# Randomized Factorial Experimental Design (RFD) Concept in Student Learning Effectiveness Assessment in Engineering Curricula

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## Abstract

Characteristic of classroom instruction in Engineering curricula is highly uni-directional and passive, and subsequent assessment of student learning effectiveness depends on specific instruction delivery mechanism and /or level of learning readiness by the recipient, students. Also, conventional assessment methodology is largely based on discretized quantification via test and assignment scores, which the very assessment efforts become reduced to mere proportional comparisons of posterity of events at a sample level that do not guarantee much needed reproducibility of desired effects or improvements under similar or the same measure implemented to the course in interest. The motivation of this research is to introduce a new pedagogical assessment framework based on statistical Randomized Factorial Design (RFD) Assessment Framework concept to capture true student feedbacks at system-level so that assessment findings can be correctly used to reproduce gains in student learning effectiveness in the future. Thus this new pedagogical assessment framework is based on an approach of logical deduction with clarity, compared to conventional assessment framework of an additive and qualitative reasoning approach, to identify what works and what does not.

## Keywords

Pedagogical assessment framework; Learning effectiveness; Statistical Randomized Factorial Design (RFD); Reproducibility

## Introduction

Compared to other disciplines, characteristic of classroom instruction in Engineering curricula is highly uni-directional and passive[1,2], and subsequent assessment of student learning effectiveness becomes equally hinged on a specific instruction delivery mechanism as well as the level of learning readiness by the recipient, students. Furthermore, conventional assessment methodology intended to measure the learning effectiveness typically focus on discretized quantification of student performance via test and assignment scores, and most of time the very assessment efforts become reduced to mere proportional comparisons of posterity of events that do not guarantee the reproducibility of desired effects or improvements under similar or the same measure implemented to the course in interest. Then the question becomes that are we capturing true response of student learning effectiveness in the first place, and what would be the best way to ensure the maximum likelihood of accomplishing desired improvement in classroom instruction by reflecting findings from such assessment.

The motivation to pursue this research is to introduce a new pedagogical assessment framework based on statistical Randomized Factorial Design (RFD) concept to capture true student feedbacks and subsequent learning effectiveness gain at system-level, instead of sample-levels. So that assessment findings can correctly identify true 'positive' factors in instruction and its delivery derivatives and also be able to discern 'false-positive' from the findings by using statistical methods. Correctly identified and verified true 'positive' factors are then used to reproduce gains in student learning effectiveness in the course of interest in the future. Thus this new pedagogical assessment framework is based on an approach of logical deduction with clarity, compared to conventional assessment framework of an additive and qualitative reasoning approach, to identify what works and what does not.

In this paper, proposed concept and methodology of the Randomized Factorial experimental design[3], criteria in establishing treatment- and block-level contrasts for student learning effectiveness assessment[4], procedure to incorporate factorial multicolinearity into assessment framework[5] to capture relevant factors including possible stratification in student demography, and subsequent *p*-value based decision criteria for identifying true reproducibility factor(s) influencing student learning effectiveness at system-level, will be discussed.

## Randomized Factorial Design (RFD) Assessment Framework

The core of the proposed Randomized Factorial Design (RFD) Assessment Framework consists with a standard Randomized Complete Block (RCB) experimental design[6], augmented by Factorial multicolinearity to reflect effect of student demographic factors.

Randomized Complete Block (RCB) experimental design is composed of treatment and block components -- dividing students enrolled in course, either temporal sequence, i.e., different semester and/or year, or same semester with multiple sections including a minimum of one base reference section as "control," or spatially distributed over multi-institutes, or traditional instruction vs. online/open access delivery settings, etc. (Treatment), and different levels of classroom instruction, both topic variation and delivery mechanism settings such as traditional instruction vs. online/open access delivery or traditional instruction vs. traditional augmented with additional supplements such as computer-based or project-based, etc. (Blocks). Elements of student learning effectiveness assessment would consist of common quantitative measures including test, quiz, lab report, exam scores and final grade.

$$y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij} \qquad (i = 1, \ldots, \text{Treatments}; j = 1, \ldots., \text{Blocks})$$

where

$y_{ij}$ = Response on (i, j) th Obs. (Student Learning outcomes – test, quiz, lab report, exam scores and final grade)
$\mu$ = Overall mean, student learning effectiveness
$\tau_i$ = i th Treatment effect (temporal and/or spatial composition of class and/or sections)
$\beta_j$ = j th Block effect (different levels of classroom instruction, both topic variation and delivery mechanism settings)
$\varepsilon_{ij}$ = Random error due to (i, j) th observation where $\varepsilon \sim NID(0,\sigma^2)$ by Gaussian Markov theorem

The main objective of the RCB design is to statistically analyze and assess student learning effectiveness by using Test of Hypotheses (T.H.) so that students' learning can be objectively measured instead of subjective "did quite well, so-so, not look good and so forth." Since student enrollment to subject courses is generally handled centrally by institute's Registrar's Office, and the instructor(s) would have no control or knowledge as to who is registering in which section, one can assume that student composition to a given class/section is a random process and ensure compliance to the Family Educational Rights and Privacy Act (FERPA)[7]. Advantage of the RCB design includes a flexibility to construct spatiotemporally "unbalanced" treatment and block levels so that variations in frequency of class offering or total number of sections offered each time can be assessed and evaluated without depreciating the validity of analysis results.

Assessment outcomes are then tested first for normality using standard Shapiro-Wilk W-statistics[8] at 95% level of confidence ($\alpha$=0.05) followed by the Multiple Means Comparison (MMC) method with Duncan's Multiple Range Test (MRT) [9] to compare the level of student learning effectiveness under treatment and block levels. In case of non-normality, a median-based one-way, pairwise nonparametric statistics, Wilcoxon Rank Sum statistics[10,11,12], can be employed alternatively. Subsequently, a series of cascade Test of Hypotheses on central tendency of treatment and block level responses are then tested to compare and measure the student learning effectiveness under specific combination of classroom instruction method implemented. For example, typical Test of Hypotheses (T.H.) would be constructed as;

TH on Dominance in Central Tendency among "Control" vs. "Experiment" group learning effectiveness (Treatment)

$H_0$: All C.T.[Treatment]$_i$ are statistically equal
$H_a$: At least one or more C.T.[Treatment]$_i$ is not equal (i = 1, 2, 3)

TH on Dominance in Central Tendency among "Instruction method j" vs. " Instruction method j+1" on learning effectiveness (Block)

$H_0$: All C.T.[Block]$_i$ are statistically equal
$H_a$: At least one or more C.T.[Block]$_j$ is not equal (j = 1, 2, 3)

Once the initial assessment of student learning effectiveness under implemented Treatment and Block level settings in classroom instruction completes, a secondary Factorial multicolinearity analysis[5,6] would be performed to correlate additional effect of student demographic factors and their sensitivity toward learning gains identified the initial assessment through RCB design.

$$y_{ij} = \mu + \tau_i + \beta_j + \tau\beta_{ij} + \varepsilon_{ij} \qquad (i = 1, \ldots, \text{Treatments}; j = 1, \ldots, \text{Blocks})$$

where

$y_{ij}$ = Response on (i, j) th Obs. (Student Learning outcomes influenced by demographic factors)

$\mu$ = Overall mean, student learning effectiveness
$\tau_i$ = i th Treatment effect (degree program-specific demographic factors)
$\beta_j$ = j th Block effect (person-specific demographic factors)
$\tau\beta_{ij}$ = Response on (i, j) th Obs. (multicolinearity, significant compounding factors incurring gains in student learning effectiveness)
$\varepsilon_{ij}$ = Random error due to (i, j) th observation where $\varepsilon \sim NID(0,\sigma^2)$ by Gaussian Markov theorem

$H_0$: All C.T.[Treatment $_i$ | Block $_j$ (Demographic Factor/Factors)]$_k$ are statistically equal
$H_a$: At least one or more differ (i, j, k = 1, 2, ..., n)

Suggested student demographic factors[4] to evaluate whether such factors contribute toward the student learning effectiveness gain under implemented classroom instruction settings are cumulative GPA, SAT Math score and High school GPAs (degree program-specific demographic factors) and student age, gender, ethnicity and class (person-specific demographic factors), and additional relevant factors can be incorporate as needed with flexibility. Use guideline of selected student demographic information should comply with the Family Educational Rights and Privacy Act (FERPA) guideline[7]. Factorial multicolinearity analysis outcomes are then evaluated by using similar procedural and componental sequence to isolate and identify individual or colinear effect toward student learning effectiveness gain.

## Conclusion

The goal of proposed Randomized Factorial Design (RFD) Assessment Framework concept is to objectively capture true student feedbacks and subsequent learning effectiveness gain at reproducible system-level, instead of temporal sample-levels. So that assessment findings can correctly identify true 'positive' factors in instruction and its delivery derivatives applicable to various student compositions and demography through Factorial multicolinearity analysis[3], and also be able to discern 'false-positive' from the findings by using statistical methods. Correctly identified and verified true 'positive' factors are then used to reproduce gains in student learning effectiveness in the course of interest in the future. Thus this new pedagogical assessment framework is based on an approach of logical deduction with clarity, compared to conventional assessment framework of an additive and qualitative reasoning approach, to identify what works and what does not.

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