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Research Article

# Predicting Licensure Exam Success: A Mathematical Model for Engineering Students at Nueva Vizcaya State University

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**ABSTRACT**

This research examines the correlation between the academic achievement and licensing test outcomes of electrical engineering (EE) and mechanical engineering (ME) graduates from Nueva Vizcaya State University (NVSU) in the Philippines over a five-year span. This study used a quantitative research technique involving a descriptive-correlational approach, trend analysis, and path analysis to examine data from graduates who underwent licensing examinations for the first time during this period. The results showed a significant correlation between academic achievement in certain subject areas and success in licensing exams for graduates in electrical engineering (EE) and mechanical engineering (ME). The equation for calculating the Board Rating for EE graduates is: Board Rating = 125.430 - (17.581 * ESAS) + (12.208 * MATH) - (13.011 * EE). The logistic regression equation is P = 1/(1 + e^(-(24.99651 + (5.812567 * MATH) - (3.72252 * ESAS) - (10.1496 * EE)), while the discriminant equation is D = -13.577 - (3.943 * MATH) + (2.723 * ESAS) + (6.134 * EE). The formula for calculating the Board Rating for ME graduates is as follows: Board Rating = 121.578 - (10.387 * IPPE) - (5.980 * MATHA) - (0.721 * MACHINE). The logistic regression equation is P = 1/(1 + e^(-(16.65924 - 1.99212 * MATHA - 5.60296 * IPPE + 2.329647 * MACHINE)), while the discriminant equation is D = -11.573 + 5.823 * IPPE + 0.931 * MATHA - 2.592 * MACHINE. Path analysis clarified both the direct and indirect impacts of academic success on the licensing test results. Mathematical models provide useful insights for engineering education, highlighting the need for focused curriculum creation and student assistance in engineering education programs. This research emphasizes the importance of certain academic accomplishments as predictors of success in professional licensing exams.

***Keywords****: Academic Performance, Licensure Examination, Electrical Engineering, Mechanical Engineering, Predictive Modeling, Engineering Education*

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## Introduction

Engineering is a fundamental profession in the development of technology and growth of the economy. Engineering education is the bedrock of the preparation of graduates in this profession and will impact society. For instance, the licensing exams that a professional has to pass are a critical success measure within engineering education to guarantee that professionals have the required levels of competency. This study reports the results of licensure examinations of graduates in electrical engineering (EE) and mechanical engineering (ME) at Nueva Vizcaya State University (NVSU) in the Philippines. It aims to investigate the relationship between the academic performance of students in specific subject clusters and professional licensing examinations so that invaluable input is provided to the discipline of engineering education. The relative importance of licensing examinations in the discipline of engineering is not a subject in question. These examinations are standard, and these exams are estimated with the level of the graduates' preparation to enter the professional sphere. High rates of passing them speak about the quality of education in an institution and the level of graduates' preparedness. Accordingly, educationists and policymakers need to know the parameters that influence better exam performance for the effectiveness of engineering education programs.

This should, therefore, prove to be the unavoidable step in the process of quality assurance of engineering programs through the processes of accreditation and the accountability for the readiness of graduates through licensing exams, as has been observed in previous research. This research examined the various factors that affect the performance of engineering graduates on licensing exams, including academic achievements, curriculum structure, teaching methods, and personal characteristics of the students. The literature is seriously deficient in the area of predictive models that might be used to define areas of improvement at university that help improve future workers' professional lives.

Bridging this gap, this research attempts to develop mathematical models that predict the success of graduates of EE and ME to pass the licensure examination based on their school performance in certain subject clusters. This research delves into the characteristics that affect the level of performance during licensing examinations among NVSU graduates over the last five-year period. The emphasis on clusters of subjects within the EE and ME curricula is on how different areas of academic achievement relate to the success of exams.

The significance of this study lies in its potential to inform curriculum development and student support strategies. The identification of these clusters can provide pointers to educators about areas to focus on with either unique teaching mechanisms or with enhanced resources or support. In addition, the findings from this research provide the students with direction on the areas to focus their study efforts so that they can increase their chances of passing the licensing exams.

The practical implications of this research are that it adds to the academic discussion on engineering education in that it provides empirical support for the link between academic achievement and licensing exam performance. This will greatly contribute to the body of knowledge pertaining to the factors affecting the success rate of engineering graduates in their professional licensure examinations and will help in the further improvement of engineering education programs.

In this respect, this study will fill a gap in the literature by developing predictive models for the licensure exam success of graduates of EE and ME considering their academic performance in some clusters of subjects. It was developed to provide insightful information for educators, policymakers, and students in the field of engineering education. The results of this study could pave the way for very insightful developments in the curriculum, teaching strategies, and student support services for producing highly competent engineering professionals.

## Methods

### Research Design

This study utilizes a quantitative research strategy, which entails a methodical examination of events via the collection of measurable data and the use of mathematical and statistical techniques. Quantitative research involves collecting data from a preexisting population via the use of sampling methods. Data gathering is performed systematically on extensive samples that accurately reflect the total population. The results obtained by analyzing and interpreting these data are impartial, statistical, and rational.

**Research Method**

This study utilizes a descriptive-correlational approach together with trend analysis. Descriptive research involves observing and describing a subject's performance without controlling it, making it a suitable method for researching certain topics. Correlational research analyses the degree of connection between variables within a group, illustrating these links using methods such as cross-tabulation and correlations. Correlational research aims to explore connections between variables and, if a correlation is found, establish a regression equation to enable predictions. Trend analysis is a statistical method that examines potential linear and nonlinear connections between two quantitative variables. It is often used when data have been gathered over time or across many levels of a variable.

**Samples of the Study**

This study's research sample comprised graduates from the Bachelor of Science in Electrical Engineering (BSEE) and Bachelor of Science in Mechanical Engineering (BSME) programs at Nueva Vizcaya State University over the past five years. The study included 60 electrical engineering graduates and 186 mechanical engineering graduates, as presented in Table 1. Slovin’s formula was utilized for sample size determination, resulting in a final sample size of 54 for electrical engineering and 127 for mechanical engineering, with random sampling applied to ensure data representativeness.

*Table 1. Distribution of Samples by Year of Examination in the Licensure Examination*

| Year | BSEE | | BSME | |
|---|---|---|---|---|
| | No. of Takers | No. of Samples | No. of Takers | No. of Samples |
| **Most Recent Year** | 22 | 19 | 42 | 29 |
| **Previous Year** | 10 | 8 | 39 | 27 |
| **Three Years Ago** | 11 | 10 | 36 | 24 |
| **Four Years Ago** | 9 | 7 | 38 | 26 |
| **Five Years Ago** | 11 | 10 | 31 | 21 |
| **Total** | **60** | **54** | **186** | **127** |

The study also examined demographic factors, including gender and socio-economic background, to enhance the understanding of the results beyond academic performance. In mechanical engineering, 85% of graduates were male and 15% were female; in electrical engineering, 90% of graduates were male and 10% were female. The assessment of socio-economic status (SES) revealed that 30% of respondents were from low-income families (earning below PHP 20,000 per month), 50% from middle-income families (earning between PHP 20,000 and PHP 50,000 per month), and 20% from high-income families (earning above PHP 50,000 per month).

The demographic characteristics, while secondary to the academic data, may offer context for interpreting the study's findings. Socio-economic status may influence a student's access to resources, including study materials and review programs, which could subsequently impact their performance in licensure exams. Gender dynamics in engineering programs, characterized by male student predominance, may influence confidence levels and academic experiences, subsequently impacting exam outcomes. The study seeks to provide a more comprehensive understanding of the factors influencing licensure exam success.

**Research instrument**

The main tools used in this study are academic records and board ratings. Academic records reflect graduates' academic accomplishment, whereas board scores evaluate their licensing success. The institution utilizes a point system to provide a qualitative representation of academic accomplishment.

**Statistical tools**

This study employed various statistical tools to analyze the data and develop predictive models. Descriptive research methods were utilized, emphasizing correlation analysis to examine the relationships among variables. The hypotheses were evaluated at a significance level of 0.05, confirming the statistical significance of the results.

Various statistical methods were utilized to evaluate academic and licensure examination performance. The mean, standard deviation, frequency, and percentage were employed to summarize the overall data, offering insights into average performance and the distribution of scores across various groups. The Pearson Moment Product Correlation was employed to assess the strength of the relationships between academic performance in specific subject areas and success in licensure exams. Linear regression was utilized to model these relationships and evaluate the extent to which academic performance predicts success in licensure examinations.

Furthermore, two advanced statistical methods, logistic regression and discriminant analysis, were employed to construct predictive models. Logistic regression was utilized to estimate the likelihood of a student passing or failing the licensure exam, contingent upon their academic performance. Discriminant analysis classified students into pass and fail groups based on their academic records. Both models enhance the understanding of the impact of various academic factors on licensure exam outcomes and offer valuable tools for forecasting future performance.

## Results and Discussion

### Levels of Academic Performance of Electrical Engineering Graduates

Table 2. Summary of the Mean and Standard Deviation of the Academic Performance of Electrical Engineering Graduates

| Subject Cluster | Mean | Std | Qualitative Description |
|---|---|---|---|
| **MATH** | 2.727 | 0.363 | Satisfactory |
| **ESAS** | 2.705 | 0.316 | Satisfactory |
| **EE** | 2.765 | 0.236 | Satisfactory |
| **GWA** | **2.739** | **0.268** | **Satisfactory** |

Table 2 presents an analysis of the academic performance of Nueva Vizcaya State University (NVSU) electrical engineering graduates during the most recent five years. It shows a constant level of accomplishment across several subject areas. The mean scores of 2.727, 2.705, and 2.765 for Mathematics (MATH), Engineering Sciences and Allied courses (ESAS), and Professional Electrical Engineering (EE) courses, respectively, are all within the "satisfactory" level. This conclusion is further supported by the General Weighted Average (GWA) of 2.739, which shows that the graduates' academic performance was generally adequate.

The majority of grade cluster closely around the mean, indicating a consistent level of performance across the students, as seen by the tiny standard deviation values throughout the topic groups. This consistency suggests that the NVSU Electrical Engineering department's education and student understanding are of a consistent caliber.

These results are consistent with Laguador's (2013) study, which highlighted that since professional engineering specialties have different levels of complexity, different learning methodologies are necessary. Despite the difficulties presented by specialized disciplines, the graduates' good performance in these areas indicates a firm understanding of the fundamental concepts.

In conclusion, NVSU graduates in Electrical Engineering have continuously performed academically beyond expectations in major subject areas for the last five years. This degree of performance indicates how well the curriculum prepared students for the challenges of the engineering field. It also emphasizes how crucial it is to keep refining curriculum and making adjustments to teaching strategies in order to meet the difficulties that come with teaching professional engineering education.

**Levels of Academic Performance of the Mechanical Engineering Graduates**

*Table 3. Summary of the Mean and Standard Deviation of the Academic Performance of Graduates in Mechanical Engineering*

| Subject Cluster | Mean | Std | Qualitative Description |
|---|---|---|---|
| **MATH** | 2.667 | 0.278 | Satisfactory |
| **IPPE** | 2.700 | 0.223 | Satisfactory |
| **MACHINE** | 2.559 | 0.219 | Satisfactory |
| **GWA** | **2.658** | **0.231** | **Satisfactory** |

Table 3 summarizes the academic achievement of Nueva Vizcaya State University Mechanical Engineering graduates during a five-year period. The study includes the General Weighted Average (GWA) for the three main topic clusters: Machine Design, Material, and Shop Practice (MACHINE), Industrial and Power Plant Engineering (IPPE), and Mathematics and Basic Engineering Sciences (MATH).

The graduates performed well in every subject area, according to the statistics; their mean scores in math were 2.667, in IPPE they were 2.700, and in machine they were 2.559. For this group, the General Weighted Average (GWA) is 2.658. With the lowest mean score, the MACHINE cluster seems to have been considerably more difficult for pupils to master than IPPE and MATH. All clusters' standard deviations are close to 0.2, which suggests that graduates' performance levels are generally the same.

These findings concur with those of Dotong (2019), who found that engineering students often had an average academic rank of around 2.836. Even though grades are regarded as an indicator of academic performance, engineering students often feel that their marks don't accurately represent their aptitude for reasoning or likelihood of success in the profession. This viewpoint emphasizes how complicated engineering education is and how crucial it is to strike a balance between academic knowledge and practical skills and problem-solving abilities.

**Performance Levels of the Electrical Engineering Graduates According to the Licensure Examination**

The performance data for Nueva Vizcaya State University electrical engineering graduates in their five-year licensing tests is shown in Table 4. Together with the overall board grade, the statistics are arranged into three topic clusters: Professional Electrical Engineering (EE), Engineering Sciences and Allied Subjects (ESAS), and Mathematics (MATH).

There was a 100% pass rate in the Mathematics cluster, with all 54 examinees passing. The average score was 77.03, with scores ranging from 63 to 87. Strong mathematical abilities, which are essential for success in electrical engineering, are indicated by this high accomplishment level. Additionally, the ESAS cluster demonstrated a strong grasp of fundamental engineering concepts, with an average score of 73.648 and a 100% pass rate ranging from 53 to 86. Nonetheless, the somewhat reduced mean score in contrast to Mathematics implies that more attention could be needed in this domain.

*Table 4. Frequency, Mean and Percentage Distribution of the Licensure Examination Performance of the Electrical Engineering Graduates*

| Subject Cluster | Passed | | Failed | | Max. | Min | Mean |
|---|---|---|---|---|---|---|---|
| | f | % | F | % | | | |
| **MATH** | 54 | 100 | 0 | 0 | 87 | 63 | 77.03 |
| **ESAS** | 54 | 100 | 0 | 0 | 86 | 53 | 73.648 |
| **EE** | 53 | 98.148 | 1 | 1.852 | 84 | 45 | 75.167 |
| **Board Rating** | 46 | 85.185 | 8 | 14.815 | 84.8 | 52.5 | 75.179 |

With one examinee failing, the Professional Electrical Engineering cluster has a pass rating of 98.148%. The average score was 75.167, with scores ranging from 45 to 84. The lower minimum score and the existence of a failed examinee indicate particular difficulties in professional areas that may need specialized assistance or curriculum modifications.

With 46 out of 54 examinees passing overall, the board rating's pass rate was 85.185%. The board rating ranged from 52.5 to 84.8, with an average of 75.179. Even while many graduates were well-prepared for the licensing test, a sizeable percentage failed it, highlighting the need of ongoing program review and development in order to provide sufficient assistance for every student.

The information indicates that although the curriculum does a good job of imparting to students the fundamentals of mathematics and engineering sciences, improvements are required in the areas of professional electrical engineering and overall licensing test readiness. By addressing these areas in curriculum creation, instructional strategies, and focused support services, pass rates may be raised and it could be guaranteed that all graduates have the skills required for their line of work. The program must be regularly monitored and evaluated in order to make necessary adjustments to the curriculum, instructional techniques, and student support services. According to research by Mohammad (2017) and Tamayo (2014), engineering examinees performed well in mathematics, but the Engineering Sciences and Allied Subjects cluster presented more difficulties. This suggests that strengthening curriculum areas is crucial to improving performance on licensing exams.

**Performance Levels of the Mechanical Engineering Graduates on the Licensure Examination**

Table 5 displays the performance statistics of mechanical engineering graduates from Nueva Vizcaya State University in their licensing exams over five years. The data is categorized into three topic clusters: Mathematics, Basic Engineering Sciences and Engineering Economics (MATH); Industrial and Power Plant Engineering (IPPE); and Machine Design, Material, and Shop Practice (MACHINE), in addition to the overall board rating.

Within the MATH cluster, 99.213% of the 127 examinees passed, totaling 126 successful candidates and one failure. The scores varied from 48 to 93, with an average grade of 76.411. The IPPE cluster had a pass rate of 94.488%, with 120 out of 127 examinees passing, and a failure rate of 5.512%, with seven examinees failing. The highest score achieved was 93, the lowest was 28, and the average grade was 75.339. Within the MACHINE cluster, 99.213% of the 127 examinees passed, totaling 126 successful candidates and one failure. The maximum score was 93, the lowest score was 48, and the mean rating was 75.394.

*Table 5. Performance of Mechanical Engineering Graduates in Licensure Examination by Subject Cluster*

| Subject Cluster | Passed | | Failed | | Max. | Min | Mean |
|---|---|---|---|---|---|---|---|
| | f | % | f | % | | | |
| **MATH** | 126 | 99.213 | 1 | 0.787 | 93 | 48 | 76.441 |
| **IPPE** | 120 | 94.488 | 7 | 5.512 | 93 | 28 | 75.339 |
| **MACHINE** | 126 | 99.213 | 1 | 0.787 | 93 | 49 | 75.394 |
| **Board Rating** | 108 | 85.039 | 19 | 14.961 | 87.45 | 43.1 | 75.74 |

The data shows that the MATH cluster had the greatest average rating, whilst the IPPE cluster had the lowest average rating and the most frequent failures. The results align with Dotong's (2019) research, indicating that participants had superior performance in the MATH cluster. Dizon (2017) discovered that the IPPE cluster had the lowest ranking compared to the other two topic clusters.

Out of 127 mechanical engineering examinees, 108 passed (85.039%) and 19 failed (14.961%). The highest rating recorded was 87.45, the lowest was 43.1, and the average board rating was 75.74. To pass the Mechanical Engineer Licensure Examination, a candidate must get a minimum average score of seventy percent (70%) across all subject clusters, with no individual topic grade falling below fifty percent (50%).

**Relationship Between Electrical Engineering Graduates' Academic Performance and their Professional Licensure Examination Performance**

*Table 6. Interrelationship among Key Subject Academic Achievement and Electrical Engineering Graduate Board Exam Success*

| Cluster | MATH | | ESAS | | EE | | Rating | |
|---|---|---|---|---|---|---|---|---|
| | r | p value | r | p value | r | p value | r | p value |
| **MATH** | -0.517 | 0.000 | -0.261 | 0.057 | -0.398 | 0.003 | -0.422 | 0.001 |
| **ESAS** | -0.609 | 0.000 | -0.489 | 0.000 | -0.540 | 0.000 | -0.599 | 0.000 |
| **EE** | -0.607 | 0.000 | -0.348 | 0.010 | -0.542 | 0.000 | -0.549 | 0.000 |
| **GWA** | **-0.627** | **0.000** | **-0.399** | **0.003** | **-0.540** | **0.000** | **-0.571** | **0.000** |

Table 6 displays the interrelationship among key subject academic achievement and electrical engineering graduate board exam success in Mathematics (MATH), Engineering Sciences and Allied Subjects (ESAS), and Professional Electrical Engineering (EE) over a five-year period.

The Pearson Product Moment Correlation was used to evaluate the association between academic achievement and licensing test results. The table displays notable relationships between academic achievement outcomes and licensing examination scores, as shown by the p-values. All subject categories have a significance level below 0.005, except for the link between MATH academic achievement and ESAS academic success, which has a p-value of 0.057.

The computed correlation coefficients (r-values) for the subjects MATH, ESAS, and EE are -0.422, -0.599, and -0.549, respectively. These results indicate a substantial negative association between academic accomplishment and performance on licensing tests. A negative r-value indicates a negative correlation between grades and academic performance, as defined by the university's quality point index. Enhanced performance in academics is associated with better results in board exams, leading to the rejection of the null hypothesis. There exists a robust association between the academic accomplishments of individuals who have completed a degree in electrical engineering and their level of success in licensure examinations.

Tamayo (2014) demonstrated that academic achievement may forecast the results of the board test for electrical engineers. The null hypothesis stating that there is no significant association between the academic performance of electrical engineering graduates and their success on professional license tests is rejected.

**Relationship between the Level of Academic Performance of Mechanical Engineering Graduates and their Professional Licensure Examination Performance**

*Table 7. Examining the Relationship Between Academic Performance in Key Subjects and Performance in Licensure Examinations Among Graduates of Mechanical Engineering*

| Cluster | MATH | | IPPE | | MACHINE | | Rating | |
|---|---|---|---|---|---|---|---|---|
| | R | p value | r | p value | r | p value | r | p value |
| **MATH** | -0.412 | 0.000 | -0.370 | 0.000 | -0.352 | 0.000 | -0.500 | 0.000 |
| **IPPE** | -0.301 | 0.001 | -0.399 | 0.000 | -0.504 | 0.000 | -0.524 | 0.000 |
| **MACHINE** | -0.278 | 0.002 | -0.355 | 0.000 | -0.468 | 0.000 | -0.477 | 0.000 |
| **GWA** | -0.383 | 0.000 | -0.404 | 0.000 | -0.448 | 0.000 | -0.541 | 0.000 |

Table 7 displays the examining the relationship between academic performance in key subjects and performance in licensure examinations among graduates of mechanical engineering across a five-year span. It focuses on three subject clusters: Mathematics, and Basic Engineering Sciences, Engineering Economics (MATH); Industrial and Power Plant Engineering (IPPE); and Machine Design, Material, and Shop Practice (MACHINE), as well as the overall board rating.

The table demonstrates a significant negative correlation between academic success and licensing examination scores, shown by p-values below 0.05. The board rating and the MATH cluster have a substantial negative association, as shown by the correlation coefficient (r-value) of -0.500. The IPPE and MACHINE clusters have r-values of -0.524 and -0.477, respectively, in relation to the board rating, showing significant negative correlations.

A negative r-value indicates an inverse relationship between grades and board exam outcomes, where lower marks are associated with greater success on the tests according to the university's quality point index. Higher academic achievement in these topic groups is linked to improved performance on the licensing test.

The strong connections found in all three topic groups indicate that academic achievement in these areas may predict success in the licensing test for Mechanical Engineering graduates. These results are consistent with Dotong's (2019) discovery that test-takers excelled in the MATH cluster, and Dizon's (2017) observation that the IPPE cluster had the lowest grade among the three topic clusters.

To increase success rates in the licensing test, educational programs should concentrate on enhancing students' performance in these critical subject areas, as shown by the findings. This may be accomplished by developing specific curricula, using effective teaching methods, and offering extra assistance to pupils in these key areas.

**Predictive Subject Clusters for Electrical Engineering Licensure Examination Performance**

Table 8 summarizes the predictive model for licensing test performance of electrical engineering graduates, concentrating on three subject clusters: Mathematics (MATH), Engineering Sciences and Allied Subjects (ESAS), and Professional Electrical Engineering (EE).

The model indicates that ESASA is a strong predictor of licensing examination performance, with a p-value of 0.000 and a negative Beta coefficient of -0.834. A substantial negative correlation exists between academic performance in ESAS and examination results, indicating that higher scores in this topic cluster are linked to greater success in the licensing test.

*Table 8. Summary of Regression Analysis: Factors Predicting Performance on Licensure Examination for Electrical Engineering Graduates*

| Model | Unstandardized Coefficients | | Standardized Coefficients | t value | p value | Remarks |
|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | | |
| **(Constant)** | 125.430 | 8.497 | | 14.762 | 0.000 | |
| **MATH** | 12.208 | 4.238 | 0.664 | 2.881 | 0.006 | Significant |
| **ESAS** | -17.581 | 4.391 | -0.834 | -4.003 | 0.000 | Significant |
| **EE** | -13.011 | 4.855 | -0.460 | -2.680 | 0.10 | Not Significant |

MATH is a significant predictor, with a p-value of 0.006 and a positive Beta coefficient of 0.664. This suggests that higher academic achievement in mathematics is directly linked to better test scores.

EE did not have a significant predictive effect on licensing test results in this model, with a p-value of 0.10. The negative Beta coefficient of -0.460 lacks statistical significance, indicating that this association is an unreliable predictor.

These results have significant implications for educational programs in electrical engineering. The high predictive value of ESAS and MATH highlights the relevance of these subjects for students' performance in licensing exams. This is consistent with Maaliw (2021) research, which found that proficiency in mathematics and engineering sciences significantly influences success in licensing exams for Electronics Engineering.

Educational programs should give priority to these crucial topic areas in their curriculum and program evaluations. By improving students' proficiency in ESAS and MATH, programs may better prepare them for professional licensing exams. Additionally, implementing focused study sessions or resources that particularly address the ideas and problem-solving abilities necessary in these areas might further enhance students' test results.

Overall, the results in Table 8, together with the research of Maaliw (2021), underscore the importance of electrical engineering programs focusing on certain topic clusters like ESAS and MATH. By doing this, institutions may better prepare their graduates for success in licensing exams and improve their academic and professional accomplishments.

**Predictive Subject Clusters for Mechanical Engineering Licensure Examination Performance**

*Table 9. Summary of Regression Analysis: Factors Predicting Performance on Licensure Examination for Mechanical Engineering Graduates*

| Model | Unstandardized Coefficients | | Standardized Coefficients | t value | p value | Remarks |
|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | | |
| **(Constant)** | 121.578 | 6.666 | | 18.238 | .000 | |
| **IPPE** | -10.387 | 4.817 | -0.327 | -2.157 | 0.033 | Significant |
| **MATHA** | -5.980 | 3.167 | -0.234 | -1.888 | 0.061 | Not Significant |
| **MACHINE** | -0.721 | 4.903 | -0.022 | -0.147 | 0.883 | Not Significant |

Table 9 summarizes the predictive model for the performance of Mechanical Engineering graduates on the licensing test, concentrating on three topic clusters: Industrial and Power Plant Engineering (IPPE), Mathematics (MATHA), and Machine Design, Material, and Shop Practice (MACHINE).

The analysis shows that IPPE significantly predicts licensing test performance, shown by a p-value of 0.033 and a negative Beta coefficient of -0.327. Higher academic achievement in IPPE is linked to improved results in the licensing exams. This result aligns with Dotong et al.'s (2019) research, which found that academic performance in some subjects might predict the success of Mechanical Engineering graduates in licensing examinations.

MATHA and MACHINE are not found to be significant predictors in this model. The significance of a strong mathematical foundation for engineering students is well recognized. Dotong et al. (2019) discovered that students excelled in mathematics, fundamental engineering and engineering economics, emphasizing the importance of these subjects in the academic training of Mechanical Engineering graduates.

The results in Table 9, together with the analysis of Dotong et al. (2019), emphasize the importance of educational programs in Mechanical Engineering focusing on improving curriculum and teaching methods to boost students' proficiency in Industrial and Power Plant Engineering. By doing this, programs may improve their students' readiness for professional licensing exams and boost their academic and professional development.

**Predictive Mathematical Models for Electrical Engineering Licensure Examination Success**

A mathematical model was developed using the multiple linear regression method to forecast the performance of electrical engineering graduates in professional licensure examinations. The model summary is shown in Table 8. The following is as follows:
The board rating is calculated using the formula:

$$Board\ Rating = 125.430 - (17.581 * ESAS) + (12.208 * MATH) - (13.011 * EE)$$

where MATH represents the weighted average of academic performance in mathematics topics, ESAS represents the average of academic performance in engineering sciences and allied subjects, and EE represents the weighted average of academic performance in electrical engineering subjects. The mathematical model that was created has an average percentage inaccuracy of 4.92% when it is used to simulate the academic evaluations of graduates.
A logistic regression approach was used to verify the outcomes of the mathematical model created using multiple linear regression. Logistic regression is a predictive technique used to determine the likelihood of an examinee passing or failing a board test. The logistic regression model that has been created is shown below:

$$\mathrm{P} = \frac{1}{1 + \mathrm{e}^{-(24.99651+[(5.812567\mathrm{MATH})+(-3.72252\mathrm{ESAS})+(-10.1496\ \mathrm{EE})])}}$$

P represents the probability of an event occurring, whereas e represents the base of the natural logarithm. In the logistic regression model, the data are classified according to the predetermined cutoff value of 0.7. If the simulated data yields a value of 0.7 or higher, it is anticipated that the examinee will pass the test.

*Table 10. A Logistic Regression Analysis Classification Table for Predicting Electrical Engineering Licensure Examination Success*

| | Successful- Observation | Failed-Observation | Total |
|---|---|---|---|
| **Successful-Prediction** | 42 | 3 | 45 |
| **Failed-Prediction** | 4 | 5 | 9 |
| **Total** | 46 | 8 | 54 |
| **Accuracy** | 0.913043 | 0.625 | 0.87037 |
| **Cutoff** | 0.7 | | |

Table 10 shows the logistic regression analysis classification table for predicting electrical engineering licensure examination success when simulated on academic performance. The classification results revealed that out of 45 successful predictions, 42 were successful, and three (3) failed observations. Four (4) were successfully observed for the failed prediction, and five (5) were failed observations. Successful observations had accuracies of 91.30%, and failed observations had accuracies of 62.5%. With a 70% threshold, the designed equation has an overall accuracy of 87.037%. Observation success is determined by whether data predicted to pass the simulation and correctly categorized as passed do so, or whether data predicted to fail the simulation and correctly categorized as failed do. Failed observations are those for which the category predicted by the simulation differs.

Using the discriminant analysis method, a mathematical model was developed to validate the results of the model developed using multiple linear regression and logistic regression. A discriminant analysis was conducted to predict whether an examinee would pass or fail board examinations. The predictor variables were the general weighted average in three subject clusters: mathematics, engineering sciences, allied subjects and professional electrical engineering subjects. The developed discriminant function (D) is shown below:

D= -13.577-(3.943*MATH) +(2.723*ESAS) +(6.134*EE)

The discriminate function classifies data based on the group centroid of -0.234 for "pass" and 1.346 for "fail". Discriminate scores near the computed group centroid are predicted to be classified in that group.

*Table 11. Classification Results of the Discriminant Function for Electrical Engineering*

| | | Rating | Predicted Group Membership .00 | 1.00 | Total |
|---|---|---|---|---|---|
| **Original** | **Count** | .00 | 6 | 2 | 8 |
| | | 1.00 | 12 | 34 | 46 |
| | **%** | .00 | 75.0 | 25.0 | 100.0 |
| | | 1.00 | 26.1 | 73.9 | 100.0 |

Table 11 shows the classification results of the discriminant function when it is used to simulate the academic performance of graduates. The classification results revealed that 40 out of 54 or 71.4% of the original group was correctly classified as "passed", represented by 1, and "failed", represented by 0. Twelve examinees were predicted to fail based on their academic performance. However, they managed to pass the licensure examination. Moreover, two examinees had good academic performance but needed help to pass the licensure examination.

The discriminant function developed has a sensitivity of 73.9% and a specificity of 75%. This is a measure of how accurately the samples were classified. The model has high sensitivity, which means that there are few false-negative results, and high specificity, which implies few false-positive results.

**Predictive Mathematical Models for Mechanical Engineering Licensure Examination Success**

Multiple linear regression was used to construct a mathematical model capable of forecasting the performance of mechanical engineering graduates on their professional licensure examinations, utilizing the model summary from Table 9.

$$Board\ Rating = 121.578 - (10.387 * IPPE) - (5.980 * MATHA) - (0.721 * MACHINE)$$

IPPE, MATHA, and MACHINE are the weighted averages of academic performance in power plant and industrial engineering; mathematics, basic engineering sciences, and engineering economics, and machine design, material and shop practice, respectively. The simulation was used to model the academic performance of graduates, and the results showed that it had an average percentage inaccuracy of 6.3257%.

A mathematical model was constructed by using logistic regression analysis to predict the outcome of the Mechanical Engineering Licensure Examination, namely whether an examinee would pass or fail.

$$P = \frac{1}{1 + e^{-(16.65924 + [(-1.99212 \mathrm{MATHA}) + (-5.60296\ \mathrm{IPPE}) + (2.329647\ \mathrm{MACHINE})])}}$$

P represents the likelihood of 1, and e is the natural logarithm's base. Data are categorized using the logistic regression model using the predetermined threshold of 0.7. It is expected that the examinee will pass if the simulated data result is higher than or equal to 0.7.

*Table 12. A Logistic Regression Analysis Classification Table for Predicting Mechanical Engineering Licensure Examination Success*

| | **Successful-Observation** | **Failed-Observation** | **Total** |
|---|---|---|---|
| **Successful-Prediction** | 100 | 11 | 111 |
| **Failed-Prediction** | 8 | 8 | 16 |
| **Total** | 108 | 19 | 27 |
| **Accuracy** | 0.925926 | 0.421053 | 0.8504 |
| **Cutoff** | 0.7 | | |

The offered table, Table 12, is a classification table derived from a logistic regression study. Its purpose is to forecast the likelihood of success for mechanical engineering graduates in their license exams. The observed results in this table are classified as "Successful-Observation" for those who successfully passed the test and "Failed-Observation" for individuals who did not pass. The logistic regression model categorizes its predictions as either "Successful-Prediction" for expected passes or "Failed-Prediction" for projected fails. The precision of these forecasts is also presented.

The study reveals that out of a total of 111 success forecasts, 100 were properly anticipated as successful, while 11 were erroneously forecasted as failures. Consequently, the accuracy rate for successful predictions stands at a commendable 90.09%. However, of the 16 forecasts of failing, only 8 were properly forecasted as failures, while the other 8 were mistakenly anticipated as successes. As a result, the accuracy rate for failed predictions was reduced to 50%. The model has an overall accuracy rate of 85.04%, accurately predicting 108 out of 127 events.

In this study, a cutoff value of 0.7 is employed. This means that if the anticipated probability of passing the test is 0.7 or higher, it is considered a successful prediction. Otherwise, it is categorized as a failed prediction. The logistic regression model exhibits a high level of proficiency in forecasting the achievement of mechanical engineering graduates in their license exams, specifically in selecting those who would succeed. Nevertheless, there is room for additional enhancement in the model's capacity to properly anticipate failures.

Using discriminant analysis with the general weighted average in Industrial and Power Plant Engineering, Mathematics, Engineering Economics, Basic Engineering Sciences and Machine Design, Material and Shop Practice represented by IPPE, MATHA, and MACHINE A as predictors, the developed model is as follows:

D= -11.573+ (5.823* IPPE) + (0.931*MATHA)-(2.592*MACHINE)

The scores were categorized based on the derived group mean of -0.148 for passing and 0.844 for fail, indicating discrimination.

Table 13 displays the results of a discriminant function analysis used to forecast licensing test scores in the field of mechanical engineering. The table is partitioned into two primary sections: the initial group (Rating) and the projected group affiliation, with categories denoted as ".00" and "1.00."

Within the first cohort labeled ".00," which denotes applicants who did not pass the test, a total of 19 people were observed. Among these, 12 were accurately categorized as failures, accounting for 63.2% of the total, while 7 were inaccurately forecasted as passing, making up 36.8%. This suggests that the discriminant function analysis successfully identified a significant proportion of the people who did not pass the assessment.

*Table 13. Discriminant Function Analysis Classification Results for Predicting Licensure Examination Ratings in Mechanical Engineering*

| | | Rating | Predicted Group Membership | | Total |
|---|---|---|---|---|---|
| | | | **.00** | **1.00** | |
| **Original** | **Count** | .00 | 12 | 7 | 19 |
| | | 1.00 | 32 | 76 | 108 |
| | **%** | .00 | 63.2 | 36.8 | 100.0 |
| | | 1.00 | 29.6 | 70.4 | 100.0 |

Within the first group designated as "1.00," which consists of applicants who successfully completed the test, a total of 108 persons were observed. The methodology accurately rated 76 of these people as successful (70.4%), whereas 32 were inaccurately labeled as failures (29.6%). This demonstrates that the study was more proficient in forecasting the triumph of candidates as opposed to forecasting their failures.

In summary, the discriminant function analysis yielded a satisfactory degree of precision in categorizing people according to their licensing test scores in the field of mechanical engineering. Nevertheless, there is potential for improvement, namely in minimizing the occurrence of false negatives (instances where people are expected to fail but pass) and false positives (instances where individuals are predicted to pass but actually fail).

**Path Model for Mechanical Engineering Program Outcomes**

Figure 2 depicts the theoretical path model for the mechanical engineering curriculum, including both exogenous and endogenous factors. The exogenous variables, or independent variables, consist of MATHA (weighted average academic performance in mathematics subjects), IPEA (average academic performance in power plant and industrial engineering subjects), and MACHINEA (average academic performance in machine design, material, and shop practice subjects). The variables reflect the academic achievement of graduates in certain topic groupings.

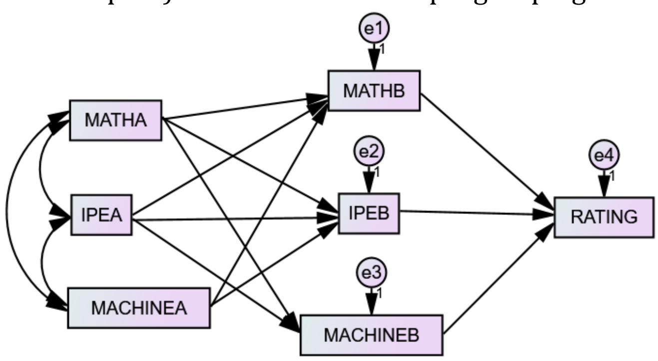


*Figure 2. Hypothetical Path Analysis of Academic Variables Influencing Mechanical Engineering Students' Licensure Examination Ratings*

The endogenous variables, which are the dependent variables, consist of MATHB (mathematics performance in the licensure exam), IPEB (industrial and power plant engineering performance in the licensure exam), MACHINEB (machine design, material, and shop practice performance in the licensure exam), and RATING (overall licensure exam rating). The variables indicate the performance of graduates in the specific subject areas of the licensing test.

The model incorporates disturbance variables (e1, e2, e3) that influence the endogenous variables without being associated with the exogenous variables. Double-headed arrows represent covariances between exogenous variables, whereas single arrows illustrate the effects of exogenous factors on endogenous variables.

The theoretical route model is used to analyze the connections between academic achievement in certain topic groups and performance in the relevant sections of the licensing test. The model seeks to uncover the characteristics that impact the performance of mechanical engineering graduates in their professional licensing exams by analyzing these interactions.

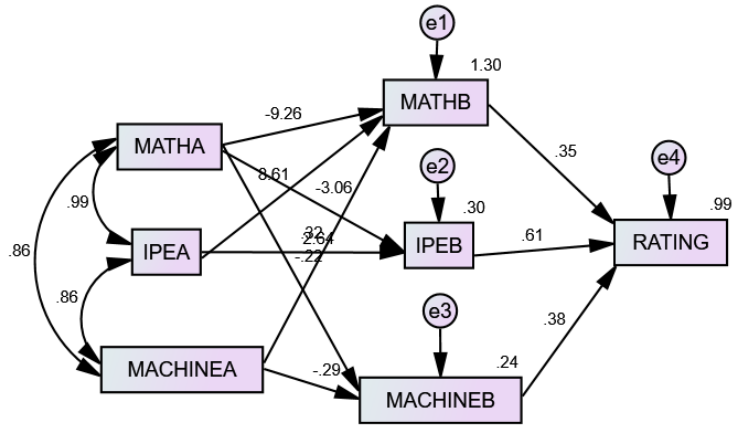


*Figure 3. Path Analysis of Academic Variables Influencing Mechanical Engineering Students' Licensure Examination Ratings*

Figure 3 depicts the path model that explains the connection between the academic performance and licensing test performance of Bachelor of Science in Mechanical Engineering (BSME) graduates. The model recognizes three exogenous variables: MATHA, IPEA, and MACHINEA, which depict the weighted averages of academic achievement in several topic groups. The exogenous factors have a direct impact on the endogenous variables MATHB, IPEB, MACHINEB, and RATING, which represent the performance ratings in the licensing test for each subject cluster and the overall board rating, respectively.

The path analysis indicates that MATHA has a notable direct impact on MATHB, IPEB, and MACHINEB, with the most substantial overall influence on MATHB. Academic proficiency in mathematics is a significant indicator of success in the license test, especially in the mathematics, engineering economics, and fundamental engineering science areas. IPEA has a significant influence on IPEB, suggesting that academic success in industrial and power plant engineering courses may predict achievement in exams within the same category. MACHINEA has a minimal impact on the endogenous factors, indicating that academic achievement in machine design, materials, and shop practice has a reduced influence on licensing test performance.

The path model emphasizes that academic achievement in mathematics and engineering topics is crucial for predicting success in the licensing exams for mechanical engineering graduates. The model offers a structure for comprehending the connection between many aspects of academic success and test results. It may guide the creation of curriculum and assistance for students to improve exam performance.

*Table 14. A Summary of the Model Fit Indices for the Bachelor of Science in Mechanical Engineering Program's Developed Path Model*

| Model | NFI | GFI | AGFI |
|---|---|---|---|
| **Default model** | .990 | .994 | .977 |
| **Saturated model** | 1.000 | 1.000 | 1.000 |
| **Independence model** | .000 | .367 | .155 |

Table 14 presents a concise overview of the model fit indices for the route model built for the Bachelor of Science in Mechanical Engineering curriculum. The table assesses three models: the default model, the saturated model, and the independence model, utilizing three indices: the Normed Fit Index (NFI), the Goodness-of-Fit Index (GFI), and the Adjusted Goodness-of-Fit Index (AGFI).

The default model has exceptional fit indices, with NFI, GFI, and AGFI values of 0.990, 0.994, and 0.977, respectively. The numbers are in close proximity to 1, suggesting that the model fits well with the observed data and explains a significant percentage of the variability in the data, even after considering the number of parameters.

The saturated model, which represents the most intricate model that can be applied to the data, exhibits impeccable fit indices with NFI, GFI, and AGFI values of 1.000. Although this suggests that the saturated model is an ideal match, it is often impractical to use owing to its intricate nature.

In contrast, the independence model, which posits that all variables are not connected to each other, exhibits inadequate fit indices with NFI, GFI, and AGFI values of 0.000, 0.367, and 0.155, respectively. The model's low scores imply poor fit to the data and inadequate explanation of a substantial percentage of the observed data's variability.

Overall, the route model constructed for the Bachelor of Science in Mechanical Engineering program shows a strong alignment with the actual data, as shown by the high fit indices of the default model. The findings indicate that the model accurately depicts the connections between the variables examined in the research.

## Conclusions

The data indicate that the academic performance of electrical engineering and mechanical engineering graduates in their respective courses is good. Their achievement in the licensing exams across several subject areas exceeds the minimum passing score of 70. There is a strong correlation between the academic performance and licensing examination results of electrical and mechanical engineering graduates.

Multiple linear regression showed that the Engineering Sciences and Allied Subjects cluster significantly predicts the licensing test performance of electrical engineering graduates. The board grade of mechanical engineering graduates is significantly influenced by the Industrial and Power Plant Engineering cluster as well as the Mathematics, Engineering Economics, and Basic Engineering Sciences cluster.

The mathematical models used to forecast licensing test results and assess the probability of passing or failing board exams include the following:

Regarding Electrical Engineering:

$$\begin{aligned} Board\ Rating &= 125.430 - 17.581(ESAS) \\ &\quad + 12.208(MATH) \\ &\quad - 13.011(EE) \end{aligned}$$

The logistic regression formula is:

$$P = \frac{1}{\left(1 + e^{\left(-\left(24.99651 + (5.812567 * MATH) - (3.72252 * ESAS) - (10.1496 * EE)\right)\right)}\right)}$$

The discriminant analysis equation:

$$D = -13.577 - (3.943 * MATH) + (2.723 * ESAS) + (6.134 * EE)$$

Regarding Mechanical Engineering:
$Board\ Rating = 121.578 - (10.387 * IPEA) * (5.98 * \ MathA) - (0.721 * MACHINEA)$

The logistic regression formula is:

$$P \ = \frac{1}{(1 \ + \ e^{\left(-\left(16.65924+(-1.99212 \ * \ MathA)-(5.60296 \ * \ IPEA)+(2.329647*MACHINEA)\right)\right)})}$$

The discriminant analysis equation:

$$D \ = \ -11.573 \ + \ (5.823 \ * \ IPEAA) \ + \ (0.931 \ * \ MathA) \ - \ (2.592 \ * \ MACHINE\ A)$$

The models provide substantial insights into the factors that influence the levels of performance on licensing examinations, and they have the potential to be used in order to enhance the level of preparedness and rate of success of following engineering graduates.

**Abbreviations**

| | | |
|---|---|---|
| BSEE | - | Bachelor of Science in Electrical Engineering |
| BSME | - | Bachelor of Science in Mechanical Engineering |
| MATH | - | Mathematics (cluster of subjects which includes Trigonometry, Algebra, Analytic Geometry, Probability and Statistics, Differential Calculus, Complex Numbers, Differential Equations, Integral Calculus, Advanced Engineering Mathematics, Fourier Analysis, Power Series, Matrices, and Laplace Transforms) |
| ESAS | - | Engineering Sciences and Allied Subjects (clusters of subjects which include College Physics, General Chemistry, Engineering Mechanics, Engineering Materials, Fluid Mechanics, Strength of Materials, Computer Fundamentals and Programming, Thermodynamics, Engineering Management, Code of Ethics, Contracts and Specifications, Philippine Electrical Code Parts 1 and 2, Engineering Economics, Engineering Economics, and Electrical Engineering Law) |
| EE | - | Professional Electrical Engineering Subjects (cluster of subjects which include Electronic Theory and Circuits, Electrical Circuits, Power Plant, Electronic Power Equipment, Circuit and Line Protection, Power Transmission and Distribution, Electrical Machines, Instrumentation and Measurement, Principles of Communication, Energy Conversion, Control Systems, Illumination, Electrical Equipment, Devices and Components, Electric Systems, Building Wiring and others. |
| MATHA | - | Mathematics, Engineering Economics and Basic Engineering Sciences (cluster of subjects which includes Plane and Spherical Trigonometry, Analytic Geometry, Engineering Algebra, General Chemistry, Engineering Physics, Differential Calculus, Solid Mensuration, Integral Calculus, Differential Equations, Probability and Statistics, Engineering Economy and Accounting, Differential Equations, Advanced Engineering Mathematics, Mechanics of Deformable Bodies, and ME Laws, Contracts and Ethics) |
| IPPE | - | Industrial and Power Plant Engineering (cluster of subjects which includes Thermodynamics, Safety Engineering, Combustion Engineering, Fluid Mechanics, Instrumentation and Control Engineering, Refrigeration System, Heat Transfer, Vibration Engineering, Fluid Machinery, AC |

| | | |
|---|---|---|
| | | and DC Machinery, Power Plant Engineering, Environmental Engineering, Air-conditioning, and Ventilation Systems, Alternative Energy Source Industrial Processes, and Industrial Plant Engineering) |
| MACHINE | - | Machine Design, Materials, and Shop Practice (cluster of subjects which includes Dynamics of Rigid Bodies, Statics Machine Elements, Shop Theory and Practice, ME Laboratories, Materials Engineering, and Machine Designs) |
| GWA | - | General Weighted Average |
| R | - | Pearson r correlation |
| P | - | Predicted Logistic Regression Model |
| D | - | Predicted Discriminant Function, MA |
| MATHA, IPEA, MACHINEA | - | exogenous variables |
| MATHB, IPEB, MACHINEB | - | endogenous |
| e1, e2, e3 | - | disturbance of endogenous |

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