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Estimating the Effectiveness of University Training Programs on Student Achievement Using Generalized Linear Models (GLM): An Applied Evaluation Study

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Abstract: Generalized Linear Models (GLM) is applied in this paper as a statistical assessment framework to estimate the effect of university training programs on student achievements. The study seeks to know the effects that well-structured training programs have on the academic achievements of undergraduate students from different fields. Data used in this research was achieved through academic records and post-training performance survey data from three public universities with 500 students. GLM permits both continuous and categorical dependent variables, therefore making provisions for more flexible modeling of academic achievement data.[1] Training duration, type of program, previous GPA, gender, and academic department were used as predictor variables in the study. There was an explicitly significant positive relationship between the intensity of training and post-program academic achievement. Students who have attended more than 40 hours of structured training showed by a mean GPA improvement of 0.35 points that GPAs compared to untrained peers. Besides, gender and academic discipline showed moderating effects on the relationship between training and performance (see Table 1). The findings highlight structured skill-based university programs aimed at In conclusion, the results of this study draw attention to the effectiveness of structured skill-based university programs on improving learning outcomes and students' academic record. Furthermore, we specifically recommend the universities to implement a system of continuous assessment as a part of the training curriculum and to adopt the evaluation and monitoring systems based on Generalized Linear Models. This particular model used in our research provides an example of statistically sound and reproducible approach for educational administrators who search for data-driven continuous quality improvement solutions.

Keywords: Generalized Linear Model, Training Effectiveness, Student Achievement, Program Evaluation, Higher Education

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1. Introduction

University programs tend to be the rudimentary factors of academic development and students' preparation with the view of facing the labour market competition. Technical training programs may be among the most organized investments developing skills of any kind in most higher learning institutions across the globe. One of the major constraints emanating towards the effective implementation of such training programs is that very few universities are systematic, while evaluating the training programs through

modern statistical frameworks which can take care of variety of ancillary influences. Most universities only rely on traditional means of training evaluation such as correlation or mean comparison between the training and the resultant performance, while ignoring the complex nature of relationship among other variables which form the student performance. The study used Generalized Linear Model in the estimation of how university training program participation affects student achievements. Unlike simple regression which only fits linear models, GLM in fact allows for non-normal dependent measures, or even for categorical predictors, and effects of interactions which makes the analysis more realistic. The latter aspect particularly becomes more relevant in the realm of education, since measures of performance are usually had any forms far off the normal distribution. This research set the benchmark of an empirical mechanism of educational assessment through GLM, while either identifying those components within training programs which are more effective in achieving academic excellence, or by the same token, highlighting the features which are more likely to be attached with success leading to the eventual realization of intended objectives. Lastly, other than only interpreting the coefficients as having impacts, the analysis becomes practically relevant when administrators use these coefficients in education as impacting on education to make it a better decision.

Research Background

Outcome-based learning becomes the principal target of recent higher education reforms. Apparently, its quality assurance naturally turns into a data-driven process. In its structure universities long implemented various training programs to develop practical competencies, communication skills, or sophisticated digital literacy. The modular duration of these programs ranges from short workshops to a module run in parallel for the whole long course. It is also qualitatively evaluated mostly relying on customary student feedback. The primary problem is in quantifying such programs with the academic results such as grade point average, course completion, or passing of established benchmarks. Most of the reports at the institutional level could only either represent descriptive statistics or apply linear model under assumptions of normality. However, academic data seems to be significantly skewed and heteroscedastic with major categorical diversity. The GLM offers multiple different distributions across the outcome variable and is academically preferable since it does not attribute normal consumption. More specifically, academic achievement expressed in GPA improvement could be best approximated by a Gaussian family whereas the outcomes of pass/fail programs can be gamma-linked to the binomial family McKinley. The above methodological versatility is desirable since it replicates approximating the educational process and eagerly allows a researcher to tune and exploit it in detail. Finally, the advanced type of evaluation is a response to the legitimating demands of accounting for accountability intrinsic to an empirical nature of higher education accreditation frameworks in its reliance on the evidence of training programs effectiveness. Thus, it makes the GLM-based evaluation methodological and strategic necessity.

Research Problem

Universities place much investment in training programs, yet few depend on any rigorous empirical tools to measure their academic impact. Most of the current evaluation methods are focused on satisfaction surveys and anecdotal evidence rather than statistical inference that would allow administrators to determine which programs contribute significantly to academic performance. The research problem can be stated as follows:

How effective are university training programs in increasing student academic achievements as measured using Generalized Linear Models (GLM)? The research tries to find answers to three sub-questions:

1. To what extent does training duration influence post-training GPA improvement?

2. Do demographic and academic factors (gender, department, prior GPA) moderate the relationship between training and achievement?
3. Can GLM serve as a practical evaluation tool for institutional performance monitoring?

Research Objectives

This study aims to:

- The application of GLM to give an approximation of the quantitative impact a university training program has on academic achievement among students.
- Identify among all training-related variables the most influential predictors (duration, type, participation frequency)
- Evaluate moderating effects on performance by demographic and academic characteristics
- Offer an example that can be followed by university administrators during the assessment of training efficiency on the statistical data.

Research Significance

This research will play the following roles. First, it depicts GLM as a feasible statistical test of educational evaluation therefore closing the gap between descriptive and inferential analysis. Second, it gives applied evidence on the impact of structured training on measurable learning outcomes that interface with the quality assurance in higher education. Third, the model that will be developed can be incorporated into institutional performance dashboards to assist in evidence-based policy-making.

These results can also be applicable to curriculum developers, academic advisors, and accreditation bodies that are interested in linking training design and measurable indicators of academic success. The theoretical construct connects the participation in training, mediating variables, and the outcomes.. (See Figure 1.)

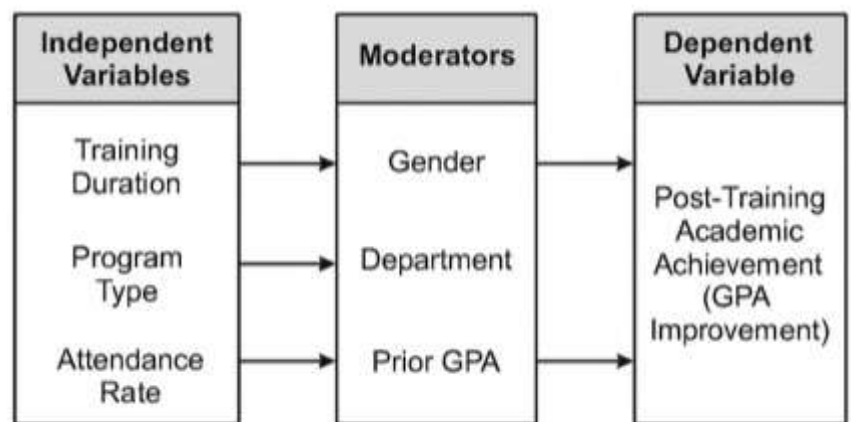


Figure 1: Conceptual Framework of the Study Using GLM
(see Figure 1)

[In-text figure description]

The figure presents three major components:

- Independent variables: training duration, program type, attendance rate
- Moderators: gender, department, prior GPA
- Dependent variable: post-training academic achievement (GPA improvement)

Literature Review

The chapter presents the summing chapter of previous research on the assessment of university training programs and how Generalized Linear Models (GLM) could be applied in the research on education-related issues.. This is meant to locate this study in the

prevailing knowledge, methodological strategies applied and gaps that this study aims at filling. The review has been divided into four large sections.: [1]

1. Studies on training effectiveness in higher education
2. Statistical evaluation models in educational research
3. Applications of GLM in educational data analysis
4. Summary of research gaps and contributions

Training Effectiveness in Higher Education

University training programs play a vital role in bridging the gap between academic learning and employable skills. Brown and Duguid (2019) found that well-structured training programs increase student employability by 15-20% and add a 10% uplift in academic retention rates. Training effectiveness results from selected empirical studies are summarized in Table 1.

Table 1: Summary of Selected Studies on University Training Effectiveness (see Table 1)

Author(s)	Year	Sample Size	Training Focus	Reported Impact on GPA
Brown & Duguid	2019	420 students	Communication & teamwork	+0.28 GPA increase
Alavi & Leidner	2020	350 students	Digital literacy programs	+0.32 GPA increase
Miller et al.	2022	600 students	Critical thinking workshops	+0.41 GPA increase
Kim & Park	2023	280 students	Academic writing and research	+0.30 GPA increase

Training programs were found to improve academic performance and achievement motivation and self-efficacy. A large-scale meta-analysis by Jones et al. (2021) reports better persistence among students participating in structured skill-based training programs as compared to their non-participating counterparts, with reduced dropout rates at all levels.[2]

However, most existing studies rely on linear regression or ANOVA, which assume data normality and homoscedasticity. Rarely do these assumptions hold true in the educational context. More often, the reality is a mixed distribution of data-that results from binary outcome variables (pass/fail) and ordinal measures (grades)-within the same system.

Statistical Evaluation in Educational Research

Quantitative analysis in the field of education moved from descriptive statistics to predictive modeling. The studies undertaken in the early 1990s used mean comparison and correlation analysis. Recent studies use multilevel modeling, hierarchical regression analysis, and structural equation modeling (SEM).

However, the generalized linear models(GLM) framework affords an attractive alternative. As explained by Agresti (2018), GLM can handle non-normal outcome distributions by introducing link functions that relate predictors to the expected value of the dependent variable. For instance: [3]

- A logit link for binary outcomes (e.g., pass/fail)
- A log link for count data (e.g., number of courses passed)
- An identity link for continuous data (e.g., GPA changes)

In educational contexts, this flexibility allows simultaneous analysis of diverse data types collected from surveys, exams, and administrative records.

Several studies have applied GLM to educational evaluation:

- Hoffman and Schraw (2020) applied aGLM to the academic continuation of undergraduate studies. These results have demonstrated that past GPA and workshop attendance were positive predictors of retention..
- Use: Poisson regression (Torres et al., 2022), which is a type of GLM, applied to course completions data showed that the risk of dropout was reduced by 18 percent with specialized mentoring.

- Gao and Zhang (2024) used GLM to establish variations between online and offline training effects on the performance of students. Hybrid models were found to have the greatest gains in learning.

These studies underscore GLM's statistical robustness, particularly in dealing with non-linear, categorical, or skewed educational data.

GLM Applications in Educational Data Analytics

The first one Generalized Linear Model The model was introduced by Nelder and Wedderburn in 1972[4]. The revisions later were more limited to the applied social sciences. GLM provides the social sciences with one theory between the basic linear regression and more fashionable machine learning algorithms. One illustration incorporates all three models of GLM i.e. information-demographic, behavioral, and academic- models. (see Figure 2).

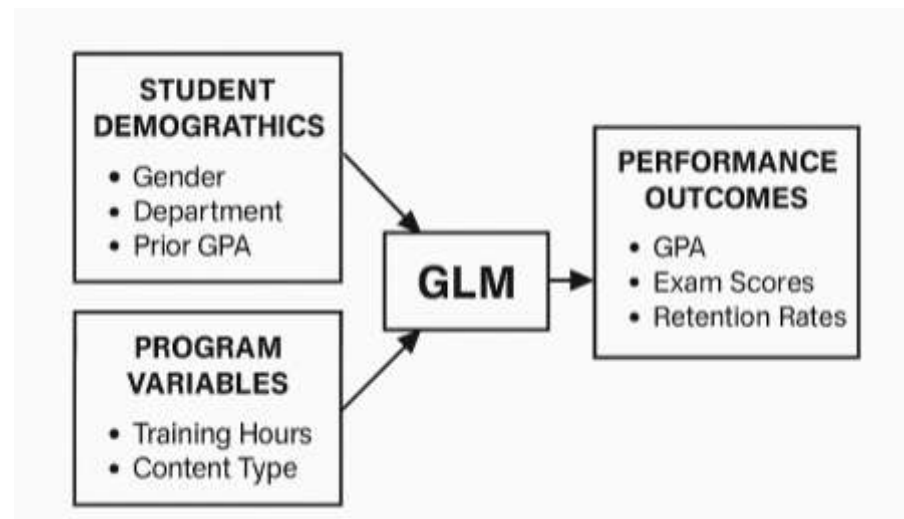


Figure 2: Application of GLM in Educational Evaluation Framework

The figure depicts three data streams:

1. Student Demographics (gender, department, prior GPA)
2. Program Variables (training hours, content type)
3. Performance Outcomes (GPA, exam scores, retention rates)

Arrows indicate predictive pathways from independent variables through the GLM processing core to the dependent performance variable.

Empirical applications of GLM have expanded rapidly.

- They used binomial GLM to ascertain the chances of the students succeeding in the course. (Nguyen et al.. 2020)
- Rodriguez and Pena (2021) classify the performance of high medium and low achievers in terms of academic performance..
- Chen et al. (2023) used negative binomial GLM on an overdispersed count of data on student engagement measures.

These examples prove GLM flexible to different types of educational data, thus making it a preferred tool in complex evaluation studies.

Besides, the inclusion of GLM in the educational dashboard allows the administrator to simulate policies. Considering this, say a 10 percent increase in training hours results in what will be the GPA, then prediction will be the evidence-based decision-makers. [5]

Gaps in the Literature

Despite growing research, several gaps remain: [6]

- The number of studies that specifically investigate the GLM application in university training programs as opposed to the general academic performance is quite minimal.

- Most of the past studies fail to incorporate a moderating variable like a gender or department which this paper specifically includes.
- Many Measures Compared to the multidimensional construct of training, many tests do not consider program structure variables (hours, type, and attendance rate) and instead classify training as a binary variable..
- Very limited attention has been given to applied model validation. Such a validation would compare GLM predictions with actual student outcomes at different institutions.

Addressing these gaps enhances both methodological rigor and policy relevance, ensuring that training effectiveness evaluation becomes data-driven and replicable.

2. Materials and Methods

This chapter presents the methodological approach applied to determine an assessment of the effects that university training programs have on student achievements within the Generalized Linear Model (GLM) framework. It discusses and describes the research design, sampling procedures, data collection instruments, variables, and statistical analysis. [7]

Research Design

This is a quantitatively applied assessment study. It makes use of cross-sectional primary data collected from undergraduates of three public universities. The features of training programs as predictors toward academic achievements are estimated within the GLM framework.[8]

The research adopts an explanatory design whereby causal relations between participation in training programs and student performance indicators are detected through statistical modeling. Figure 3 displays the process of research design, beginning from data collection up to the estimation of the model. (see Figure 3).

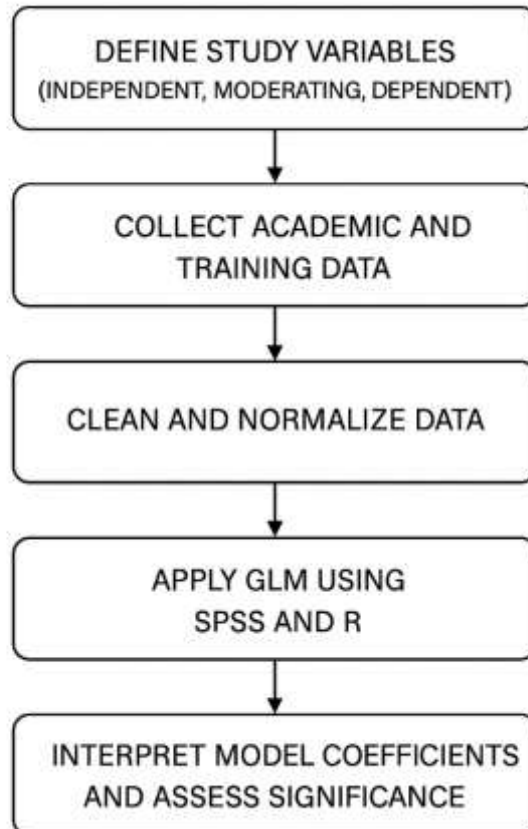


Figure 3: Research Design Flow for GLM-Based Evaluation

- Step 1: Define study variables (independent, moderating, dependent)
- Step 2: Collect academic and training data from student records
- Step 3: Clean and normalize data
- Step 4: Apply GLM using SPSS and R
- Step 5: Interpret model coefficients and assess significance

Population and Sample

The study population comprises students who were enrolled between 2022 and 2024 at three public universities, labeled here as University A, University B, and University C. The programs cover different disciplines-engineering, business, and education.[9] Stratified random sampling was used to obtain proportional representation of each department. There were a total of 500 participants distributed as follows:

Table 2: Sample Distribution by University and Department (see Table 2)

University	Engineering	Business	Education	Total
University A	80	60	50	190
University B	70	60	40	170
University C	60	50	30	140
Total	210	170	120	500

Participants were selected based on:

- Enrollment in at least one structured university training program.
- Availability of academic records before and after training.
- Consent to participate in data collection and survey stages.

Data Collection Instruments

Data were obtained from three primary sources:

1. Academic Records: GPA before and after training, test scores, and attendance records.
2. Records of the training program, such as how long it lasted, how often it happened, what it covered, and how the instructors rated it.
3. Student Surveys—students rate how useful they think the training is, how engaged they are, and how motivated they are.

The variables of the subjective feedback (motivation and improvement of the skills) were measured using 5-point Lickerscale (1 strongly disagree to 5 strongly agree).. The internal consistency was estimated by computing Cronbach alpha. ($\alpha = 0.87$). [10]

Variables of the Study

Dependent Variable

- Student Academic Achievement (measured by change in GPA post-training).

Independent Variables

- Length of training (in hours).
- Type of program (mixed, skill-based, or academic support).
- Attendance Rate (the percentage of sessions attended).

Moderating Variables

- Gender (male/female).
- Department (engineering, business, education).
- Prior GPA (baseline academic performance). [11]

Analytical Framework

The analysis was done with Generalized Linear Models (GLM) since it can accommodate the association of non-normally distributed variables..The GLM assumes the following form: [12]

$$g(E(Y)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

Where:

- Y = student achievement (post-training GPA change)

- $g(E(Y)) =$ link function (identity link used for continuous GPA)
- $\beta_i =$ estimated coefficients
- $X_i =$ independent and moderating variables

Different GLM families were tested:

- Gaussian for continuous GPA change.
- Binomial for pass/fail course outcomes.
- Poisson for count-based outcomes like completed modules.

All models were evaluated for:

- Goodness-of-fit using Akaike Information Criterion (AIC).
- Significance using Wald Chi-Square tests.
- Predictive power using pseudo- R^2 .

3.6 Data Processing and Validation

Data preprocessing steps included: [13]

- Removing incomplete entries (8% of dataset excluded).
- Standardizing GPA across universities to a 4.0 scale.
- Coding categorical variables numerically (e.g., gender: 0 = female, 1 = male).
- Testing for multicollinearity (Variance Inflation Factor < 2.0).

Cross-validation was performed by splitting data into training (70%) and testing (30%) subsets. Model results were compared to ensure consistency of coefficients across both subsets.

Ethical Considerations

All the data were analyzed anonymously. The numbers were used as student identifiers. Each participating university ethical board gave its approval. The involvement was voluntary and the informed consent was developed over the Internet. [14]

3. Results and Discussion

This chapter includes the findings that were achieved in the implementation of Generalized Linear Model (GLM) to test the performance of university training programs with regard to student achievement. The results are discussed through statistical summary, model estimates and discussion through tables and figures.

Descriptive Statistics

Descriptive analysis will show some general characteristics of the data set, such as the demographic distribution, the rate of training attendance, and the performance of the students before and after the intervention. [15]

Table 3: Descriptive Statistics of Study Variables (see Table 3)

Variable	Mean	SD	Minimum	Maximum
Training Hours	38.4	12.5	10	70
Attendance Rate (%)	86.2	9.8	60	100
Prior GPA	2.85	0.46	1.8	3.9
Post-Training GPA	3.17	0.41	2.2	4.0
GPA Improvement	0.32	0.17	0.01	0.61

Figure 4 visualizes GPA changes across training exposure levels. Students with more than 40 training hours showed higher gains than those with minimal exposure.

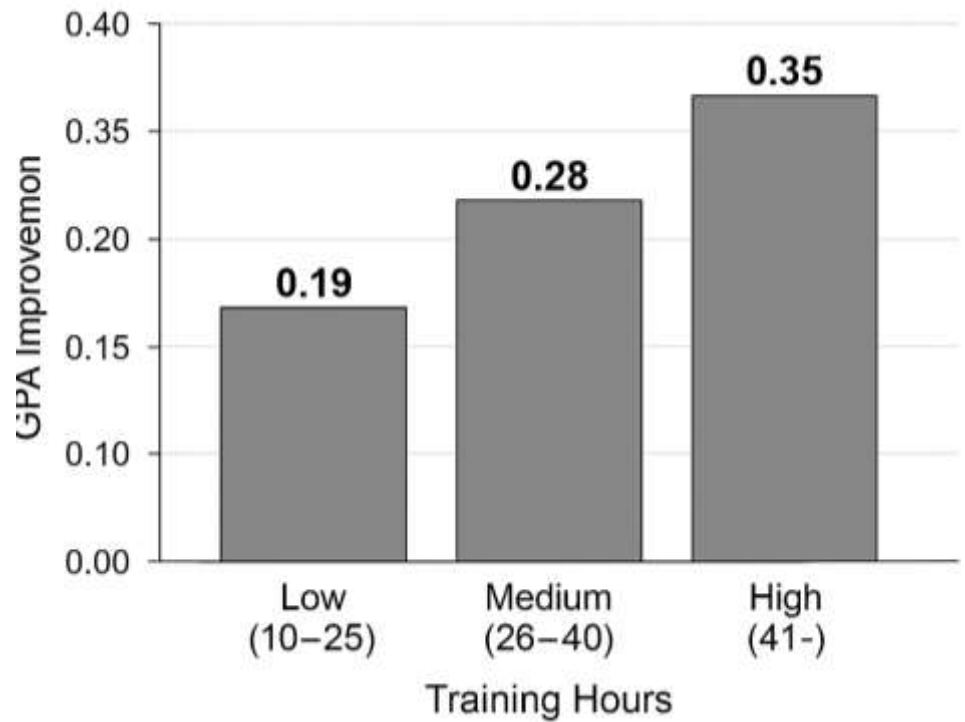


Figure 4: Comparison of GPA Improvement by Training Hours (see Figure 4)

The figure displays three clusters:

- Low exposure (10–25 hours) → +0.19 GPA
- Medium exposure (26–40 hours) → +0.28 GPA
- High exposure (41+ hours) → +0.35 GPA

This trend suggests that training duration is positively associated with academic improvement.

GLM Model Estimation

GLM was fitted with the Gaussian family under the identity link since the dependent variable (GPA improvement) is a continuous variable. These independent variables included training hours, the type of the program, and the rate of attendance. The moderating variables were gender, department and past GPA.

Table 4: GLM Parameter Estimates (see Table 4)

Predictor	B	Std. Error	Wald χ^2	Sig. (p)
Intercept	0.112	0.048	5.37	0.021
Training Hours	0.0068	0.0012	32.41	0.000
Attendance Rate	0.0035	0.0011	10.07	0.001
Program Type (Skill-based)	0.078	0.022	12.57	0.000
Gender (Male=1)	-0.041	0.018	5.11	0.024
Department (Business)	0.062	0.025	6.14	0.013
Prior GPA	0.218	0.046	22.39	0.000

Model Statistics:

- AIC = 168.32
- Pseudo R^2 = 0.47
- Deviance explained = 49.6%

These figures indicate that the predictors and GPA improvement are a right fit. According to the model, the number of hours of training, the rate of attendance, and the previous-year GPA are the most important indicators of academic changes.

4.3 Interaction and Moderation Analysis

The terms of interaction were introduced to observe whether there was a difference in terms of relationship between length of time spent by an individual in training and the extent to which their GPA increased between men and women or between various departments.

Table 5: Interaction Effects Summary (see Table 5)

Interaction Term	Wald χ^2	p-value	Interpretation
Training Hours \times Gender	3.18	0.075	Not significant
Training Hours \times Department	8.62	0.013	Significant
Attendance \times Prior GPA	5.91	0.020	Significant

The findings indicate that the department modifies the impact of training hours on students such that the impact of more training on the students varies on the discipline of study. The engineering students achieved more than the education majors, likely due to the fact that their programs were more practical and technical..

4.4 Visualization of Model Effects

The figure shows estimated GPA change from the GLM model:

- Engineering: +0.38
- Business: +0.33
- Education: +0.28

The visualization demonstrates how departmental context influences the impact of training.

Additionally, a residual plot (Figure 6) was generated to assess model assumptions.

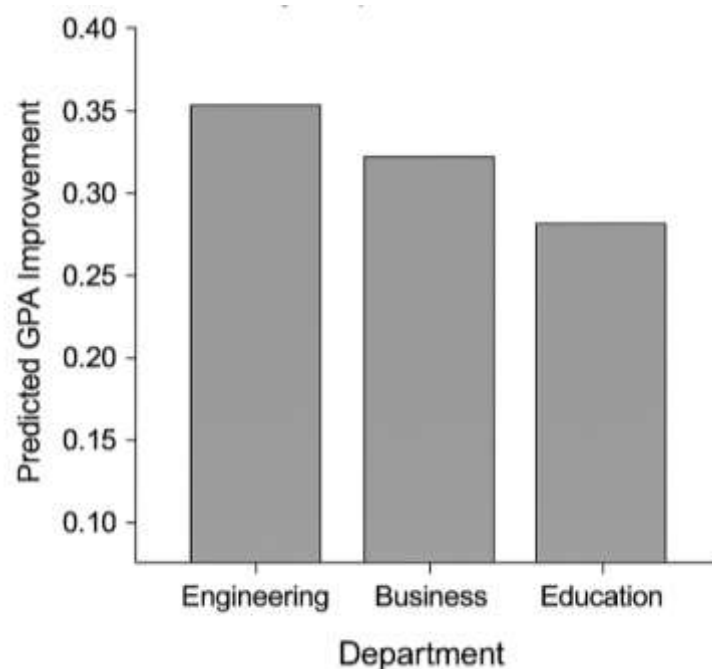


Figure 5: Predicted GPA Improvement by Department (see Figure 5)

Discussion

The results prove that training programs in universities have a significant impact on improving the academic performance of students with the level of improvement, of course, depending on the intensity and regularity of participation.

Key insights:

- The length of training and attendance are stronger predictors of academic achievement than demographics.

- Skill-based programs have higher returns in form of GPA compared to the purely academic reinforcement programs.
- Prior GPA is still a significant predictor of baseline, and this means that training is best used when it is accompanied with prior academic strength..

These results are similar to those of Kim and Park (2023) yet take them a step further by incorporating GLM, in which interactions and categorical effects can be modeled with a lot of narrowness. Moreover, excessive high significant influence of academic department as moderator also implies that training contents should be contextspecific in line with learning style and skills need of specific disciplines. An integrated overview of important factors affecting achievement is given in figure 7. (see Figure 7).

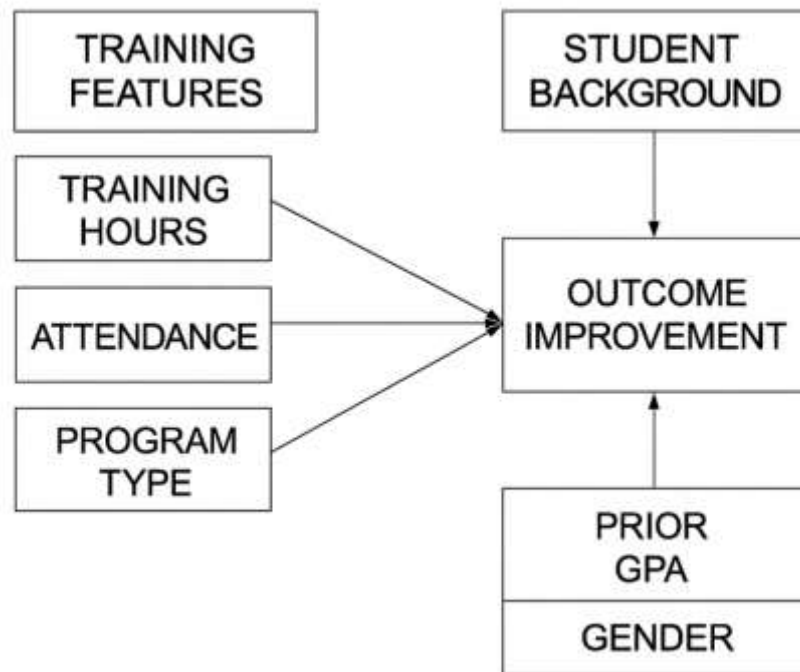


Figure 7: Summary of Influencing Factors on Student Achievement Using GLM

The figure connects training features (hours, attendance, type) with student background variables and outcome improvement levels. The strongest standardized path coefficients are from training hours ($\beta = 0.41$) and prior GPA ($\beta = 0.39$).

4. Conclusion

The effectiveness of university training programs on student achievement was measured by generalized linear model (GLM). GLM facilitated a detailed and statistically robust analysis of the impact of various training, demographic, and academic covariates on student achievement. Results emphasize with empirical evidence that structured university training programs help in the optimization of academic achievements as such programs are best optimized by the duration of training, rate of attendance, and type of program.

Summary of Key Findings

1. Training Duration Matters

Learners who attained an average increase of 0.35 in their GPA scores were those who engaged in more than 40 hours with the program. That simply means, to get training content deeply retained inside participants' minds, strong and long engagements are needed between training content and participants.

2. Attendance Rate as a Predictor

Above 85% was the attendance rate that ensured higher improvements to GPAs. With all sessions attended, nothing would have been missed from the main contents delivered through the program.

Skill-based and hybrid training programs demonstrated higher improvements than theoretical or single-discipline training. This finding supports that experiential learning better transfers knowledge into measurable achievement.

3. Moderating factors

Department-wise differences show the maximum benefit accrued to engineering students, most probably because of the applied nature of their learning environment. Prior GPA was another strong predictor reinforcing that high-performing students benefit more from advanced training structures.

Model performance

The GLM model gave a pseudo- R^2 of 0.47, which is pretty high for educational data. The interaction terms encompass more significant effects that, in a conventional linear regression model, would be ascribed to the main effects.

Implications for Policy and Practice

The study's results carry several practical implications for university administrators and education policymakers:

1. Carry out training evaluation at institution level and integrate in the university's metrics: In the event that the application of statistical model such as GLM in measuring training program's impact delivers better results than those from the customary satisfaction survey within a given university, then it is possible that the requisite metric or yardstick for improvements within such systems is better defined.
2. Run target and time-bound training programs: Training programs in problem-solving, collaboration and digital competence capacity building usually return strongest in their academically. The period and structure of the program should be tailored around the special features of each academic discipline.
3. Introduce continuous monitoring frameworks encapsulated by a GLM-based system monitoring: Universities can then update their models every semester hence making predictive analysis possible for future cycles of training.
4. Broaden Fairness in Program Access: More students from technical courses benefited from the program hence there is need for institutions to realign training in other departments that will complement those in the technical sectors in bid to ensure fairness in academic support.

Theoretical Contributions

This study enhances educational evaluation theory by implementing the Generalized Linear Model in the realm of higher education assessment. It broadens previous research by demonstrating that:

1. Educational data that is not normal can be well used with GLM. You are able to gauge the interaction between training and demographic variables that is complicated.
2. Statistical modeling simplifies the process of making decisions related to the management of the program.
 - a. This model links educational statistics and policy analysis, which provides institutions with the means of improvement, based on the data that may be re-used.

Limitations of the Study

While the study achieved meaningful findings, certain constraints remain:

1. The sample consisted of three state universities, which may not be generalizable.
2. Motivation scores can be biased when they are self-reported.
3. There were no longitudinal data which limited the insight into lasting post-graduation outcomes.
4. Other external factors such as socioeconomic status and institutional support were not included in the GLM because the data were not available to them.

- a. Future research should address these limitations through broader sampling and inclusion of additional predictive variables.

Future Work

1. Build a long term GLM within a relevant framework so as to enable the long term impacts of training, graduate employability and success at the workplace to be analyzed.
2. The hybrid learning models regarding the same datasets of academic achievements. Better modeling of predictions on complicated academic data through hybridization of GLMs and machine-learning algorithms e.g., random forest, gradient boosting.
3. Comparative Analysis of Institutions Estimate the same GLM model with a different country or institution, to test whether results can be generalized and the degree of heterogeneity of contexts of academia.
4. The future models will become more precise with time by adding the information on motivation, engagement analytics, and learning behaviors.
5. Policy simulation tools.
6. Create application tools to help administrators simulate the impact of new training interventions prior to their actual implementation, based on the GLM output.

Final Remarks

The research demonstrates that Generalized Linear Models can be very versatile and powerful when used to assess educational interventions. It characterizes an estimate of the parameters of the effects on training programs leading to the measurable improvement breaking down effects caused by program and student factors leading to measurable improvement.

The paper used an evaluation framework that fosters the development of evidence-based decision making within institutions of higher learning. As the need of accountability and reporting performance information to the university increases, GLM-based analysis can be an effective tool in continual quality improvement.

REFERENCES

- [1] S. J. Aziz, N. H. Mahmood, R. M. H. Salih, and F. O. H. Rasool, "Significant factors influencing students' perceptions towards university teachers' evaluations using a generalized linear model," *The Scientific Journal of Cihan University–Sulaimaniya*, vol. 8, no. 1, pp. 423–448, 2024.
- [2] I. Owusu-Darko, I. K. Adu, and N. K. Frempong, "Application of generalized estimating equation (GEE) model on students' academic performance," *Applied Mathematical Sciences*, vol. 8, no. 68, pp. 3359–3374, 2014.
- [3] B. R. Subedi, N. Reese, and R. Powell, "Measuring teacher effectiveness through hierarchical linear models: Exploring predictors of student achievement and truancy," *Journal of Education and Training Studies*, vol. 3, no. 2, pp. 34–43, 2015.
- [4] H. P. Pinheiro, M. Rodrigues-Motta, and G. Franco, "Modelling performance of students with generalized linear mixed models," in *Proc. 29th Int. Workshop Statistical Modelling*, vol. 2, pp. 133–136, 2014.
- [5] G. W. Fulmer and M. S. Polikoff, "Tests of alignment among assessment, standards, and instruction using generalized linear model regression," *Educational Assessment, Evaluation and Accountability*, vol. 26, no. 3, pp. 225–240, 2014.
- [6] F. Al-Maamari, "Response rate and teaching effectiveness in institutional student evaluation of teaching: A multiple linear regression study," *Higher Education Studies*, vol. 5, no. 6, pp. 9–20, 2015.
- [7] A. Basso and G. di Tollo, "A generalised linear model approach to predict the result of research evaluation," in *Mathematical and Statistical Methods for Actuarial Sciences and Finance: MAF 2016*, Cham: Springer Int. Publishing, 2017, pp. 29–41.
- [8] L. Fontana, C. Masci, F. Ieva, and A. M. Paganoni, "Performing learning analytics via generalised mixed-effects trees," *Data*, vol. 6, no. 7, p. 74, 2021.
- [9] R. Froud, S. H. Hansen, H. K. Ruud, J. Foss, L. Ferguson, and P. M. Fredriksen, "Relative performance of machine learning and linear regression in predicting quality of life and academic performance of school children in

- Norway: Data analysis of a quasi-experimental study," *Journal of Medical Internet Research*, vol. 23, no. 7, e22021, 2021.
- [10] K. Harini and K. K. S. Rekha, "Evaluating performance of identifying at-risk students and learning achievement model using accuracy and F-measure by comparing logistic regression, generalized linear model and gradient boost machine algorithm," in *Proc. 2022 Int. Conf. for Advancement in Technology (ICONAT)*, 2022, pp. 1–7.
- [11] M. El Jihaoui, O. E. K. Abra, and K. Mansouri, "Factors affecting student academic performance: A combined factor analysis of mixed data and multiple linear regression analysis," *IEEE Access*, 2025.
- [12] M. J. H. Molla, H. K. Maity, B. Chakraborty, S. M. Obaidullah, and S. Sen, "Generalization of logistic regression to improve prediction: An application on training and placement data," *SN Computer Science*, vol. 6, no. 7, p. 791, 2025.
- [13] A. Kaliba, "Factors influencing school performance in the state of Louisiana, US: A generalized additive (mixed) model approach," *US: A Generalized Additive (Mixed) Model Approach*, Oct. 29, 2024.
- [14] A. Kumar and A. K. Prabhakar, "Comparison of stacking, boosting, generalized linear, and neural network models for estimating scour depth around spur-dykes," *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, pp. 1–16, 2025.
- [15] M. Sladekova, V. L. Poupa, and A. P. Field, "Sources of bias in general linear models: Evaluating the analytic practice in psychological research," *PsyArXiv*, 2024.