting time for securing a first job (Figure 4), with a correlation coefficient of just 0.098. This indicates that the study duration does not substantially affect how quickly graduates find employment, possibly reflecting the varied nature of job markets across different fields and locations.

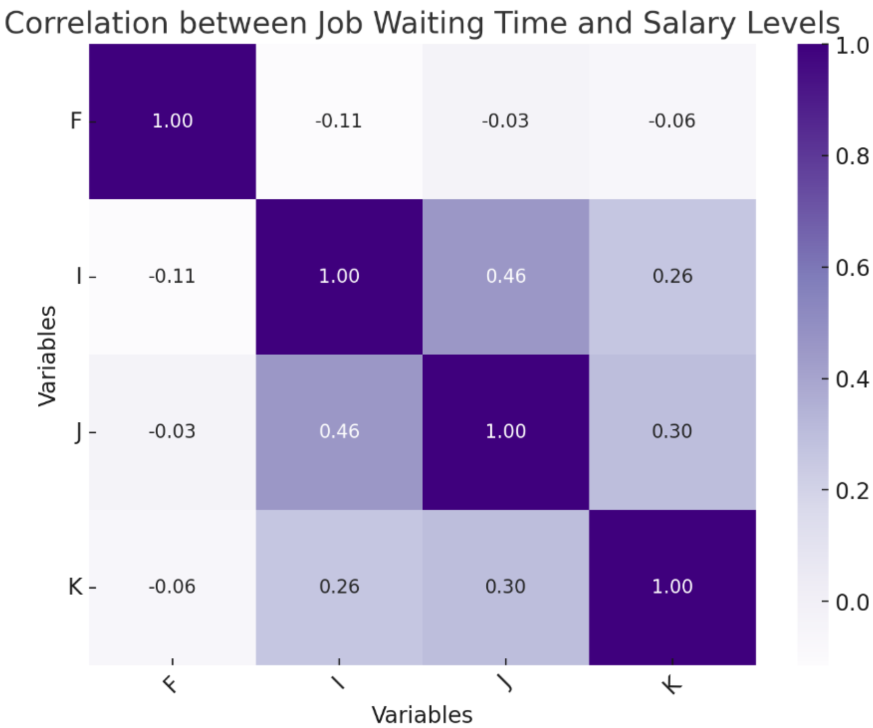

Figure 5. Correlation Heatmap of Job Waiting Time and Salary Levels.

Lastly, the relationship between the waiting time for the first job and various salary components was examined (Figure 5). A slight negative correlation was found between waiting times and main salary (r = -0.114809), suggesting that longer waiting times might be associated with slightly lower salaries. This could be attributed to the competitive disadvantage of gaps in professional activity or the acceptance of lower-paid positions out of necessity.

These insights are crucial for educational institutions and policymakers to consider how academic and financial support structures affect educational outcomes and transition into the workforce. Understanding these relationships helps tailor more effective educational programs and support systems that align better with job market demands and personal career goals.

Exploring Predictive Variables for Student Prosperity After Graduation

We conducted a logistic regression analysis to understand factors influencing graduates' prosperity, defined as earning wages at or above IDR 3,049,743 (Indonesia Minimum Wages 2024). This study incorporated variables such as finance support, GPA, study period, waiting time, first job, permanent job, and various salary components.

The logistic regression model was evaluated using a training set to predict outcomes on a test set. As visually presented in Figure 6, the accuracy achieved was 52%, indicating moderate effectiveness. Specifically, the model's precision was 60% for predicting non-prosperous outcomes and 33% for prosperous outcomes. This disparity in precision suggests that while the model is relatively reliable in identifying non-prosperous graduates, it struggles with accurately predicting prosperity.

Recall rates further emphasize this point, with 69% for non-prosperous and only 25% for prosperous outcomes. This shows the model's tendency to under-predict prosperity among graduates. The overall f1-scores were 0.64 for non-prosperous and 0.29 for prosperous classifications, reflecting the challenges in achieving balanced predictive performance.

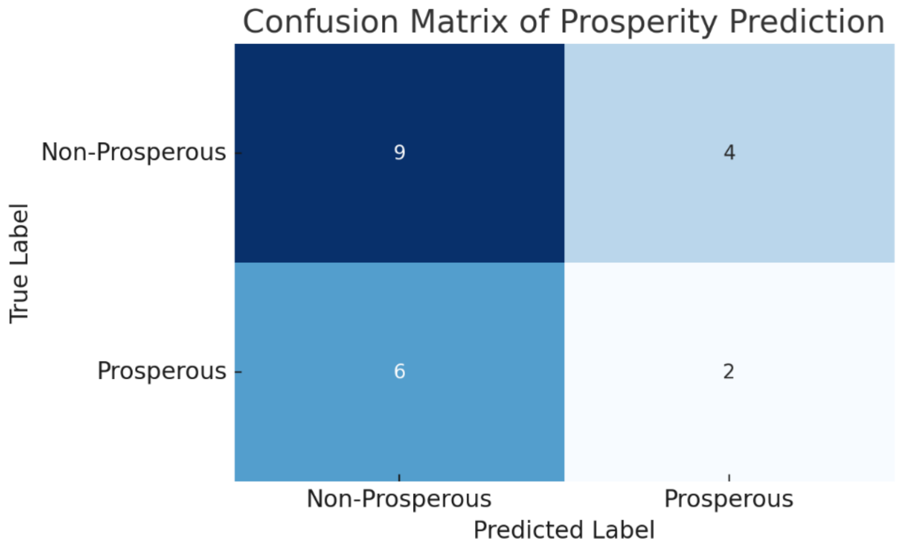

Figure 6: Confusion Matrix of Prosperity Prediction

The confusion matrix from the model provided the following insights: (1) True Negatives (correct non-prosperous predictions) are 9; (2) False Positives (non-prosperous predicted as prosperous) are 4; (3) False Negatives (prosperous predicted as non-prosperous) are 6; (4) True Positives (correct prosperous predictions) are 2. These numbers highlight the conservative nature of the model, particularly its cautious approach to predicting prosperity. This could be due to the complexity of the factors determining graduate earnings, which the model may not fully capture.

As presented in Figure 7, predicting graduate prosperity based on the selected variables is challenging. Factors like GPA and financial support show some correlation with prosperity. However, the relationships are not strong enough to ensure highly accurate predictions. This suggests the need for a more nuanced understanding of how different elements of a graduate's academic and early career experiences contribute to their financial success.

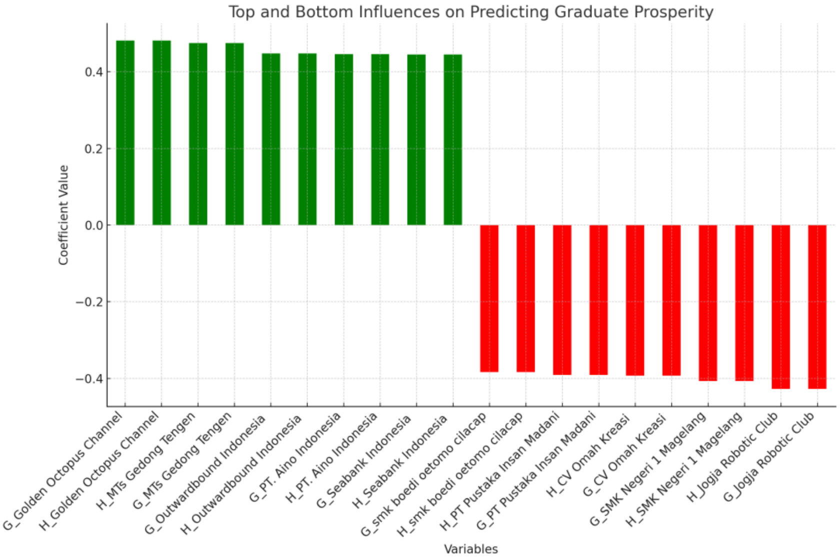

Figure 7. Top and Bottom 10 Influences on Graduate Prosperity

This study underscores the importance of using a multifaceted approach to predict graduate outcomes. Educational institutions could benefit from these insights by tailoring their student support services more effectively, ensuring that graduates are better prepared for the job market. Additionally, understanding these dynamics helps graduates set realistic expectations and strategize their career paths more effectively.

CONCLUSION

This study investigated the influence of academic and financial factors on the career outcomes of engineering graduates, focusing on three key research questions. We found a positive correlation between financial support and academic performance, with students who received scholarships achieving higher GPAs compared to those financially supported by their parents. This suggests that scholarships, often tied to maintaining specific academic standards, motivate students to excel academically, contributing to better outcomes.

The analysis also revealed that higher GPAs are associated with better starting salaries, underscoring the importance of academic achievement in securing higher-paying jobs. However, a longer study period did not lead to higher salaries, indicating that extended academic engagement without corresponding practical experience may not result in financial benefits. Graduates with prolonged study periods may face diminishing returns in the job market, which highlights the need for a balanced approach between academics and practical exposure.

The logistic regression model aimed to predict graduate prosperity, showing moderate success but greater effectiveness in identifying those who would not achieve prosperity. This suggests that factors beyond academic performance, such as timely entry into the job market and securing a good first job, significantly influence financial success. Multiple variables interact in complex ways to shape the financial outcomes of graduates, highlighting the need for educational programs to provide support that prepares students not only academically but also for the realities of the job market.

Limitations

The study, while comprehensive, encounters several limitations that must be acknowledged. One of the primary constraints is the reliance on a relatively small sample size, which might not capture the total variability and complexity of graduate experiences across different disciplines and economic sectors. Additionally, the study's focus on quantitative data limits the depth of understanding regarding the qualitative aspects of job satisfaction and career fulfilment, which are crucial to defining graduate prosperity. Although practical, the use of logistic regression models also presents limitations in predicting complex human behavior outcomes like career success, which are influenced by a myriad of interdependent factors not fully accounted for in the model.

Future Study

Future studies should address the limitations identified in the current research by incorporating a more extensive and diverse sample of graduates, enhancing the findings' generalizability. Expanding the scope to include qualitative data could also provide deeper insights into graduates' perceptions of job satisfaction and career fulfilment, offering a more holistic view of what constitutes prosperity. Additionally, exploring more sophisticated predictive models, such as machine learning techniques, could improve the accuracy of predictions regarding graduate success by capturing the complex interactions between multiple factors influencing career outcomes.

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