DJE - 2025 4(1):36–46

Dilla Journal of Education

https://www.du.edu.et/duj

# Effect of Slide Projector-assisted Classroom Instruction on Students' Exam Scores in a One-Group Quasi-experimental Study

**Anemut Mehari**[1*] **and Bezina Kassahun**[1]

[1]Department of Psychology, Dilla University, Dilla, Ethiopia

Received: 08 January 2025 Accepted: 27 March 2025 Published: 19 April 2025

ARTICLE INFO.

**Key words/phrases**: Classroom Instruction, Effect, Exam Scores, Slide Projector, Students

**Abstract**

*This study aims to examine the role of slide projector-assisted classroom instruction in enhancing students' achievement. A quasi-experimental design was employed, including 21 psychology students at Dilla University. Using a Bayesian paired-sample t-test and Bayesian ANCOVA tests, the findings show that there is a statistically significant improvement in the posttest scores, with a moderate effect size (Cohen's d = 0.50). The sensitivity analysis further confirmed that the finding was robust. The findings suggest that slide projector-assisted instruction is an effective and reliable approach for enhancing academic achievement.*

## 1 Introduction

This study was grounded in the argument that when comprehensive instructional materials are adequately provided, students' academic achievement may reflect their independent engagement, such as study behaviors, rather than instructional methods (McKeachie, 1963, as cited in Dunkin, 2006). Under such conditions, students may even be capable of compensating for suboptimal or ineffective teaching approaches. Despite the potential efficacy of self-directed learning, higher education institutions continue to allocate substantial resources to teaching roles, reflecting persistent institutional prioritization of instructor-led pedagogy (Kimbrel, 2019; Maynes & Hatt, 2015). Ethiopian universities, including Dilla University, are not exceptions to this trend, as they invest significantly in instructional staffing and infrastructure.

It has long been believed that improving learner outcomes requires effective teaching. As a result, educational institutions spend many resources employing qualified teachers (Kimbrel, 2019; Maynes & Hatt, 2015). Interestingly, few systematic assessments of how lecture-based approaches especially affect academic attainment exist. By conducting an empirical evaluation of the effectiveness of slide projector-assisted lectures in a university setting, this study seeks to address this gap.

The lecture method continues to be one of the most frequently used instructional methods at all educational levels worldwide, despite a variety of pedagogical approaches (Yu & Liu, 2008). Using chalkboards, whiteboards, or projector displays, this conventional method presents ideas, facts, concepts, and generalizations orally. It basically consists of a thorough, instructor-led presentation of the course material. However, detractors frequently describe this approach as spoon-feeding, in which students take on a passive role in learning (Umoren, 2001; Vincent & Akpan, 2014). Research showing that this one-way transmission model has little effect on long-term retention highlights its shortcomings; Bales (1996) reported that only approximately 5% of the material presented in typical lectures is retained over time.

Effective learning necessitates active student involvement with content, demonstrations, and real-



*Corresponding Author; Email: anemutm@du.edut.et;
Article DOI:10.20372/dje.v04i01.04

world applications—elements that are frequently lacking in traditional lecture forms, according to contemporary educational theory (Bernstein & Nash, 2008). Classroom instruction can be presented through a variety of modalities, such as PowerPoint slides, chalkboard presentations, or oral discourse. Despite its widespread use, very few thorough empirical studies have examined how this instructional method actually affects students' learning outcomes in contexts in which adequate learning materials are provided. This study focuses on slide projector-assisted classroom instruction, a technique commonly used in university settings (Umoren, 2001; Vincent & Akpan, 2014), including Ethiopian higher education institutions.

An Experimental Psychology (Psyc-2035) course was chosen to examine these dynamics, and the students were given complete course materials for independent study and evaluation. As part of reflective teaching practice, the course instructor (corresponding author) administered the study via an action research framework (Kemmis & McTaggart, 2005). This strategy made it possible to evaluate how slide projector-assisted classroom instruction and organized learning resources interact to influence student outcomes iteratively. Therefore, on the basis of the aforementioned evidence, the following hypothesis was developed.

$H_1$: *Slide projector-assisted classroom instruction significantly improves students' exam scores.*

The directional hypothesis is also consistent with current pedagogical studies on the effectiveness of visually aided instructional methods in improving learning outcomes (Clark & Mayer, 2016; Mayer, 2009) and the cognitive theory of multimedia learning (Mayer, 2014), which holds that learning is improved when verbal and visual information are presented in coordinated, meaningful ways. It also acknowledges ongoing discussions in educational psychology about the relative efficacy of various instructional modalities (Kozma, 1991; Clark, 1994) and is consistent with action research principles that emphasize the methodical investigation of teaching interventions (Stringer, 2014) and standard hypothesis testing procedures in educational research (Creswell, 2012).

## 2 Methods

### 2.1 Research Design

Assuming the number of participants, we employed a one-group pretest–posttest quasi-experimental design. Internal validity, history effects, and practice effects are known threats associated with this research design (Knapp, 2016; Spurlock, 2018). However, total population sampling and systematically designed time intervals between pre- and posttests can mitigate selection bias and testing effects, respectively (Brown *et al.*, 2008). The latter also accounts for participant history and maturation effects (Knapp, 2016; Spurlock, 2018).

### 2.2 Participants and Sampling

Twenty-one psychology students (9 male, 12 female) participated in both the pretest and posttest studies. The project was administered in the 2021–22 academic year. The Experimental Psychology (Psyc-2035) course was selected. Given the principal investigator's dual role as a course instructor and researcher, the study aligns methodologically with action research paradigms, wherein pedagogical practice and systematic inquiry are integrated to enhance educational outcomes (Stringer, 2014). All the students enrolled in the target cohort (Year II, Semester I) were involved.

### 2.3 Intervention

For the intervention, we prepared a 30-page slide. Three weeks after the PDF reading material was distributed, we conducted a pretest. As a result, the students were able to have adequate time for individual study and exam preparation. On the basis of the content provided in the material, the participants took a pretest. Following that, they participated in a structured three-hour slide projector-assisted instruction, which was in line with conventional instructional techniques used in academic settings.

Forty-three days after the pretest, the same exam was administered. This time frame was deliberately chosen to minimize possible testing effects while providing enough time to assess knowledge retention. This interval allows the examination of sustained information acquisition as opposed to short-term memorization and is consistent with accepted cognitive science perspectives (Bjork & Bjork, 2011). It also allows for the measurement of long-term learning retention while effectively mitigating recall bias (Brown *et al.*, 2014).

### 2.4 Measures

A 20-item multiple-choice test (each with four response options) midterm exam was developed in accordance with standard assessment procedures (table of specification method), making up 30% of the course evaluation. The instructor methodically selected these items from a randomly chosen course chapter. The multiple-choice item format was chosen because of its proven impartiality and ability to reduce subjectivity (Gupta *et al.*, 2021). The items were thoroughly examined by subject matter specialists in educational assessment and evaluation to guarantee psychometric quality. They evaluated the items' cognitive difficulty levels and content suitability. For additional analysis, participant background variables such as sex, weekly study hours, and cumulative grade point average (CGPA) were recorded.

### 2.5 Data Collection Procedures

Identical test administration protocols across both assessments, including timing, classroom conditions, and examination procedures, were followed. On October 10, 2022, from 9:00 AM to 10:35 AM, baseline data were collected. Forty-three days later, posttest data were gathered on November 22, 2022, from 9:00 AM to 10:35 AM.

### 2.6 Data Analysis

We used Jeffrey's Amazing Statistics Program (JASP-0.9) for data analysis. Both the Bayesian paired-sample t-test and Bayesian analysis of covariance (ANCOVA) were performed. The tests provide a Bayes factor that quantifies evidence for or against a hypothesis, providing a more nuanced interpretation than p-values alone, and their confidence intervals (CIs) can be more informative because they reflect the probability that the parameter is within a specific range (Cleophas & Zwinderman, 2018; Fritz & Berger, 2015). They also allow the inclusion of prior beliefs or data, which can improve the analysis, particularly in a small sample size, such as the present study.

## 3 Results

### 3.1 Participants' Sociodemographic Characteristics

A class of 21 students (12 females and 9 males) participated in both the pretest and posttest measurements. As indicated in Table 1, the pretest mean (14.0, SD = 6.55) versus posttest mean (18.6, SD = 6.70) shows that the posttest scores were higher on average, suggesting an improvement after the slide projector-assisted classroom instruction. The 95% credible intervals (pretest: [11.1, 17.0]; posttest: [15.5, 21.6]) do not overlap, reinforcing a likely meaningful difference.

**Table 1:** Descriptive statistics of pre-post scores

| | | | | | **95% Credible Interval** | |
|---|---|---|---|---|---|---|
| | **N** | **Mean** | **SD** | **SE** | **Lower** | **Upper** |
| Pretest score | 21 | 14 | 6.55 | 1.43 | 11.1 | 17 |
| Posttest score | 21 | 18.6 | 6.7 | 1.46 | 15.5 | 21.6 |

The Bayes factor ($BF_{10}$ = 4.68) indicates moderate evidence (Lee & Wagenmakers, 2003, revision of Jeffreys, 1961) in favor of the alternative hypothesis (i.e., a true mean difference exists between the pretest and posttest). The data were 4.68 times more likely under the alternative hypothesis (difference exists) than under the null hypothesis (no difference). The error percentage (0.00%) suggests high computational reliability (Table 2). Furthermore, the graphical display of the means associated with the 95% credible interval in Figure 1 suggests that this difference was statistically meaningful.

### 3.2 Bayesian Paired Samples test Analysis

**Table 2:** Bayesian Paired Sample t test Statistics

| | $BF_{10}$ | error % |
|---|---|---|
| Pretest score - Posttest score | 4.68 | 0.00 |

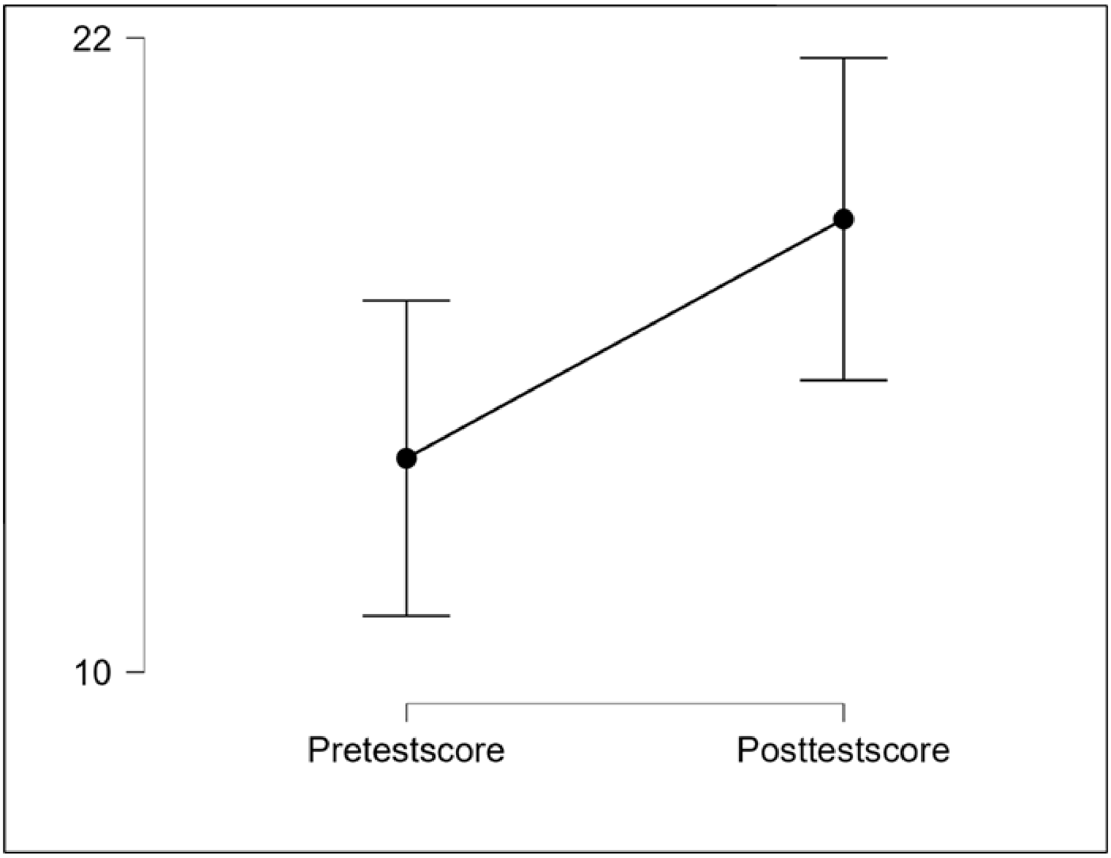


**Figure 1:** Bayesian Paired Sample test Plot

A Bayes factor robustness check in Figure 2 indicates that the BF remains stable ($BF_{10}$ = 3.33–4.94) across different prior widths, suggesting that the result was robust to prior specifications and in favor of the alternative hypothesis. This strengthens confidence in the conclusion. The Cohen's d was 0.50 (moderate effect) (Figure 2), with a 95% credible interval of [-1.01, -0.12] (Figure 3). The negative sign indicates that the posttest mean was higher, since the analysis computed pretest minus posttest. The interval excludes zero, supporting a statistically meaningful effect (Cohen, 1988). The result is interpreted as the average score of students' exam scores after a slide projector-assisted lecture being 0.5 standard deviations greater than the average score of students before the lecture. On the other hand, the average score of students before the lecture was 0.50 standard deviations lower than the average exam score after the lecture, hence exceeding the scores of 50% of students' scores in the pretest (Cohen, 1988). Generally, we accepted the research hypothesis that states that classroom instruction via the slide projector-assisted method significantly improves students' exam scores.

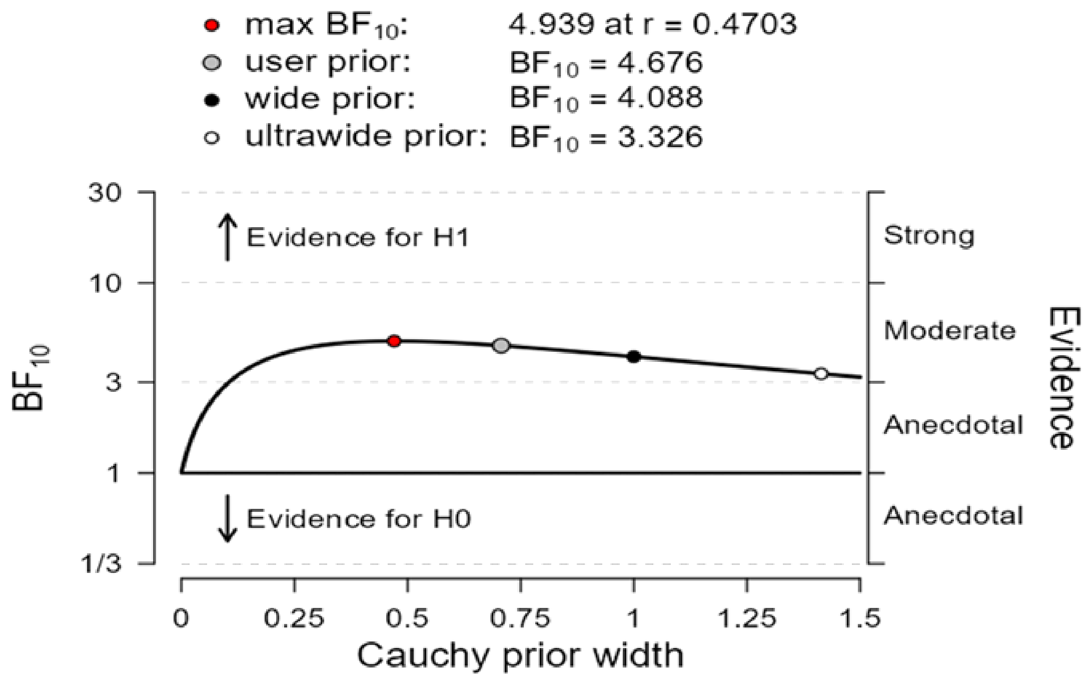


**Figure 2:** Bayes Factor Robustness Check

The posterior distribution was shifted away from the prior (default Cauchy prior, r = 0.707), confirming that the data strongly update beliefs toward a nonzero effect. Visual alignment with higher posttest scores supports the intervention's efficacy (Figure 3).

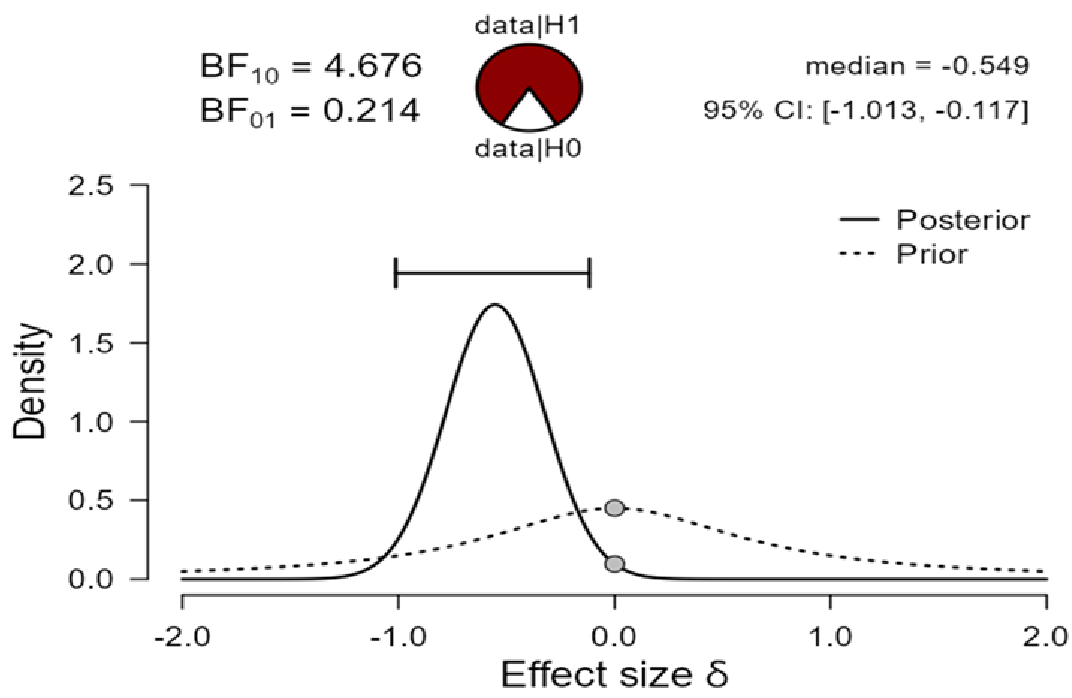


**Figure 3:** Prior and Posterior Plots

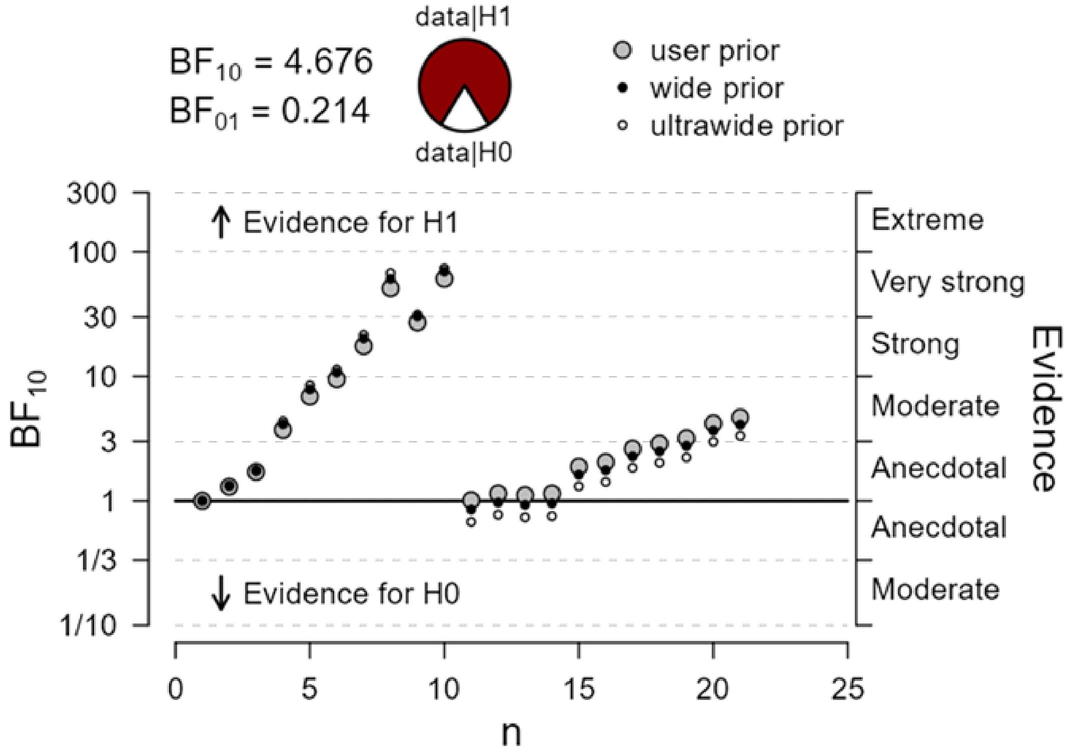


**Figure 4:** Sequential Analysis

Figure 4: The x-axis represents the number of observations (sample size) or the order of data collection, and the y-axis represents $BF_{10}$, indicating the strength of evidence for the alternative hypothesis over the null hypothesis. Initially, with small sample sizes, the BF fluctuates markedly, as each new data point has a large impact, indicating that the initial evidence lacks stability. As the sample size increases, the BF stabilizes toward a consistent value (e.g., approaching BF = 4.68 in earlier results), indicating that the final BF is robust and representative of the true effect.

### 3.3 Bayesian Covariance Analysis

As shown in Table 3, multiple model comparisons were made to determine the best model that explains the posttest data. A combination of variables, including the pretest score, sex, study hours, and CGPA, was included in each model. Prior probability of the model (P(M)) (all models start with equal priors, 0.06, since there are 16 possible combinations of four predictors). The posterior probability of the model given the data (P(M|data)). Higher values indicate better support from the data. Bayes factor for the model (BFM) compared with the null model. Values > 1 favor the model over the null model. BF comparing the model to the null model ($BF_{10}$). Values > 1 suggest that the model is more likely than the null model. Estimation error (error %) for the BF (a lower value is better).

The findings indicate the top models (highest P(M|data)): pretest score + study hours: strong support (P(M|data) = 0.28, BFM = 5.84). Pretest score + sex + study hours, additionally, was well supported (P(M|data) = 0.24, BFM = 4.67). These models were 5–6 times more likely than the null model (BFM > 1).

Weak models show that models with sex or CGPA alone perform poorly (e.g., sex: P(M|data) = 0.02, BFM = 0.23). The null model was outperformed by most models but was still a baseline reference. This means that the pretest score and study hours are the most important predictors, especially when they are combined. Sex and CGPA have little explanatory power unless they are combined with other variables.

**Table 3:** Bayesian ANCOVA Model Comparison Posttest Score

| Models | P(M) | P(M\|data) | $BF_M$ | $BF_{10}$ | error % |
|---|---|---|---|---|---|
| Null model | 0.06 | 0.039 | 0.61 | 1.00 | |
| Pretest score | 0.06 | 0.05 | 0.70 | 1.15 | 0.00 |
| Sex | 0.06 | 0.02 | 0.23 | 0.4 | 0.00 |
| Pretest score + Sex | 0.06 | 0.02 | 0.28 | 0.48 | 0.74 |
| Study hours | 0.06 | 0.03 | 0.45 | 0.75 | 0.00 |
| Pretest score + Study hours | 0.06 | 0.28 | 5.84 | 7.21 | 0.00 |
| Sex + Study hours | 0.06 | 0.01 | 0.18 | 0.31 | 1.21 |
| Pretest score + Sex + Study hours | 0.06 | 0.24 | 4.67 | 6.10 | 0.63 |
| CGPA | 0.06 | 0.02 | 0.33 | 0.56 | 0.00 |
| Pretest score + CGPA | 0.06 | 0.02 | 0.33 | 0.55 | 0.00 |
| Sex + CGPA | 0.06 | 0.01 | 0.13 | 0.21 | 1.01 |
| Pretest score + Sex + CGPA | 0.06 | 0.01 | 0.14 | 0.23 | 0.98 |
| Study hours + CGPA | 0.06 | 0.04 | 0.54 | 0.90 | 0.00 |
| Pretest score + Study hours + CGPA | 0.06 | 0.12 | 2.06 | 3.106 | 0.00 |
| Sex + Study hours + CGPA | 0.06 | 0.02 | 0.25 | 0.413 | 0.86 |
| Pretest score + Sex + Study hours + CGPA | 0.06 | 0.09 | 1.52 | 2.364 | 0.80 |

Table 4 shows the importance of individual predictors across all the models. P(incl): prior inclusion probability (0.5 for all, assuming equal chance). Posterior inclusion probability given the data (P(incl|data)) of higher values indicates stronger evidence for the predictor's importance. The Bayes factor for including the predictor (BFInclusion) values > 1 suggests that the predictor should be included. Therefore, the strong predictors include the pretest score: P(incl|data) = 0.82, BF = 4.67, and study hours: P(incl|data) = 0.82, BF = 4.63, which show very strong evidence for inclusion. The weak predictors include sex: P(incl|data) = 0.41, BF = 0.69, and CGPA: P(incl|data) = 0.32, BF = 0.48, both showing weak evidence or favoring exclusion. This means that the pretest score and study hours were critical for explaining the posttest score. Sex and CGPA were less important and may be omitted unless theoretically justified. Therefore, the best model for predicting the posttest score includes the pretest score plus study hours. Adding sex or CGPA to the model did not significantly improve the predictions. Only the pretest score and study hours strongly predict and show consistent evidence of inclusion, suggesting that both variables affect students' exam scores.

**Table 4:** Analysis of Effects – Posttest Score

| Effects | P(incl) | P(incl\|data) | $BF_{Inclusion}$ |
|---|---|---|---|
| Pretest score | 0.5 | 0.82 | 4.67 |
| Sex | 0.5 | 0.41 | 0.69 |
| Study hours | 0.5 | 0.82 | 4.63 |
| CGPA | 0.5 | 0.32 | 0.48 |

# 4 Discussion

The effect of slide projector-assisted classroom instruction on students' exam scores was examined. The pretest and posttest data were compared, and the posttest scores were significantly improved over the pretest scores in a sample of twenty-one students. The 95% CIs for the pretest and posttest did not overlap, suggesting a significant difference between the two situations (Kruschke, 2015). The quantitative learning benefits are strengthened by the use of slide projectors in classroom instruction.

## 4.1 Bayesian t-test for Paired Samples

According to the Bayesian paired-sample t-test analysis, the results were 4.68 times more likely under the hypothesis that posttest scores were higher than under the null hypothesis of no difference. This indicates that a real mean difference was detected between the pretest and posttest scores. The presence of an effect was supported by moderate evidence. An extremely low error percentage further validates computational reliability, as per Lee and Wagenmakers's (2013) interpretation of Jeffreys's (1961) classification.

A moderate effect size was indicated by the estimated Cohen's d (Cohen, 1988). This shows that students' posttest values exceeded 50% of the pretest distribution. According to Cohen's U3 convention, this implies a significant improvement in academic achievement, since the average posttest score was higher than 69% of the pretest scores. This finding was consistent with the existing educational research literature that highlights how effectively visual aids improve learning outcomes (Mayer, 2009).

## 4.2 Sensitivity and Robustness Evaluations

The Bayes factor robustness result shows that the $BF_{10}$ remains between 3.33 and 4.94 for different prior widths. This implies that the outcome was resilient to modifications in prior specifications, increasing confidence in the findings (Kass & Raftery, 1995; Rouder *et al.*, 2012). The Bayes factor was utilized in a sequential analysis over progressively increasing sample sets. Confidence in the effect was increased by the convergence of $BF_{10}$ at approximately 4.68 with increasing sample size, which implies that early fluctuations did not influence the outcome (Schönbrodt *et al.*, 2017). This suggests that the $BF_{10}$ levels vary as a result of early sample addition due to the high sensitivity to initial data. However, $BF_{10}$ stabilizes around the final estimate (4.68) as the sample size increases, indicating that the outcome is stable and indicative of a real effect (Rouder *et al.*, 2009). The observed data also strongly suggest a nonzero effect, as evidenced by the posterior distribution shifting away from the prior distribution (default Cauchy prior, $r = 0.707$). The effect of instruction on student achievement was highlighted by this visual proof.

## 4.3 Bayesian Covariance Analysis

We compared many models that use posterior model probabilities and Bayes factors to predict posttest scores. The null model (intercept-only) has a posterior probability, P(M|data) = 0.04, and a Bayes factor BFM = 0.61, indicating weak evidence against it compared with the best-performing models (Rouder *et al.*, 2012).

The model that combines the pretest score plus study hours has the highest posterior probability (P(M|data) = 0.280) and a substantial Bayes factor (BFM = 5.84), suggesting strong evidence in favor of this model (Kass & Raftery, 1995). The full model (pretest score plus sex plus study hours) also performs well (P(M|data) = 0.24, BFM = 4.67), reinforcing the importance of these predictors.

Models including sex or CGPA alone have low posterior probabilities (P(M|data) < 0.05) and Bayes factors (BFM < 0.5), indicating minimal explanatory power. With respect to the error rates, most models exhibit low estimation errors (< 1%), except for those including sex, which show greater variability (with an error of up to 1.2%).

Study hours and pretest results were found to be significant predictors of posttest exam achievement. This finding is in line with those of previous studies. Credé and Kuncel (2008) and Schneider and Preckel (2017), for instance, identified prior achievement and study habits as significant determinants of students' academic performance. Sex and CGPA seemed to have less of an impact on the posttest score. According to Jeffreys (1961), thresholds and Bayes factors greater than three were regarded as moderate evidence, whereas those greater than ten were regarded as strong evidence. Only the pretest score plus study time met this requirement in this case. Further research is necessary, since the significant error rates for sex-based models point to possible multicollinearity or measurement noise.

## Limitations

First, the sample size was small, warranting caution regarding external validity. Therefore, replication with a larger sample size is needed. Second, it lacks randomization and comparison groups, which restricts the ability to draw strong causal inferences. Without a comparison group, it is difficult to know whether changes were due to classroom instruction or other factors (e.g., maturation, historical events). To mitigate such potential knowledge-sharing behaviors, two dichotomous (yes/no) items were administered. These were: Did you discuss answers to the pretest questions with peers? and Did you discuss potential posttest content with classmates prior to the examination? These items were designed to evaluate the extent of interstudent information exchange regarding assessment content across testing phases. The participants gave "no" responses for both items. Finally, the lack of alternative instructional methods for comparison limits the generalizability of the findings to other instructional approaches.

## 5 Conclusion

Slide projector-assisted classroom instruction significantly improves students' achievement. Pretest scores and study hours significantly predicted posttest achievement. The model with these variables provides the strongest explanatory evidence. Overall, we conclude that even with sufficient provision of instructional materials, students' academic achievement may not accurately reflect their autonomous engagement with the content; rather, it may also reflect methods of instruction, particularly those that use slide projectors.

### Ethical Statement

The study was conducted in accordance with the ethical standards of research involving human participants and the Helsinki Declaration of 2008. The study's purpose was explained, and written informed consent was obtained from each participant prior to participation. Participation was voluntary. All the data were kept confidential, and no personal identifiers were reported. The instructional activities related to the lecture intervention were conducted independently prior to the regular class schedule, and all collected data were used solely for research purposes.

## Declarations

### Ethical Approval

Ethical approval was not required for this study in accordance with institutional guidelines, because the study involved routine educational practices and did not collect sensitive personal data.

### Consent to Participate

Written informed consent was obtained from all participants prior to their inclusion in the study.

**Consent to Publish:** Not applicable.

### Data Availability

Data are available from the corresponding author upon reasonable request.

### Competing Interests

The authors declare that they have no competing interest.

### Article Preparation

Springer Nature CURIE and GPT-5 were used solely for language editing. The authors take full responsibility for the manuscript's content.

## References

Bales, E. (1996). *Corporate universities versus traditional universities: friends or foes. Key Note Address at the Conference on Innovative Practices in Business Education, Orlando*, FL, 4-7

Bernstein, D. A., & Nash., P. W. (2008). *Essentials of Psychology* ($4^{th}$ Ed.). New York: Houghton Mifflin Company

Bjork, R. A., & Bjork, E. L. (2011). *Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning*. In M. A. Gernsbacher, R. W. Pew, L. M. Hough, & J. R. Pomerantz (Eds.), Psychology and the real world: Essays illustrating fundamental contributions to society ($2^{nd}$ ed., pp. 56–64). Worth Publishers.

Brown, P. C., Roediger, H. L., & McDaniel, M. A. (2014). *Make it stick: The science of successful learning*. Harvard University Press.

Clark, R. C., & Mayer, R. E. (2016). *E-learning and the science of instruction* ($4^{th}$ ed.). Wiley.

Clark, R. E. (1994). Media will never influence learning. *Educational Technology Research and Development*, 42(2), 21-29. https://doi.org/10.1007/BF02299088

Cleophas, T. J., & Zwinderman, A. H. (2018). *Bayesian Paired t Test* (pp. 49–58). Springer, Cham. https://doi.org/10.1007/978-3-319-92747-3_5

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* ($2^{nd}$ ed.). Routledge.

Credé, M., & Kuncel, N. R. (2008). Study habits, skills, and attitudes: The third pillar supporting collegiate academic performance. *Perspectives on Psychological Science*, 3(6), 425-453.

Creswell, J. W. (2012). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* ($4^{th}$ ed.). Boston, MA: Pearson.

Dunkin, M. J. (2006). A Review of Research on Lecturing. *Journal of Higher Education Research and Development* 2 (1): 63-78. https://doi:10.1080/0729436830020105

Fritz, M., & Berger, P. D. (2015). *Comparing two designs (or anything else!) using paired sample t tests* (pp. 71–89). https://doi.org/10.1016/B978-0-12-800635-1.00003-3

Jeffreys, H. (1961). *Theory of Probability* ($3^{rd}$ ed.). Oxford University Press, Oxford, UK.

Kass, R. E., & Raftery, A. E. (1995). Bayes Factors. *Journal of the American Statistical Association*, 90(430), 773–795.

Kimbrel, L. (2019). Teacher Hiring: The disconnect between research-based best practice and processes used by school principals: Connecting Education, Practice, and Research. *Administrative Issues Journal* 9 (2): 12-27. https://doi:10.5929/9.2.2

Knapp, T. R. (2016). Why Is the One-Group Pretest-Posttest Design Still Used? *Clinical nursing research* 25 (5): 467–472. https://doi.org/10.1177/1054773816666280

Kozma, R. B. (1991). Learning with media. *Review of Educational Research*, 61(2), 179-211. https://doi.org/10.3102/00346543061002179

Kruschke, J. K. (2015). *Doing Bayesian data analysis* ($2^{nd}$ ed.). Academic Press.

Lee, M. D., & Wagenmakers, E. J. (2003). Bayesian statistical inference in psychology. *Psychological Review*, 110(4), 678–688. https://doi:10.1037/0033-295X.110.4.678

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press.

Mayer, R. E. (2009). *Multimedia learning* ($2^{nd}$ ed.). Cambridge University Press.

Maynes, N., & Hatt, B. E. (2015). Teacher Hiring: Exploring the Dilemmas and the Solutions. *Journal of Studies in Education* 5 (2).

Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, 56 (5), 356–374. https://doi.org/10.1016/j.jmp.2012.08.001

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, 16(2), 225–237.

Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin*, 143(6), 565-600.

Schönbrodt, F. D., Wagenmakers, E.-J., Zehetleitner, M., & Perugini, M. (2017). Sequential hypothesis testing with Bayes factors: Efficiently testing mean differences. *Psychological Methods*, 22(2), 322–339. https://doi.org/10.1037/met0000061

Spurlock, D. R. (2018). The Single-Group, Pre- and Posttest Design in Nursing Education Research: It is Time to Move on. *The Journal of nursing education* 57(2): 69–71. https://doi.org/10.3928/01484834-20180123-02

Stringer, E. T. (2014). *Action research* ($4^{th}$ ed.). SAGE Publications.

Umoren, D. N. (2001). Suggested methods of teaching. In: DN Umoren, CM Ogbodo (Eds.), *A Hand Book on Teaching Profession in Nigeria*. Uyo: Guidepost Publishers, 9-14

Vincent, E. O., & Akpan, U. T. (2014). Instructional strategies and students' academic performance in electrical installation in technical colleges in Akwa Ibom State: Instructional skills for structuring appropriate learning experiences for students. *International Journal of Educational Administration and Policy Studies* 6 (5): 80-86.

World Medical Association. (2008). *Declaration of Helsinki: Ethical principles for medical research involving human subjects*.

Yu, F.Y., & Liu, Y. H. (2008). The Comparative Effects of Student Question Posing and Question-Answering Strategies on Promoting College Students' Academic Achievement, Cognitive and Metacognitive Strategies Use. *Journal of Education and Psychology* 31 (3): 25-52.