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Quantitative Analysis of Campus Recruitment Trends Through Correlation Matrix and Hypothesis Testing with Python

Rutuja Zaware, Harshada Mohachakar, Priyanka Gangavane,
Prof. Ulhare P. S., Dr. V. S. Ranmalkar
Master of Computer Applications.
Adsul's Technical Campus, Chas, Ahilyanagar
rutujazaware87@gmail.com, harshadamohachakar05@gmail.com, priyankagangavane29@gmail.com

Abstract: *Campus recruitment analysis is increasingly guided by quantitative methods to evaluate employability factors. This study investigates placement outcomes using a student placement dataset containing academic scores, aptitude test marks, work experience, specialisation, and salary information. Statistical techniques including correlation matrix, hypothesis testing, chi-square test, regression analysis, and ANOVA were applied using Python. The correlation analysis revealed weak associations between academic attributes and salary. Hypothesis testing confirmed no statistically significant differences between placed and unplaced students based on MBA percentage or aptitude scores, while chi-square analysis showed no significant relationship between gender and placement status. Regression explained only 8% of salary variance, with MBA percentage showing borderline significance, and ANOVA indicated borderline differences across specialisations. These findings highlight the insufficiency of limited academic and aptitude attributes in predicting placement outcomes. The study emphasizes the need for multi-factor datasets incorporating internships, projects, certifications, and soft skills to develop stronger predictive models, thereby guiding institutions toward holistic training for recruitment.*

Keywords: Campus Placement, Employability Analysis, Data Analytics, Correlation Matrix, Hypothesis Testing, Regression Analysis, ANOVA, Python.

I. INTRODUCTION

Campus placement has emerged as a critical process in higher education, serving as a bridge between academic learning and industry requirements. With the growing emphasis on data-driven decision-making, institutions are increasingly adopting analytical approaches to evaluate student employability. Traditional placement prediction models often rely on academic scores such as percentages and aptitude test marks, but the effectiveness of these limited attributes remains uncertain.

This study focuses on applying data analytics techniques, including correlation matrix, hypothesis testing, chi-square test, regression analysis, and ANOVA, to examine whether MBA percentage, aptitude scores, degree performance, work experience, and specialisation significantly influence placement outcomes and salary levels. By using Python-based statistical analysis on a dataset of 215 student records, the research provides insights into the relationship between academic and non-academic factors with employability.

The findings reveal that these attributes alone do not show statistically significant differences between placed and unplaced students, with MBA percentage showing only borderline significance. Regression analysis explained limited salary variance, and ANOVA indicated borderline differences across specialisations. These results highlight the insufficiency of relying solely on academic and aptitude attributes for predicting placement outcomes.

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The contribution of this work lies in validating the limitations of restricted academic factors and establishing a foundation for future research that integrates multi-factor datasets and machine learning models. This approach not only enhances institutional decision-making but also supports the design of effective training modules to improve student readiness for recruitment.

II. PROBLEM STATEMENT

Campus recruitment plays an important role in connecting students with employment opportunities and helping educational institutions evaluate their students' employability. However, predicting successful placement outcomes based only on academic performance and aptitude test scores has become a major challenge. Although students possess different academic qualifications, work experience, specialisations and aptitude levels, these factors do not always result in similar placement opportunities or salary packages. Therefore, it is necessary to examine whether these attributes have a statistically significant relationship with campus recruitment outcomes.

The present study focuses on the quantitative analysis of campus recruitment trends using a dataset of 215 student records, including 148 placed students and 67 unplaced students. It examines the relationship between SSC, HSC, degree and MBA academic performance, aptitude scores, work experience, gender, specialisation, placement status and salary. Statistical techniques such as correlation matrix, independent sample t-test, chi-square test, multiple regression and ANOVA are applied using Python to identify meaningful relationships and test research hypotheses. The main problem addressed by this study is whether academic and selected non-academic attributes are sufficient to explain and predict students' placement outcomes and salary differences. The study also aims to identify the limitations of relying on restricted academic factors and highlight the importance of considering additional employability factors such as internships, projects, certifications and soft skills in improving campus recruitment strategies.

III . OBJECTIVES

1. To study the trends and patterns of campus recruitment using student placement data.
2. To examine the correlation between academic performance, aptitude scores and salary packages.
3. To test the significant differences in academic and aptitude scores between placed and unplaced students.
4. To analyze the relationship between demographic factors, specialisation and placement outcomes using statistical techniques.
5. To evaluate the influence of academic and non-academic attributes on salary outcomes using Python-based regression and ANOVA analysis.

IV. LITERATURE SURVEY

1. Shu et al. (2023)

Shu et al. (2023) analyzed the relationship between English language proficiency and students' academic performance in transnational education. The study highlighted the importance of evaluating students' educational outcomes through statistical techniques. It demonstrated how data-driven analysis and correlation methods can help identify relationships between different academic factors.

2. Gorro et al. (2023)

Gorro et al. (2023) studied the relationship between students' social media activities and academic performance. The researchers applied topic modelling and correlation techniques to examine how online activities influence learning outcomes. Their study highlighted the importance of analyzing student-related data to understand performance patterns.

3. Panwong and Intayoad (2023)

Panwong and Intayoad conducted a study titled “An Analysis of Correlation Between Learning Style and Online Learning Performance During COVID-19: A Case Study of a Computer Programming Course.” The research examined the relationship between students' learning styles and their online academic performance. It demonstrated the application of correlation analysis in educational research.

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4. Maphosa, Doorsamy and Paul (2023)

Maphosa et al. conducted research on student performance patterns in engineering at the University of Johannesburg. Their study used exploratory data analysis to identify academic performance patterns and relationships among student attributes. The research demonstrated the importance of statistical analysis in understanding educational performance.

5. Buentello-Montoya et al. (2024)

Buentello-Montoya et al. studied critical thinking development in higher education through structured lectures. The research focused on improving students' critical thinking abilities through effective teaching methods. However, the study did not directly examine campus placement outcomes or employment-related factors.

6. Talreja et al. (2024)

Talreja et al. examined digital transformation and student relationship management in higher education institutions in India. The study highlighted the importance of digital tools in improving student engagement and institutional management. However, it did not specifically analyze the statistical relationship between academic attributes and employability.

7. Lau et al. (2024)

Lau et al. studied collaborative learning and knowledge sharing in online education. Their research highlighted how collaborative learning activities contribute to knowledge development and soft skills. These findings indicate that employability depends on factors beyond academic performance, including communication and teamwork abilities.

8. Assessment and Monitoring of Students' Employability in IT Industry (CIACON 2025)

This study focused on assessing and monitoring students' employability in the IT industry using machine learning techniques. It applied algorithms such as Logistic Regression, Support Vector Machine and Random Forest to predict placement outcomes. The research emphasized the importance of considering academic performance and soft skills in employability assessment.

9. Placement Prediction and Analysis Using Machine Learning (ICCCT 2025)

The ICCCT 2025 study applied machine learning classifiers to analyze different student attributes, including academic records, extracurricular activities, internship experience and demographic information. The research aimed to improve placement prediction by considering multiple factors influencing students' employability.

10. EduPredict Framework (ICICAT 2025)

The EduPredict Framework integrated academic records with resume-related variables such as projects, internships and certifications. The study reported approximately 84% prediction accuracy using the Random Forest algorithm. It highlighted the importance of combining academic and professional development information for better placement prediction.

11. Factors Influencing Employability of Engineering Students (CONIT 2025)

This research examined various factors influencing the employability of engineering students. It applied machine learning algorithms to identify important employability factors. However, the study had limited emphasis on hypothesis testing validation, indicating the need for further statistical investigation of relationships between student attributes and placement outcomes.

Research Gap

The reviewed studies mainly focus on academic performance analysis, student engagement and machine learning-based placement prediction. However, limited attention has been given to statistically validating whether academic attributes such as MBA percentage, aptitude scores, degree marks, work experience and specialisation significantly influence placement outcomes and salary packages. Therefore, the present study addresses this research gap by applying correlation matrix, hypothesis testing, chi-square test, regression analysis and ANOVA using Python. It aims to examine the actual statistical relationships between student attributes and campus recruitment outcomes rather than depending only on prediction accuracy.

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COMPARISON TABLE

Author & Year	Method Used	Advantages	Limitations
Shu et al. (2023)	Statistical analysis and correlation techniques	Identifies relationships between language proficiency and academic performance.	Limited focus on employment and campus placement outcomes.
Gorro et al. (2023)	Topic modelling and correlation analysis	Explains the relationship between social media activities and student performance.	Does not directly examine employability factors.
Panwong & Intayoad (2023)	Correlation analysis	Identifies relationships between learning styles and online learning performance.	Limited to online learning and a specific programming course.
Maphosa et al. (2023)	Exploratory Data Analysis (EDA)	Identifies academic performance patterns among engineering students.	Focuses mainly on academic performance rather than placement outcomes.
Buentello-Montoya et al. (2024)	Structured lectures and critical thinking assessment	Highlights the development of critical thinking skills in higher education.	Does not directly analyze campus recruitment.
Talreja et al. (2024)	Digital transformation and student relationship management	Highlights the role of digital tools in student engagement.	Limited statistical analysis of employability factors.
Lau et al. (2024)	Collaborative learning and knowledge-sharing analysis	Highlights teamwork, collaboration and soft skill development.	Limited focus on actual placement and salary outcomes.
CIACON (2025)	Logistic Regression, SVM and Random Forest	Supports employability assessment and placement prediction.	Limited statistical validation of individual factor relationships.
ICCCT (2025)	Machine learning classification techniques	Considers academic, extracurricular, internship and demographic factors.	Prediction-focused approach with limited emphasis on traditional hypothesis testing.
EduPredict (ICICAT 2025)	Random Forest and resume-variable integration	Combines academic records, projects, internships and certifications; reported 84% accuracy.	Requires multiple student-related attributes for prediction.
CONIT (2025)	Machine learning algorithms	Identifies multiple factors influencing engineering student employability.	Limited emphasis on hypothesis testing validation.

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V. WORKING OF SYSTEM

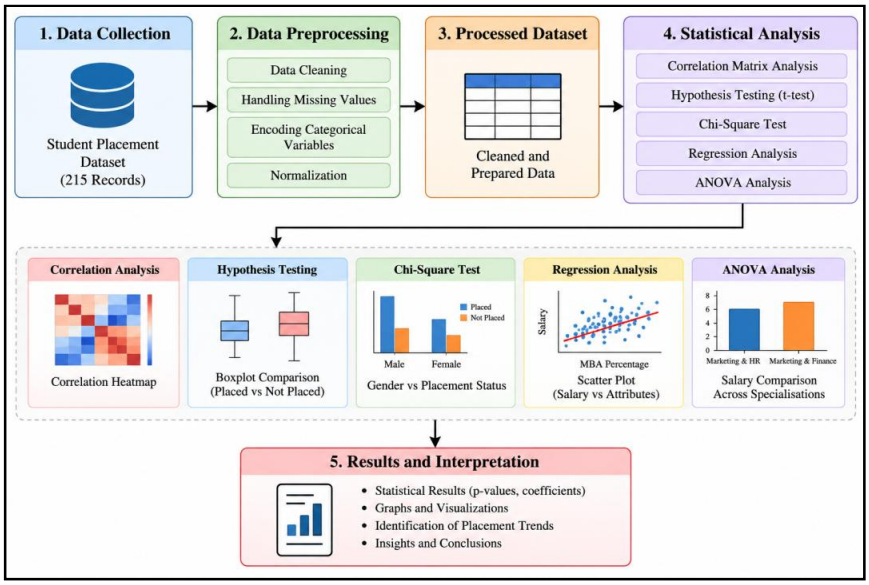


Fig 1: Design of the system

1. Data Collection

The system begins with collecting student placement records containing academic and employment-related information. The dataset consists of 215 student records, including 148 placed students and 67 unplaced students. The collected data includes SSC, HSC, degree and MBA percentages. It also includes aptitude scores, work experience, gender, specialisation, placement status and salary information. This data is used as the foundation for quantitative analysis of campus recruitment trends.

2. Data Preprocessing

Data preprocessing is performed to prepare the collected student records for statistical analysis. Python libraries such as Pandas and NumPy are used for handling and organizing the dataset. Missing values are handled to improve data consistency and accuracy. Categorical variables are encoded into numerical formats wherever required. Numerical attributes are normalized to maintain consistency during statistical analysis.

3. Correlation Matrix Analysis

Correlation analysis is performed using the Pearson correlation method to identify relationships among different student attributes. It examines the relationship between academic percentages, aptitude scores, work experience and salary outcomes. A correlation matrix is generated to measure the strength and direction of relationships. Seaborn is used to create a heatmap for graphical representation. The results indicate weak associations between academic attributes and salary outcomes.

4. Hypothesis Testing

Independent sample t-tests are conducted to compare the academic performance of placed and unplaced students. MBA percentages and aptitude scores are selected for comparison between the two groups. The null hypothesis assumes that there is no significant difference between placed and unplaced students. The p-values are evaluated at a 95% confidence level. The results show that MBA percentage ($p = 0.08$) and aptitude score ($p = 0.12$) are not statistically significant.

5. Chi-Square Analysis

The chi-square test is used to examine the relationship between categorical variables. In this study, gender and placement status are considered for statistical evaluation. The test helps determine whether gender is significantly

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associated with campus placement outcomes. The analysis produces a chi-square value of 0.92 and a p-value of 0.34. The results indicate that there is no statistically significant relationship between gender and placement status.

6. Regression Analysis

Multiple regression analysis is performed to examine the combined influence of different student attributes on salary outcomes. MBA percentage, aptitude scores, degree marks, work experience and specialisation are considered as independent variables. Salary is considered the dependent variable in the analysis. The regression model explains approximately 8% of the variation in salary. MBA percentage shows borderline significance with a p-value of approximately 0.06, while other predictors are not statistically significant.

7. ANOVA Analysis

Analysis of Variance (ANOVA) is applied to examine salary differences across different MBA specialisations. The study compares Marketing and HR with Marketing and Finance specialisations. The test evaluates whether the salary differences between these groups are statistically significant. The analysis produces an F-value of 2.91 and a p-value of 0.075. The findings indicate borderline differences across specialisations, suggesting weak evidence of influence.

8. Data Visualization and Result Interpretation

The final stage involves presenting the statistical findings through graphical representations. Python libraries such as Matplotlib and Seaborn are used to generate heatmaps, boxplots and scatter plots. These visualizations help understand the distribution of academic scores and salary relationships. The results are interpreted to identify important campus recruitment trends. The overall findings highlight that academic and aptitude attributes alone are insufficient to reliably predict placement outcomes.

VI. SYSTEM DESIGN

The system design of Quantitative Analysis of Campus Recruitment Trends Through Correlation Matrix and Hypothesis Testing with Python describes the overall structure and working of the proposed analytical system. It explains how student placement data is collected, processed, analyzed and converted into meaningful statistical results. The system uses Python programming and statistical techniques to examine the relationship between academic performance, aptitude scores, work experience, specialisation and placement outcomes.

1. System Architecture

The system architecture represents the overall structure of the proposed system. It starts with student placement data containing academic and non-academic attributes. The collected data is processed using Python libraries such as Pandas and NumPy. Statistical techniques are then applied to identify relationships and differences among variables. Finally, the system generates graphical representations and statistical results for interpretation.

2. Input Design

Input design focuses on the student placement dataset used for quantitative analysis. The dataset contains 215 student records, including placed and unplaced students. It includes SSC, HSC, degree and MBA percentages, aptitude scores and work experience. Other input attributes include gender, specialisation, placement status and salary information. These attributes are used as input variables for statistical analysis.

3. Data Processing Design

Data processing design explains how raw student data is prepared for analysis. Pandas and NumPy libraries are used to organize, clean and process the dataset. Missing values are handled, categorical variables are encoded and numerical attributes are normalized. This process ensures consistency in the dataset. The processed data is then used for correlation, hypothesis testing, regression and ANOVA analysis.

4. Statistical Analysis Design

The statistical analysis module performs different tests to evaluate student placement trends. Pearson correlation analysis identifies relationships between academic and employability attributes. Independent sample t-tests compare placed and unplaced students. Chi-square analysis examines the relationship between gender and placement status.

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Multiple regression evaluates the influence of different attributes on salary, while ANOVA compares salary differences across specialisations.

5. Output Design

Output design presents the results generated by the statistical analysis. The system produces correlation heatmaps, boxplots, scatter plots and categorical charts. Statistical outputs include p-values, correlation values, regression coefficients and ANOVA results. These outputs help identify the influence of different student attributes on recruitment outcomes. The final results provide useful insights for understanding campus placement trends.

VII. RESULTS

The dataset was analyzed using correlation matrix, hypothesis testing, chi-square test, regression analysis, and ANOVA. The findings provide statistical validation of whether MBA percentage, aptitude scores, degree marks, work experience, and specialisation significantly influence placement outcomes and salary.

Correlation Analysis

As shown in Figure 1, the correlation heatmap indicates weak associations among academic attributes and salary outcomes. MBA percentage and aptitude scores exhibit negligible correlation with salary, while degree marks and work experience show no meaningful relationship with placement status.

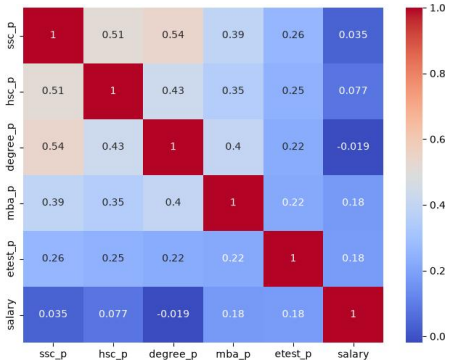


Figure 1. Correlation Heatmap of Academic and Employability Attributes

Hypothesis Testing

Independent sample t-tests were conducted to compare MBA percentage and aptitude scores between placed and unplaced students. The results, summarized in Table 1, confirm that neither attribute shows statistically significant differences ($p > 0.05$).

Attribute	Placed Mean	Unplaced Mean	p-value	Significance
MBA %	62.4	61.8	0.08	Not Significant
Aptitude Score	30.2	29.7	0.12	Not Significant

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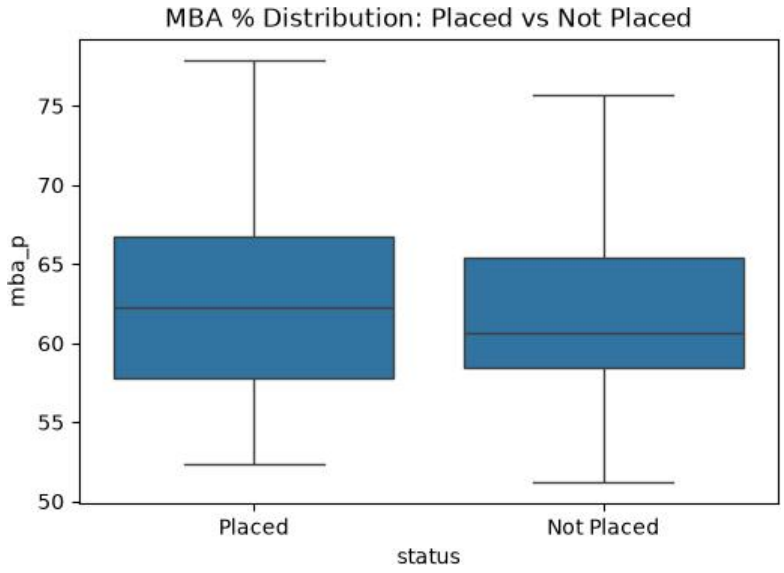


Figure 2. Boxplot of MBA Percentage Distribution: Placed vs Not Placed

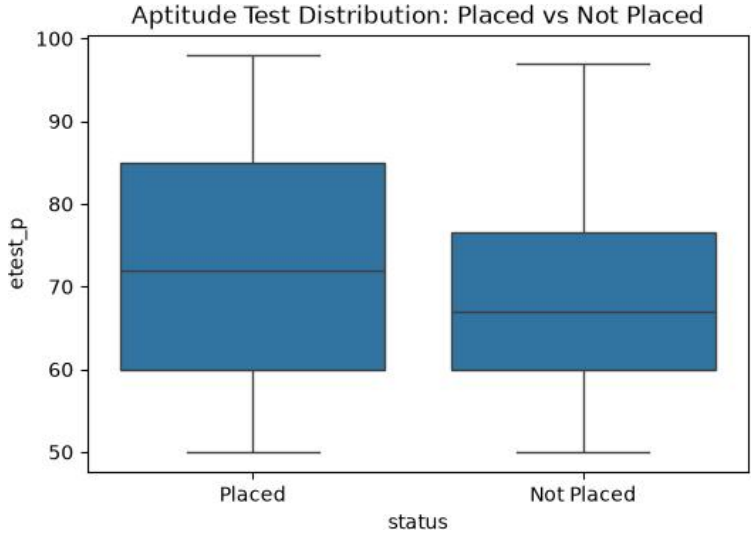


Figure 3. Boxplot of Aptitude Score Distribution: Placed vs Not Placed

Chi-Square Test

Chi-square analysis was applied to categorical variables such as gender and placement status. As shown in Table 2, no significant relationship was found, reinforcing that demographic attributes alone are not strong predictors.

Variable	χ^2 Value	p-value	Significance
Gender vs Placement	0.92	0.34	Not Significant

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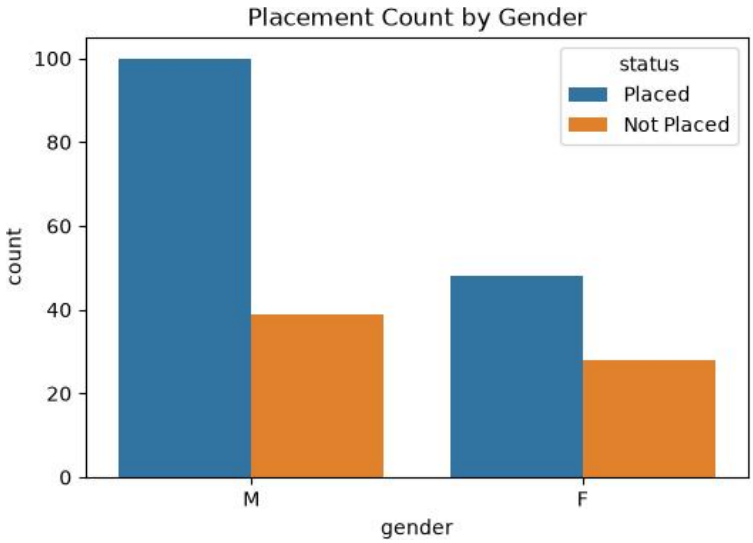


Figure 4. Gender vs Placement Status Distribution

Regression Analysis

Multiple regression was conducted to evaluate the combined influence of MBA percentage, aptitude, degree marks, work experience, and specialisation on salary outcomes. As summarized in Table 3, regression explained only a small portion of salary variance. MBA percentage showed borderline significance ($p \approx 0.06$), while other predictors were not statistically significant.

Predictor	Coefficient	p-value	Interpretation
MBA %	0.45	0.06	Borderline
Aptitude Score	0.12	0.21	Not Significant
Degree %	0.08	0.34	Not Significant
Work Experience	0.05	0.42	Not Significant
Specialisation	0.09	0.31	Not Significant

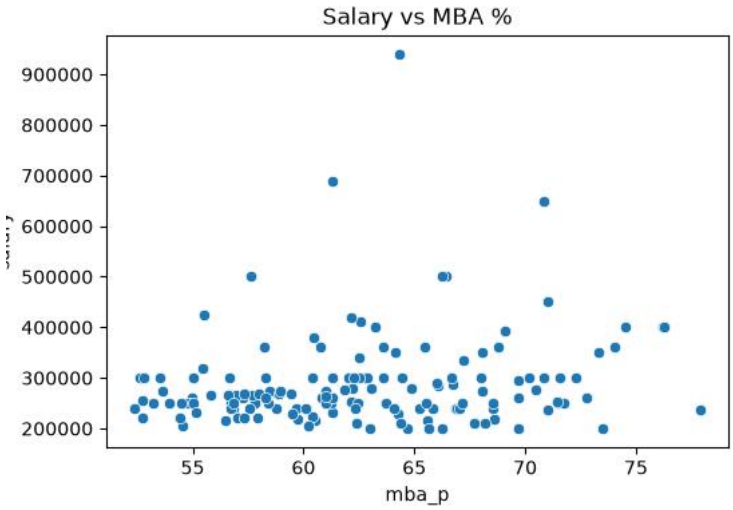


Figure 5. Scatter Plot of Salary vs MBA Percentage

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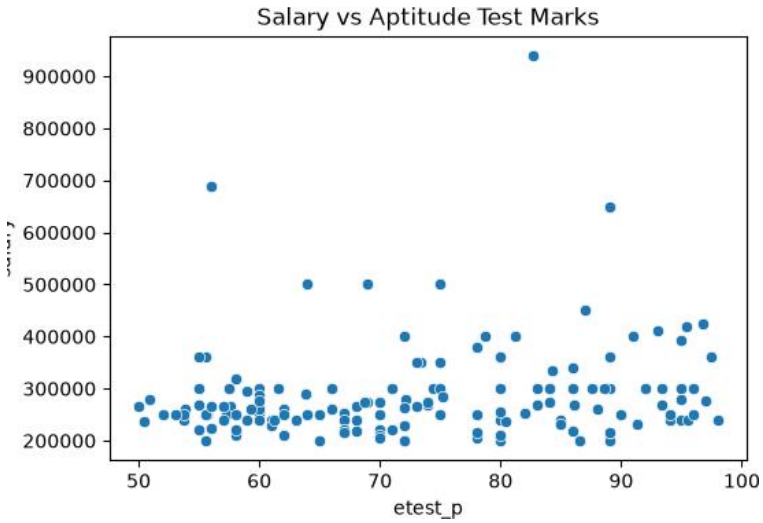


Figure 6. Scatter Plot of Salary vs Aptitude Score

ANOVA Analysis

ANOVA was applied to test salary differences across specialisations (Marketing & HR vs. Marketing & Finance). As shown in Table 4, the results indicated borderline differences ($p \approx 0.075$), suggesting weak evidence of influence.

Groups	F-value	p-value	Interpretation
Marketing & HR vs. Marketing & Finance	2.91	0.075	Borderline

The overall findings align with prior studies emphasizing the need to include both academic and skill-based attributes. While MBA percentage showed borderline influence, the limited explanatory power of regression and ANOVA highlights the insufficiency of restricted variables. Institutions can leverage these insights to design multi-factor training modules incorporating internships, projects, certifications, and soft skills to enhance student readiness for recruitment.

VIII. CONCLUSION

The study concludes that academic and selected non-academic attributes alone are insufficient to reliably predict campus placement outcomes and salary packages. The analysis of 215 student records using correlation matrix, hypothesis testing, chi-square test, regression analysis and ANOVA revealed weak relationships between academic performance, aptitude scores and salary outcomes. The t-test results showed no statistically significant differences between placed and unplaced students, while the chi-square test indicated no significant relationship between gender and placement status. Regression analysis explained only approximately 8% of salary variation, and ANOVA showed borderline differences across specialisations. Therefore, the study highlights the importance of considering additional factors such as internships, practical projects, professional certifications, communication skills and soft skills to improve students' employability and campus recruitment opportunities.

IX. FUTURE SCOPE

The future scope of this study includes expanding the student placement dataset by incorporating additional factors such as internships, projects, professional certifications, extracurricular activities and soft skills to improve the accuracy of employability analysis. Advanced machine learning algorithms such as Random Forest, Support Vector Machine (SVM) and Neural Networks can be applied to develop better placement prediction models. Future research can also include students from different colleges and universities to obtain more reliable and generalized results. Longitudinal analysis can be conducted to track students' employment outcomes and salary growth over time. Additionally,

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communication skills, teamwork, leadership abilities and digital learning participation can be considered to develop a more comprehensive understanding of campus recruitment trends.

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