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STUDENT PERFORMANCE AND PLACEMENT ANALYTICS USING BUSINESS ANALYTICS FOR ENHANCING DECISION-MAKING AT TRISHANA TECHNOLOGIES

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ABSTRACT

Training institutions collect a large volume of student data every day, yet much of it rarely informs strategic decisions about learning or employability. This study explores how Business Analytics can close that gap at Trishana Technologies, Chennai — an IT training institute offering programmes in Data Analytics, Python, Power BI, and Full Stack Development. Data was gathered from 100 students through a structured questionnaire and supplemented by institutional records covering attendance, weekly test scores, and placement reports. Using Percentage Analysis, Pearson Correlation, Chi-Square testing, and One-Way ANOVA — processed in Microsoft Excel, Power BI, and SPSS — the study uncovers several meaningful patterns. Attendance and test scores share a moderate positive relationship ($r = 0.68$), and the Chi-Square test confirms that academic performance significantly influences placement success ($\chi^2 = 16.66$, $p < 0.05$). ANOVA further reveals that Analytics students consistently outperform their peers across other course categories ($F = 4.50$, $p < 0.05$). Overall, 65% of the surveyed students secured employment, underscoring the practical value of the institute's training approach. The findings offer concrete, visualization-supported recommendations that institutions can act on to improve both academic outcomes and placement rates.

KEYWORDS: Business Analytics, Student Performance, Placement Outcomes, Pearson Correlation, Chi-Square Test, ANOVA, Trishana Technologies, Educational Decision-Making, IT Training Institutions, Descriptive Analytics.

INTRODUCTION

The IT training industry has grown rapidly in recent years, largely because demand for skilled professionals in data, cloud computing, and software development continues to outpace the supply. Institutions like Trishana Technologies play a bridging role — taking students from varying academic backgrounds and preparing them for careers that require specific technical competencies. What often goes unnoticed, however, is how much useful information these institutions already hold in the form of attendance registers, test records, and placement logs, yet seldom analyse in a structured way.

Business Analytics offers a practical solution. By applying statistical techniques to existing student data, institutions can identify who is struggling early enough to intervene, understand which programmes deliver the strongest employment outcomes, and make planning decisions based on evidence rather than assumption. This study does exactly that, using Trishana Technologies as a case setting to demonstrate how analytics can work in an educational context.

"Institutions already hold the data they need to make better decisions — the missing piece is a structured framework to analyse and act on it."

Trishana Technologies Private Limited was established in 2015 in Bangalore, Karnataka, and operates branches in Kalyan Nagar, Bellandur, BTM Layout, and Chennai. The institute offers training in AWS, Data Analytics with Python, Power BI, Big Data, Full Stack Development, SQL, Data Science, and Digital Marketing. It also provides placement support through mock interviews, aptitude coaching, resume preparation, and industry-connect programmes — making it a suitable environment in which to study the relationship between academic monitoring and employment outcomes.

1. REVIEW OF LITERATURE

Research in this area has grown considerably over the past decade. **Rawat (2019)** demonstrated that decision tree classifiers can predict student placement outcomes with high accuracy when trained on academic and skill-based attributes, establishing a foundation for data-driven placement forecasting. Building on this, **Gaftandzhieva et al. (2022)** proposed analytics-based monitoring models that helped higher education institutions track student progress, flag dropout risks, and improve retention — findings that translate naturally to the training institution context.

Clemente and Kwak (2022) pushed prediction accuracy further, achieving 90.85% using a Random Forest model on campus placement data. They found that coding proficiency and aptitude scores were the strongest predictors of placement success — a finding echoed in this study's course-wise performance results. **Duch et al. (2023)** showed that learning analytics embedded within Moodle could identify at-risk students early, and a Random Forest classifier outperformed other models in predicting final academic outcomes.

Sithumini et al. (2024) conducted a systematic review confirming that data analytics supports personalised learning and institutional planning, particularly in digital environments. **Cho et al. (2024)** found that self-regulated learning behaviours and consistent engagement are more predictive of success than a student's prior academic record alone. Most recently, **Talari et al. (2025)** developed a predictive framework that achieved above 90% accuracy in forecasting career outcomes, highlighting the value of targeting skill gaps through analytics-informed intervention. Taken together, the literature points to a clear gap: most studies focus on advanced machine learning techniques that require considerable technical infrastructure, and few address how simpler, widely available tools — Excel, Power BI, SPSS — can support decision-making in smaller training institutions. This study addresses that gap directly.

2 RESEARCH METHODOLOGY

The study adopts a **descriptive and analytical research design**. The descriptive component summarises student characteristics — attendance patterns, test score distributions, course preferences — while the analytical component tests relationships between these variables using inferential statistics.

Sample: One hundred students enrolled in various training programmes at Trishana Technologies were selected using convenience sampling, given the constraints of time and access. Although convenience sampling has known limitations, the sample size of 100 is considered adequate for the statistical techniques applied.

Data collection: Primary data was collected through a structured questionnaire covering five sections: demographic information, attendance and academic performance, learning experience, placement and outcomes, and analytics perception. Secondary data came from institutional records — attendance sheets, weekly test reports, and placement logs.

Statistical tools used: Percentage Analysis (for descriptive summaries), Pearson Correlation (attendance vs. test scores), Chi-Square Test (academic performance vs. placement status), and One-Way ANOVA (test score variation across course categories). Data was processed in Microsoft Excel and SPSS, with visualisations prepared in Microsoft Power BI.

Hypotheses tested:

H_1: There is a significant relationship between student attendance and academic performance.

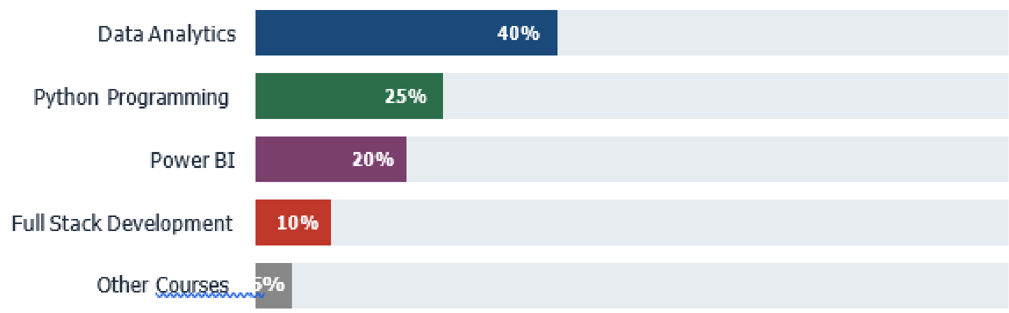
H_2: There is a significant relationship between academic performance and placement outcomes.

H_3: There is a significant difference in test scores across different course categories.

Figure 1

Course Enrolment Distribution at Trishana Technologies

Percentage share of students across training programmes (n = 100)



Note. Data Analytics, Python, and Power BI together account for 85% of total enrolments, reflecting the current industry demand for data and business intelligence skills.

3. DATA ANALYSIS AND INTERPRETATION

3.1 Descriptive findings. Most students — 65% — maintained attendance above 75%, and 60% reported attending classes regularly. The largest group (35%) scored in the 71–85% range in weekly tests, with 25% scoring above 85%. Undergraduate students formed the majority of participants (45%), followed by postgraduates (30%), diploma holders (15%), and others (10%). Afternoon batches had the highest attendance (40%), and enrolment was highest during the early months of the year, peaking in March (25%).

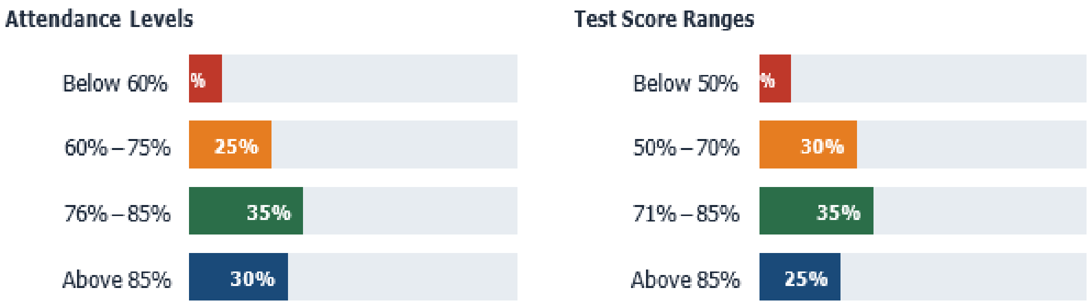
Importantly, 80% of students reported believing that attendance improves academic performance, and 85% agreed that analytics-based tracking is a useful tool — suggesting that students themselves recognise the value of structured monitoring.

3.2 Correlation Analysis (Attendance vs. Test Scores). Applying the Pearson formula to a representative sample of five student records yielded a correlation coefficient of **r = 0.68**. This indicates a moderate positive relationship: students who attend more consistently tend to achieve higher test scores. While this does not establish causation — other factors such as prior knowledge and study habits also play a role — it does suggest that attendance is a meaningful input worth tracking closely.

Figure 2

Attendance Distribution vs. Test Score Distribution

Percentage of students falling in each bracket; reflects correlation between the two variables (n = 100)



Note. The similar shape of both distributions supports the correlation finding (r = 0.68): brackets with more students tend to mirror each other across attendance and performance.

Table 1 Course-wise Academic Performance and Placement Comparison.

Mean test scores and placement rates by training programme category (n = 100; 25 students per category)

COURSE CATEGORY	NO. OF STUDENTS	MEAN SCORE (%)	TESTPLACEMENT RATE (%)	PERFORMANCE LEVEL
Analytics	25	**78**	**72**	**Strong**
Programming	25	75	68	**Strong**
Cloud	25	71	65	**Moderate**
Testing	25	69	60	**Moderate**
Overall Average	**100**	**73.25**	**66.25**	—

Note. ANOVA confirms that variation across course categories is statistically significant (F = 4.50 > F-critical 2.70, p < 0.05). Analytics students outperform Testing category students by a margin of 9 percentage points in mean test scores.

Hypothesis Testing Results — Summary of Statistical Findings

All tests conducted at $\alpha = 0.05$ significance level

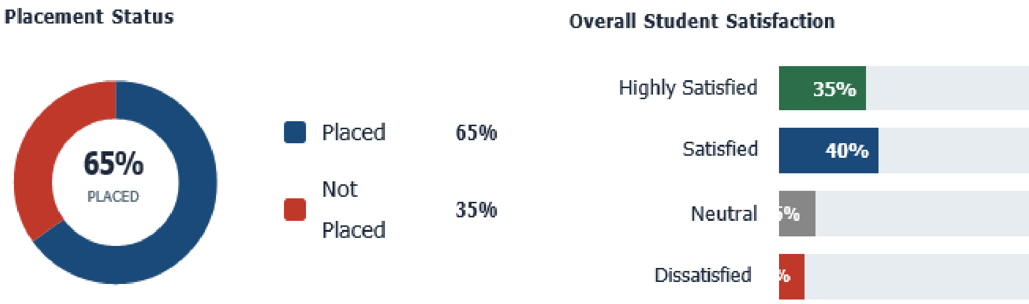
HYPOTHESIS	TEST APPLIED	VARIABLES	CALCULATED VALUE	CRITICAL VALUE	OUTCOME
H_1	Pearson Correlation	Attendance × Test Score	$r = 0.68$	—	✓ **Accepted**
H_2	Chi-Square Test	Academic Performance × Placement	$\chi^2 = 16.66$	3.84 (df = 1)	✓ **Accepted**
H_3	One-Way ANOVA	Test Scores across Courses	$F = 4.50$	2.70 (df 3, 96)	✓ **Accepted**

Note. All three null hypotheses were rejected. The Chi-Square table value of 3.84 corresponds to one degree of freedom at α = 0.05. The ANOVA critical value of approximately 2.70 corresponds to df(3, 96) at the same significance level.

Figure 3

Student Placement Status and Overall Satisfaction Levels

Placement outcomes (left) and satisfaction ratings (right) among surveyed students (n = 100)



Note. A combined 75% of students reported satisfaction with their training experience, which aligns with the 65% placement rate achieved during the study period.

Table 3 One-Way ANOVA Summary — Test Score Variation Across Course Categories

H_0: No significant difference in mean scores across course categories. $\alpha = 0.05$, df(between) = 3, df(within) = 96 **Placement Status**

SOURCE OF VARIATION	SUM OF SQUARES (SS)	DEGREES OF FREEDOM (DF)	MEAN SQUARE MS)	F-(RATIO	DECISION
Between Groups	540	3	180.00	**4.50**	**Reject H_0**
Within Groups (Error)	3,840	96	40.00	—	—
Total	**4,380**	**99**	—	—	—

Note. F-calculated (4.50) exceeds F-critical (≈ 2.70) at α = 0.05. The null hypothesis is rejected, confirming that meaningful score differences exist across course categories. Post-hoc comparison identifies Analytics (M = 78) versus Testing (M = 69) as the most divergent pair.

4. KEY FINDINGS

Several findings stand out from the analysis. First, demand for data-oriented programmes is clearly reflected in enrolment patterns — Data Analytics, Python, and Power BI together account for 85% of students, pointing to where the current job market is headed. Second, most students demonstrate reasonable academic discipline: 65% maintain attendance above 75%, and the majority score in the 71–85% test range. Third, the correlation analysis ($r = 0.68$) confirms that attendance contributes meaningfully to performance, though it is not the only factor at play.

The Chi-Square result ($\chi^2 = 16.66$, $p < 0.05$) is perhaps the most practically significant finding: it confirms that academic performance is not just correlated with placement — it is statistically linked to it. Students scoring highly are substantially more likely to be placed. This gives institutions a clear lever: improving academic outcomes is also a placement strategy. Finally, ANOVA shows that Analytics students outperform those in Testing by nearly 9 percentage points, suggesting that programme design and the nature of content may influence not just knowledge acquisition but employment readiness.

Low attendance (35%) and insufficient practice (30%) were the two most commonly cited reasons for underperformance, which is actionable information for trainers and administrators.

5. RECOMMENDATIONS

Based on the findings, this study offers the following recommendations for Trishana Technologies and similar training institutions:

Implement digital attendance monitoring. Given the strong link between attendance and performance, a real-time tracking system would allow trainers to flag students at risk before their scores decline, rather than after.

Increase hands-on, practical content. Students identified lack of practice as the second-largest reason for poor performance. Incorporating more live projects, peer exercises, and case-study-based assessments could directly address this gap.

Introduce structured remedial support. Only 65% of students confirmed receiving remedial classes. Formalising this as a standard offering — with clear eligibility criteria based on test score thresholds — would make support more consistent and equitable.

Strengthen placement preparation activities. Mock interviews, aptitude workshops, and industry interaction should be scheduled regularly rather than treated as one-off events, particularly in the months leading up to active recruitment seasons.

Use Power BI dashboards for ongoing monitoring. Eighty-five percent of students believe analytics tracking is useful. Making performance dashboards accessible to both trainers and students creates a shared understanding of progress and builds accountability.

6. CONCLUSION

This study set out to demonstrate that Business Analytics is not just a subject taught in training classrooms — it is a tool that those same classrooms can use to improve what they do. By applying relatively simple statistical techniques to data that Trishana Technologies already collects, the study surfaces clear and actionable patterns: attendance matters for scores, scores matter for placement, and course design matters for outcomes across the board.

The findings do not resolve every challenge facing IT training institutions, and the limitations of a single-site, 100-person study are acknowledged. But they do provide a practical starting point — a framework that institutions can adopt, refine with their own data, and scale over time. When training institutions make decisions based on evidence rather than intuition, students are more likely to succeed, and that is the purpose of this work.

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