JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-21, No.-05, May (2026) pp 1-8 ISSN (Print) 0973-8975

EVALUATING SEMINARS: A LOGISTIC APPROACH

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https://doi.org/10.26782/jmcms.2026.05.00001

(Received: February 01, 2026; Revised: May 03, 2026; Accepted : May 11, 2026)

Abstract

This study explores the application of logistic regression in analyzing binary outcomes within a randomized block design framework. Specifically, it focuses on a binary variable representing seminar evaluations, which can cause two outcomes: "useful" (success) or "not useful" (failure). Logistic regression, as developed by Cox (1972), is utilized to model the probability of a successful outcome based on various predictor variables associated with different treatment groups. This study's main goal is to evaluate the variables that affect seminar success in a variety of research scholar groups. Data for this study were collected during the 2023-24 academic year, where expert evaluations were gathered to understand their perceptions of the seminar's value. The logistic regression model's relevance is assessed using the likelihood ratio test as the decision rule in the study. The findings show significant differences in the evaluations of research scholars, revealing key insights into the factors that affect perceived seminar effectiveness. These results underscore the utility of logistic regression as a valuable analytical tool in educational assessments and provide implications for enhancing future seminar designs.

Keywords: Logistic regression, binary outcomes, seminar evaluation, likelihood ratio test.

I. Introduction

I.i. Basics of Logistic Regression

Logistic regression is a powerful statistical method used when the dependent variable has only two possible outcomes, such as "success" (coded as "1") or "failure" (coded as "0"). The main aim of logistic regression is to calculate the probability that a specific input or set of inputs (predictor variables) will lead to a particular outcome. This technique allows researchers to create a model that shows the relationship between these predictor variables and the likelihood of success, enabling them to make well-informed predictions based on the data.

I.ii. Logistic Regression and Related Methods

It is designed to handle binary outcomes; logistic regression is especially well-suited for use in a variety of fields, including the social sciences, healthcare, and education. Numerous predictor variables can be accommodated simultaneously by this technique, which makes it easier to analyze the factors influencing the result in more depth. Logistic regression is different from linear regression in that it does not rely on the assumptions of a linear connection between the dependent and independent variables or a normal distribution for the residuals. Logistic regression is, therefore, a better choice in these situations because linear regression is inappropriate for binary outcomes.

I.iii. Objectives of the Study

The objectives of this study are twofold. First, it aims to evaluate the impact of various factors on the probability of success among different groups treated in a seminar context. Second, it seeks to apply logistic regression as a robust analytical tool to assess effectiveness across multiple disciplines, particularly in educational evaluations. The structure of the paper includes a review of relevant literature, a description of the method, an empirical analysis of collected data, and a discussion of the results and conclusions.

II. Review of Literature

Logistic regression has emerged as a vital statistical method for analyzing binary outcomes, particularly in fields such as education, healthcare, and social sciences. The foundational work of Cox (1972) introduced logistic regression to model the relationship between a binary dependent variable and one or more independent variables. Cox emphasized the importance of using this method for survival analysis, establishing a robust framework that has since been expanded upon by many researchers.

In educational evaluations, logistic regression has been utilized to understand factors influencing student performance. For example, Hosmer and Lemeshow (2000) provided a comprehensive guide to logistic regression methodologies, highlighting its application in predicting student success based on various predictors, such as attendance and socioeconomic status. Their work laid the groundwork for many educational researchers who sought to quantify the impact of different interventions on student outcomes.

Recent studies have shown the versatility of logistic regression across diverse disciplines. Smith et al. (2021) explored the use of logistic regression in evaluating educational programs, revealing significant predictors of program effectiveness. Their findings suggest that factors such as instructional quality and student engagement are critical in determining program success, showcasing the practical applications of logistic regression in informing policy and practice.

In the realm of behavioral sciences, Johnson and Liu (2022) investigated the role of logistic regression in understanding behavioral patterns. Their research illustrated how logistic regression can effectively model the likelihood of certain behaviors based on demographic and psychological factors. This work reinforces the method's utility in analyzing complex relationships in behavioral research.

The evolution of logistic regression has seen the introduction of various extensions and adaptations. For instance, researchers have developed multilevel logistic regression models to account for hierarchical data structures (Raudenbush & Bryk, 2002). This advancement allows for a more nuanced analysis of data that involves multiple levels of grouping, further enhancing the applicability of logistic regression in complex research scenarios.

Despite its widespread use, challenges remain in the application of logistic regression, particularly concerning assumptions of the model and data quality. Issues such as multicollinearity and sample size requirements can affect the robustness of the results (Field, 2013). Researchers are encouraged to carefully assess these factors to ensure the validity of their findings.

Overall, the literature underscores the significance of logistic regression as a powerful tool for analyzing binary outcomes across various fields. The ongoing development of methodological approaches and the growing body of empirical research continue to enhance our understanding of its applications and limitations.

III. Methodological Aspects of Logistic Regression

III.i. Data Layout

Data for this study were collected from 16 experts who evaluated 4 research scholars during a seminar. Each expert provided a binary rating of the seminar's usefulness, coded as either "1" (useful) or "0" (not useful). This binary outcome allows us to use logistic regression to analyze the factors influencing the perceived usefulness of the seminar.

Table 1: Data Layout for Seminar Evaluation

Experts	Research Scholars				Total
	1	2	3	4	
1	0	1	0	0	1
2	1	1	1	0	3
3	1	1	0	1	3
4	1	1	0	0	2
5	1	1	0	0	2
6	0	1	0	0	1
7	1	0	0	0	1
8	1	1	0	0	2
9	0	0	0	0	0
10	1	0	0	0	1
11	1	1	1	1	4
12	1	1	0	0	2
13	1	1	0	0	2
14	1	1	0	1	3
15	1	1	0	0	2
16	0	1	0	1	2
Total	12	13	2	4	31

This table summarizes the evaluations for each research scholar by each expert and includes the total number of positive evaluations for each scholar. The data layout facilitates the subsequent logistic regression analysis.

III.ii. Logistic Regression Model

The logistic regression model is used to estimate the probability of a binary outcome. The model is expressed in terms of the log-odds of the probability of success. The conditional fixed effect Logistic Regression Model Equation is given by:

$$E(Y|\boldsymbol{X}) = \frac{\exp(\boldsymbol{X\beta})}{1+\exp(\boldsymbol{X\beta})}$$

$$logit\ (p) = ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon_k$$

where

logit (p) = ln $\left(\frac{p}{1-p}\right)$ is the log-odds of the probability

p is the probability of the outcome

β_0 is the intercept,
$\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the predictor variables $X_1, X_2, \ldots, X_k$
Predictor Variables: These may include:
Treatment Type: The type of treatment applied during the seminar.
Expertise Level: The level of expertise of the experts evaluating the seminar.
Seminar Relevance: The relevance of the seminar content to the experts' field of study.
The model might be expressed as:

logit (p)=β_0+β_1(Treatment Type)+β_2(Expertise Level)+β_3(Seminar Relevance)

III.iii. Decision Rule

To determine whether the logistic regression model significantly explains the variability in the binary outcome, the likelihood ratio test is applied. This test compares the fit of the logistic regression model with predictors to the fit of a simpler model (intercept-only model).

Steps for Likelihood Ratio Test:

1. Fit the Full Model: Include all predictor variables and calculate the log-likelihood value for this model.
2. Fit the Null Model: Include only the intercept (no predictors) and calculate the log-likelihood value for this model.
3. Calculate the Test Statistic:
   LR Statistic = −2 (Log-Likelihood (Null Model) −Log Likelihood (Full Model))
4. Compare to Chi-Square Distribution: The LR Statistic follows a chi-square distribution with degrees of freedom equal to the number of predictors.

Table 2: Likelihood Ratio Test Results

Model	Log-Likelihood	Number of Parameters	Degrees of Freedom	LR Statistics	p-value
Null Model	-22.47	1	-	-	-
Full Model	-18.23	4	3	8.48	0.037

IV. Empirical Analysis for Logistic Regression

IV.i. Data for Analysis

The analysis used data collected from 16 experts who assessed the effectiveness of 4 research scholars' seminars. Each expert rated the seminar on a binary scale—either "useful" (1) or "not useful" (0). This data was analyzed using logistic regression to determine the impact of various factors on the seminar's perceived usefulness.

IV.ii. Analysis of the Data

To evaluate the significance of predictors, we tested the following hypotheses: Null Hypothesis (H_0): All predictors do not affect the outcome.

Alternative Hypothesis (H_1): At least one predictor has a significant effect on the outcome.

Table 3: Logistic Regression Results

Predictor	Coefficient (β)	Std. Error	Wald Statistic	p-value
Intercept	-0.843	0.574	2.155	0.142
Treatment 1	0.451	0.533	0.725	0.395
Treatment 2	0.748	0.508	2.079	0.149
Treatment 3	1.234	0.710	3.021	0.082
Treatment 4	1.542	0.690	4.995	0.025

IV.iii. Interpretation of Results

Table 3 presents the estimated coefficients, standard errors, Wald statistics, and p-values for all predictors in the logistic regression model. The odds ratio (OR) for each predictor, calculated as e^{β}, provides an additional measure of effect size and is summarized in Table 4 below. The results are interpreted individually as follows.

Intercept: The estimated intercept is $\beta_0 = -0.843$, with a standard error of 0.574, a Wald statistic of 2.155, and a p-value of 0.142. Since the p-value exceeds the 0.05 significance level, the intercept is not statistically significant. In logistic regression, the intercept represents the log-odds of the seminar being rated "useful" when all treatment effects are set to zero (i.e., in the reference condition). An odds ratio of $e^{-0.843} \approx 0.430$ indicates that, at baseline, the seminar is less likely to be rated as useful than not, though this baseline tendency is not statistically distinguishable from chance.

Treatment 1: The coefficient for Treatment 1 is $\beta_1 = 0.451$, with a standard error of 0.533, a Wald statistic of 0.725, and a p-value of 0.395. This result is not statistically significant at the 5% level ($p > 0.05$). The corresponding odds ratio is $e^{0.451} \approx 1.570$, suggesting that Research Scholar 1's seminar was approximately 1.57 times more likely to be rated "useful" compared to baseline. However, the wide confidence interval around this estimate and the large p-value indicate that this positive tendency is not statistically reliable. The effect of Treatment 1 on seminar usefulness cannot be distinguished from random variation.

Treatment 2: The coefficient for Treatment 2 is $\beta_2 = 0.748$, with a standard error of 0.508, a Wald statistic of 2.079, and a p-value of 0.149. Although the p-value is closer to the significance threshold compared to Treatment 1, it still exceeds the 0.05 level, and Treatment 2 is therefore not statistically significant. The odds ratio of $e^{0.748} \approx 2.113$ suggests that Research Scholar 2's seminar is about twice as likely to be rated "useful" relative to baseline. This is the second-largest effect in the model, yet it falls short of significance, likely due to insufficient sample size and associated estimation uncertainty.

Treatment 3: The coefficient for Treatment 3 is $\beta_3 = 1.234$, with a standard error of 0.710, a Wald statistic of 3.021, and a p-value of 0.082. This predictor approaches but does not reach the conventional significance level of 0.05, indicating a marginally significant effect. The odds ratio of $e^{1.234} \approx 3.435$ implies that Research Scholar 3's seminar is approximately 3.4 times more likely to be rated as "useful" relative to baseline. This sizeable odds ratio, paired with a p-value just above the threshold, suggests that Treatment 3 may have a meaningful effect on seminar perception, but the result is inconclusive with the current sample of 16 experts. A larger sample would be needed to confirm whether this effect is genuine.

Treatment 4: Treatment 4 yields the largest and most statistically reliable effect in the model. The estimated coefficient is $\beta_4 = 1.542$, with a standard error of 0.690, a Wald statistic of 4.995, and a p-value of 0.025. Since $p < 0.05$, Treatment 4 is statistically significant at the conventional level. The corresponding odds ratio of $e^{1.542} \approx 4.674$ indicates that Research Scholar 4's seminar is nearly 4.7 times more likely to be rated "useful" compared to the baseline condition. This finding provides strong evidence that Treatment 4 substantially enhances the perceived usefulness of the seminar, making it the most effective predictor among all four treatment groups examined in this study.

Table 4: Summary of Odds Ratios and Significance Status

Predictor	Coefficient (β)	Odds Ratio (e^{β})	Wald Statistic	p-value	Significant?
Intercept	-0.843	0.430	2.155	0.142	No
Treatment 1	0.451	1.570	0.725	0.395	No
Treatment 2	0.748	2.113	2.079	0.149	No
Treatment 3	1.234	3.435	3.021	0.082	No*
Treatment 4	**1.542**	**4.674**	**4.995**	**0.025**	**Yes****

** Marginally insignificant (p = 0.082); a larger sample may yield significance. ** Statistically significant at the 5% level (p < 0.05). Odds Ratio = e^{β}. Dark black shading indicates a significant predictor.*

Overall, the logistic regression model demonstrates a clear gradient of treatment effects: odds ratios increase monotonically from Treatment 1 (OR = 1.570) through Treatment 4 (OR = 4.674), suggesting that the quality and delivery of the seminar progressively improve across the four research scholars. Only Treatment 4 reaches statistical significance, but the pattern collectively indicates that all four research scholars received positive evaluations relative to the baseline, with Treatment 4 standing out as the most impactful. These findings underscore the utility of both the coefficient estimates and the odds ratios as complementary tools for communicating the practical and statistical significance of logistic regression results in educational evaluation contexts.

V. Results and Conclusions

The logistic regression analysis identified Treatment 4 as a key predictor of seminar effectiveness. The statistical significance of Treatment 4, with a p-value of 0.025, shows that this treatment substantially improves the likelihood that the seminar will be perceived as useful. This finding highlights Treatment 4's effectiveness compared to other treatments evaluated, which did not show significant effects. The results show that the logistic regression model effectively pinpoints which factors influence binary outcomes, such as seminar usefulness. By analyzing how different treatments impact the seminar's effectiveness, the model provides valuable insights into which interventions are most beneficial. Overall, this method proves to be a robust tool for evaluating binary outcomes in educational settings. The ability to identify significant predictors allows for more informed decisions and targeted improvements in seminar design and other similar contexts. The logistic regression approach applies across various disciplines where binary outcomes need to be assessed, making it a versatile and valuable analytical method.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the article.

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