Analyzing the Impact of Technological Intervention on Enhancing Student Learning, Engagement, and Workforce Readiness in Higher Education

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Abstract:

Technology integration in higher education has significantly transformed traditional teaching methods, offering new avenues to enhance student learning, engagement, and workforce readiness. This study examines the impact of technological interventions on these crucial outcomes within higher education settings. By examining how digital learning tools complement conventional classroom instruction, the research seeks to understand their influence on student academic performance, levels of engagement, and preparedness for the modern job market. This study will employ a cluster randomized controlled trial (cRCT) methodology to assess the effectiveness of technological interventions and distinguish between intervention and control groups. Advanced statistical techniques, including logistic regression, will be used to analyze the data, allowing for a detailed examination of the relationship between technological interventions and student outcomes while considering relevant demographic variables. By integrating factors such as gender and students' classification into the analysis, the study aims to identify potential moderating influences on the effectiveness of technological interventions.

Introduction:

In today's rapidly evolving educational landscape, integrating technology with traditional classroom learning is revolutionizing higher education, offering students enriched learning experiences and better preparing them for the demands of the contemporary workforce (Castro, 2019; Siemens et al., 2013). The fusion of digital learning tools and core curriculum instruction presents a synergistic approach to education, providing students with diverse pathways to acquire knowledge, develop critical skills, and engage with course content in meaningful ways (Alenezi et al., 2023; Mayes R. et al., 2015; Mishra & Koehler, 2006). Technology intervention programs are commonly employed to address specific challenges faced by students and foster their academic growth by understanding the knowledge and research needs for student engagement (Wang et al., 2022; Sartika et al.; B., 2023). As universities navigate this digital transformation, examining the intersection between digital and traditional learning modalities is imperative to optimize educational outcomes and enhance student readiness for the workforce.

In response to the evolving educational landscape, universities actively integrate innovative teaching methods, leverage technology, and facilitate experiential learning opportunities

(Brown & Green, 2019; Bernacki et al., 2020). However, pursuing educational excellence goes beyond mere adoption (means et al., 2013); it necessitates a comprehensive evaluation of the effectiveness of these initiatives. Robust evaluation mechanisms are crucial for garnering empirical evidence that underscores the positive influence of these innovations on students' academic achievements, critical thinking capacities, and practical skill development (Graham. R, 2018)

This study explores the intricate dynamics between digital technologies and core classroom learning in higher education settings. The aim is to understand whether technological intervention and traditional learning enhance the student's output. By investigating how these components complement and enrich each other, the research seeks to elucidate the impact of integrated technological interventions on student learning outcomes, engagement levels, and workforce readiness. Highlighting the integration of digital and conventional learning methods, the research investigates how technology improves the delivery of core curriculum and cultivates a more robust learning atmosphere for students.

This study explores the impact of technological interventions on student learning, engagement, and workforce readiness within higher education contexts, particularly in conjunction with core classroom learning experiences. By examining technology integration into the curriculum alongside traditional face-to-face instruction, the research aims to assess its influence on student outcomes, including academic achievement, digital literacy, and employability skills. By implementing cutting-edge teaching approaches and embracing technological advancements, universities aim to enhance the overall learning experience and better prepare students for the demands of the modern workforce. However, to truly understand the impact of these initiatives, it is imperative to establish rigorous evaluation frameworks. Through meticulous assessment, institutions can ascertain the efficacy of these innovations in fostering student success and empowering learners to thrive in an increasingly complex and dynamic world.

To address this imperative, we employ a cluster randomized controlled trial (cRCT) method (a robust research design, which is an advanced iteration of the traditional randomized controlled trial (RCT) methodology) to evaluate interventions in educational settings, mainly when individual randomization is impractical or when the interventions are implemented at a group level. While both cRCT and RCT designs share the same principle of randomization to ensure an unbiased comparison between intervention and control groups, cRCTs introduce an additional layer of complexity by randomizing clusters rather than individual participants (Donner et al., 2000). This approach is instrumental in educational research when individual randomization is impractical or when interventions are implemented at the group level (Torgerson et al., 2008; Spybrook et al., 2020). The research will proceed with a robust statistical methodology, including logistic regression analysis incorporating demographic variables. The logistic regression model is of paramount importance for analyzing categorical variables in research due to its specialized capacity to model binary and multinomial outcomes, making it a versatile tool across diverse fields.

Further, integrating with demographic variables offers a powerful tool for understanding, predicting, and controlling the influence of demographic factors on various outcomes. This multifaceted approach allows for a rigorous examination of the effectiveness of technological interventions within the educational context, considering the influence of demographic factors on student outcomes. Through meticulous assessment and rigorous evaluation, institutions can ascertain the efficacy of these innovations in fostering student success and empowering learners to thrive in an increasingly complex and dynamic world. Our study aims to bridge the gap between theoretical frameworks and practical implications, offering insights that can inform evidence-based decision-making within educational institutions.

Deciphering these factors extends beyond the academic realm, resonating with educators and policymakers alike. For educators, insights from this study can inform pedagogical approaches tailored to enhance student success. Understanding how student grades, gender, and exposure to innovative teaching methods impact task completion equips educators with valuable information to adapt teaching strategies to diverse student needs. On the other hand, policymakers can leverage these findings to shape educational policies that foster an environment conducive to positive student outcomes.

Literature Review:

In contemporary higher education, technological interventions have garnered significant attention for their potential to revolutionize teaching and learning practices. Numerous studies have explored the impact of technology integration on various aspects of higher education, ranging from student learning outcomes to workforce readiness. These interventions encompass various tools and strategies, including online learning platforms, multimedia resources, and interactive simulations. One of the primary areas of focus in the literature is the effect of technological interventions on student learning outcomes. Research suggests that well-designed digital learning experiences can enhance student engagement, motivation, and academic achievement (Ferrer et al., 2022). Moreover, technology-enabled pedagogies, such as flipped classrooms and blended learning approaches, have improved critical thinking skills and knowledge retention (Cavanagh et al., 2020).

In addition to academic performance, technological interventions in higher education have implications for students' readiness for the workforce. Employers increasingly value digital literacy and technical skills in prospective hires, making it essential for higher education institutions to equip students with these competencies (Qureshi et al., 2021). Studies have highlighted the role of technology-enhanced learning environments in developing students' employability skills, such as problem-solving, communication, and collaboration (Hassan et al., 2018; Ismail, M., 2019; Larrabee, 2019). In addition, integrating technology in higher education has emerged as a transformative force, reshaping traditional teaching methods and providing new opportunities to enhance student learning outcomes (Imhof et al., 2020). Researchers have highlighted the potential of technology to improve student learning experiences by facilitating personalized learning, fostering collaboration, and promoting critical thinking skills (Selwyn, N. 2018). Moreover, technological interventions have increased student engagement by offering interactive and immersive learning experiences catering to diverse learning styles (Yassin & Almasri, 2015).

Some other studies have investigated the relationship between technological interventions and student workforce readiness, emphasizing the role of digital literacy and technical skills in preparing students for the demands of the contemporary job market (Haleem et al., 2022). By integrating technology into the curriculum, higher education institutions aim to equip students with the digital competencies and practical skills needed to succeed in a rapidly evolving workplace environment (Cheng et al., 2014). Additionally, technological interventions have been associated with improved student employability outcomes, including higher job placement rates and increased career opportunities (Abes et al., 2023; Astin, A.W., 2014).

However, despite the potential benefits of technological interventions, challenges still need to be addressed in effectively implementing and evaluating these initiatives. Researchers have highlighted the importance of considering factors such as access to technology, digital equity, and faculty readiness in designing successful interventions (Cabaguing, J. M & Lacaba, T.V.G., 2022; Siemens, G., 2013). Furthermore, while technological interventions have shown promise in enhancing student learning and engagement, studies have underscored the need for rigorous evaluation methodologies to assess their effectiveness (Dziuban et al., 2018). Future research in this area should focus on employing robust research designs, such as cluster randomized controlled trials (cRCTs), and advanced statistical techniques to analyze technological interventions' impact on student outcomes comprehensively. By addressing these challenges and leveraging the potential of technology, higher education institutions can continue to enhance student learning, engagement, and workforce readiness in the digital age.

Cluster randomized trials (cRCTs) have emerged as a robust methodological approach in educational research, particularly for evaluating the effectiveness of interventions at the group or cluster level. In cRCTs, clusters such as classrooms, schools, or districts are randomly assigned to intervention or control conditions, allowing researchers to assess the impact of interventions while accounting for group-level effects and potential contamination (Donner & Klar, 2004). Recent advancements in cRCT methodology have focused on addressing methodological challenges and enhancing the validity and reliability of study findings. For example, innovative statistical methods, such as multilevel modeling and generalized estimating equations, have improved the analysis of clustered data and facilitated more accurate estimation of treatment effects (Eldridge et al., 2016).

A growing body of literature underscores the methodological advantages of cRCTs in educational research. These trials offer increased statistical power and ecological validity compared to individual-level randomized trials, allowing for more precise estimation of intervention effects within real-world educational contexts (Choi et al., 2021). Recent studies have also highlighted the importance of rigorous study design and implementation strategies to overcome challenges related to sample size determination, cluster allocation, and participant recruitment in cRCTs (Hemming et al., 2024). Additionally, advances in ethical guidelines and informed consent procedures have contributed to the ethical conduct of cRCTs in educational settings, ensuring participant autonomy and research integrity (Weijer et al., 2012).

The transition from traditional randomized controlled trials (RCTs) to cluster randomized controlled trials (cRCTs) represents a significant evolution in research methodology, particularly in fields where interventions are implemented at the group or community level. While RCTs have long been regarded as the gold standard for evaluating the efficacy of medical treatments and interventions, they are only sometimes feasible or appropriate when interventions are delivered to entire groups or communities rather than individuals. In such cases, cRCTs offer a more practical and ethically sound approach by randomizing clusters or groups of individuals rather than individual participants.

Overall, the transition from RCTs to cRCTs represents a methodological advancement that acknowledges the complexities of evaluating interventions implemented at the group level (Murray, 2022). By embracing cluster-based randomization, cRCTs offer researchers a more realistic and practical approach to assessing the effectiveness of interventions in diverse settings, ultimately enhancing the validity and generalizability of research findings.

Cluster randomized controlled trials (cRCTs) have emerged as a valuable methodology for evaluating interventions, particularly in public health and educational research (Murray et al., 2018). It emphasizes the importance of robust design and analysis techniques in cRCTs, highlighting recent advancements in trial practices. Eldridge et al. (2008) conducted a systematic review of cRCTs in primary care, identifying lessons for enhancing the design and implementation of such trials.

Hemming et al. (2018) discuss the reporting standards for stepped wedge cluster randomized trials, extending the CONSORT guidelines. Ethical considerations unique to cRCTs are explored by Hutton, J.L. (2001), who examines the need for distinctive ethical principles in cluster trials. Arnold et al. (2013) present the rationale and design of cluster-randomized trials assessing water, sanitation, hygiene, and nutritional interventions in rural settings.

Methodological aspects of RCTs, including design considerations and analysis techniques, are addressed by Hussey et al.,2007 and Wolfenden et. Al., 2021). Torgerson (2008) also provides an introductory guide to designing randomized trials across various disciplines, emphasizing the importance of rigorous methodology and human-centered design. Kjeld et al. (2023) analyzed the impact of multicomponent intervention on reducing smoking in schools.

cRCTs are commonly employed in various fields to evaluate interventions at the group level, necessitating robust statistical methodologies for analysis. While cRCTs provide valuable insights into the effectiveness of interventions, appropriate analytical techniques are crucial to derive meaningful conclusions from the data. Logistic regression emerges as a widely used follow-up methodology to analyze the outcomes of cRCTs, offering a versatile approach to modeling binary or categorical outcomes within clustered data structures. Bechter et al.. (2019) studied the effects of a teacher training program targeting student-centered learning strategies.

Several studies have demonstrated the utility of logistic regression in analyzing cRCT data across diverse research domains. For instance, Turner et al. (2017) discuss the application of logistic regression in assessing the impact of interventions in public health settings, highlighting its ability to account for clustering effects while examining binary outcomes. Moen et al. (2016) emphasize the importance of employing appropriate regression models, such as logistic regression, to accurately estimate intervention effects and adjust for potential confounders in RCTs. Furthermore, studies by Hemming et al. (2018) discuss the application of logistic regression in the analysis of cRCTs across different research contexts, reinforcing its versatility and efficacy in modeling clustered data.

In educational research, logistic regression is considered an essential tool for analyzing the effectiveness of interventions aimed at improving student outcomes. Kestner et al. (2019) discuss the use of logistic regression to assess the impact of educational interventions in primary care settings, emphasizing its role in identifying significant differences in outcome measures between intervention and control groups. Additionally, Hussey et al. (2007) provide insights into designing and analyzing stepped wedge cluster randomized trials, highlighting logistic regression as a preferred method for analyzing binary outcomes in longitudinal studies.

Logistic regression with demographic variables is integral to various research endeavors due to its ability to elucidate the relationships between individual characteristics and outcomes of interest. Demographic factors such as age, gender, education level, and socioeconomic status significantly influence outcomes across diverse domains, including health behaviors, educational attainment, and employment status (Adams et al., 2014; Marmot, M., 2020). By incorporating these variables into logistic regression models, researchers can effectively assess the impact of demographic characteristics on the likelihood of specific outcomes occurring, thereby enhancing our understanding of population-level disparities and inequalities (Subramanian et al., 2021; Williams et al., 2010). Furthermore, logistic regression facilitates the control of confounding variables, allowing researchers to isolate the effects of interventions or exposures while accounting for potential confounders such as demographic factors (Greenland & Robins (1986); Agresti, A. (2012)). This approach enhances the validity and reliability of study findings and informs the development of tailored interventions to address disparities and promote equity within populations (Stringhini et al., 2010). Ultimately, logistic regression with demographic variables is a powerful analytical tool for uncovering patterns, predictors, and disparities in outcomes, informing evidence-based policies, interventions, and practices to improve population health and well-being.

Methodology:

Cluster randomized controlled trials (cRCTs) followed by logistic regression analysis offer a robust methodological approach for evaluating interventions and understanding their effects on outcome variables. Incorporating demographic variables into a logistic regression model allows one to account for participant characteristics and explore subgroup differences, thereby enhancing the validity and generalizability of study findings. Moving forward, utilizing cRCTs and logistic regression analysis generates rigorous evidence for the effectiveness of interventions and informs evidence-based practice in various fields.

Unlike traditional randomized controlled trials (RCTs), cRCTs randomize groups, making them particularly well-suited for evaluating interventions implemented at the group level (Hemming et al., 2015). The use of cRCTs allows cluster-level variability, providing robust evidence for the effectiveness of interventions. This approach reduces the risk of contamination and accounts for intra-cluster correlation, factors that can influence the accuracy of standard errors in individually randomized trials. By recognizing and incorporating the shared characteristics within clusters, cRCTs provide a more realistic representation of the social and environmental contexts in which interventions are implemented. This methodology enhances the external validity of study findings and improves the generalizability of results to the target population (Donner & Klar, 2000). Following the implementation of a cRCT, statistical analysis techniques such as logistic regression were employed to examine the impact of interventions on outcome variables of interest while controlling for potential confounding factors.

The Logistic regression model is a widely used statistical model that analyzes binary outcome variables in cRCTs, allowing the assessment of the relationship between intervention exposure and outcomes while adjusting for covariates. By fitting logistic regression models to cRCT data, we can estimate intervention effects and assess the significance of associations between intervention exposure and outcomes. Logistic regression also accounts for baseline differences between intervention and control groups, thereby improving the validity and reliability of study findings.

In addition to intervention effects, demographic variables are essential in understanding the determinants of outcomes in cRCTs. Adding demographic variables to logistic regression models allows us to examine how participant characteristics, such as gender and classification, influence intervention outcomes. By including demographic variables as covariates in logistic regression, we can control for potential confounding effects and explore subgroup differences in intervention effects. This enhances the generalizability of study findings and provides valuable insights into the differential impacts of interventions across diverse populations.

The logistic regression model is formulated as follows:

$$\text{logit}(p)=\beta 0+\beta 1X1+\beta 2X2+\ldots+\beta kXk$$

Where:

logit(p) is the natural logarithm of the odds of the outcome variable (p) being in the "success" category.

$\beta 0$ is the intercept term.

$\beta 1,\beta 2,\ldots,\beta k$ are the regression coefficients associated with the predictor variables $X1,X2,\ldots,Xk$

Research Design:

This study employs a clustered randomized controlled trial (cRCT) design followed by logistic regression analysis to explore the effects of integrating technological intervention alongside traditional instructional methods. The intervention, comprising a technological intervention program closely aligned with traditional in-class learning, is scrutinized for its impact on student success, engagement, and workforce development. Various incentive methodologies are employed to advise students, allowing for a comprehensive assessment of the intervention's effectiveness. By comparing outcomes between groups exposed to the intervention and those following traditional instruction, the study aims to discern how much technological intervention influences student performance and involvement.

The research comprises two groups: a treatment group and a control group. In the treatment group, students receive comprehensive and explicit information regarding the intervention. They were notified that incorporating technological intervention, such as completing tasks beyond the class, would form a crucial part of their classroom learning. The emphasis was placed on the importance of successfully fulfilling these tasks for academic progress. In contrast, the control group receives limited instructions and is informed that completing the technological task will allocate additional value for academic advancement. This setup allows for a comparative analysis of the impact of the intervention on student outcomes, providing valuable insights into the efficacy of integrating technological interventions with traditional instructional methods in educational settings.

Data Collection:

This study primarily focuses on students at the University of Arkansas at Pine Bluff. The students were drawn from various courses they registered for, with particular emphasis on finance-related subjects. The research used a clustered Randomised Control trial method (cRCT) to collect the data. The cRCT method is chosen because the research aims to include technological intervention within the registered classes, which may be challenging in other sampling methods. In this research, the students who registered for classes were considered as a group, and from the registered groups, a few were selected randomly to be included in the study. Once the cluster is selected, again, they will be selected randomly to be a part of either the control or treatment group. Once the groups are finalized, all the individuals from that cluster are included in the sample. Each of these groups comprised roughly 50% of the total sample. This approach was carefully adopted to counteract the potential limitation of insufficient representation within individual clusters, ensuring a more balanced representation across the study.

Control Group:

In this group, students were informed that successfully completing the technology intervention is an optional part of their in-class learning, which will incentivize their engagement with technological aspects and prepare them for future job prospects. This strategy aimed to foster deeper understanding and proficiency in traditional academic content and technology, creating a more conducive learning environment. The supplementary incentive not only aimed to boost students' enthusiasm for technological learning but also held the potential to impact their overall academic performance within the course positively. This approach will record the effectiveness of external motivational factors, driving student engagement with technological interventions, and gauge the subsequent impact of this engagement on overall academic performance.

Treatment group:

In this group, students receive explicit instructions regarding the essential role of technological intervention that will lead to a successful career opportunity if seamlessly integrated with their classroom learning. Emphasis is placed on the mandatory nature of completing the technology intervention in fulfilling academic requirements, reflecting an intrinsic motivation approach to student incentivization. This instructional strategy aims to cultivate a sense of personal responsibility and ownership in students' learning journeys, fostering more profound engagement.

Results and Discussion:

In this section, we embark on a detailed exploration of the statistical outcomes and empirical revelations, aiming to unravel the complex relationships inherent in our study. We seek to shed light on the nuanced associations and patterns discerned within the data through meticulous analysis. Our examination encompasses a comprehensive review of the diverse statistical methodologies, from descriptive statistics providing foundational understanding to empirical statistics elucidating the relationship between variables. Analytical approaches contribute to a deeper understanding, scrutinizing outcomes through various statistical techniques to uncover meaningful insights and draw informed conclusions. Traversing numerical representations and graphical visualizations, we synthesize findings to provide a comprehensive analysis, illuminating empirical realities and offering valuable insights for future research and practical applications.

Cross Table:

A cross table is used as a valuable tool in the realm of descriptive analysis in this study. When examining the cross table, we observed variations in completion rates across different demographic groups and intervention conditions. For instance, within the female cohort, the Treatment group exhibited a higher proportion of completions than the Control group, where no completions were recorded. Conversely, while completion rates were generally lower among males, the Treatment group demonstrated a notable improvement compared to the Control group. These findings suggest the potential effectiveness of the treatment intervention, particularly among specific demographic segments.

Female	0 (Not Completed)	1(Completed)
Control	29	0
Treatment	17	17

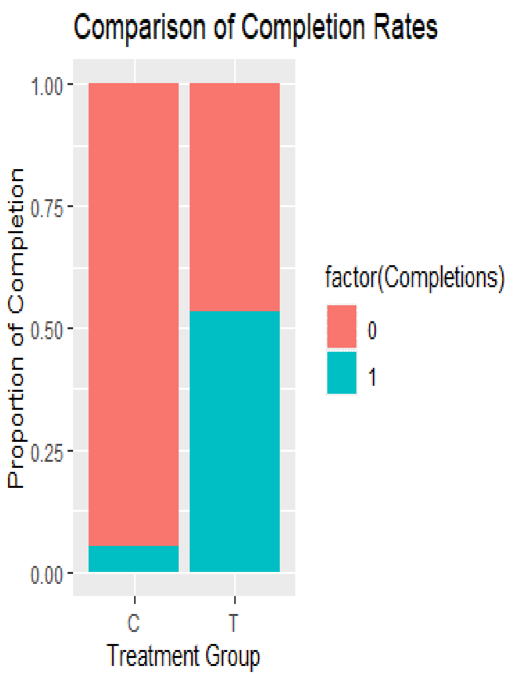
Male	0 (Not Completed)	1(Completed)
Control	24	03
Treatment	17	22

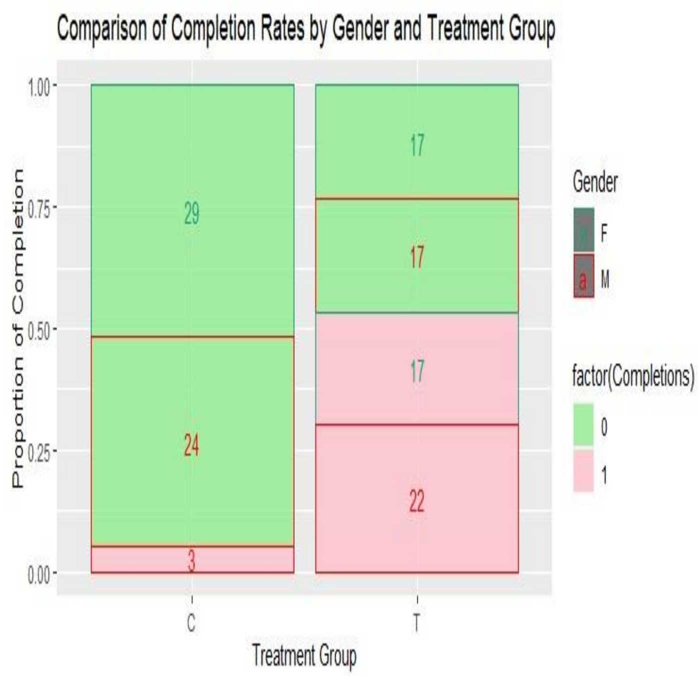
Proportion Table:

To bolster the cross table, we also used a proportion table as a part of descriptive statistics. The proportion table provided a more nuanced understanding of completion rates, revealing the relative distribution of completions within each subgroup. Notably, within the Treatment group, both female and male cohorts displayed comparable completion proportions, indicating a positive impact of the intervention across genders. However, in the control group, completion proportions varied significantly, with males exhibiting slightly higher completion rates than females.

Female	0 (Not Completed)	1(Completed)
Control	0.52	0.00
Treatment	0.23	0.23

Male	0 (Not Completed)	1(Completed)
Control	0.43	0.05
Treatment	0.23	0.30





The clustered randomized control trial, a cornerstone of empirical research, unfolds its narrative as we juxtapose the control and treatment groups and the demographic variables. The dynamics of these groups, accentuated by the divergent instructions provided (Control vs. Treatment), unveil the varying influences on student performance.

However, cluster sampling in cRCTs introduces specific considerations, such as the potential for between-cluster variability and the need to adjust for intra-cluster correlation. Statistical methods, including multilevel modeling, account for these complexities and yield unbiased estimates.

Analyzing intra-cluster correlation (ICC) is crucial in cluster randomized trials (cRCTs) or other studies where observations within clusters may be correlated. ICC quantifies the proportion of total variance in the outcome attributable to between-cluster variation. A higher ICC suggests a more significant similarity of outcomes within clusters, emphasizing the importance of accounting for this correlation in the analysis. In contrast, a low ICC suggests there is a minimal variation between the clusters.

Using a mixed-effects model, we can calculate the Intra-Cluster Correlation (ICC) in R. To calculate the Intra-Cluster Correlation (ICC) in R, we used the lme4 package and fit a mixed-effects model.

In calculating the Intra-Cluster Correlation (ICC), the ratio of the cluster-level Variance to the total variance is typically calculated. The cluster-level variance is obtained from the random effects output, and the scaling factor (the scaling factor squared is used to rescale the estimated variances of the random effects. The scaling factor is an internal parameter used during the optimization process derived by the lme4 package in R,) and is used to convert it back to the original scale.

Random effects:

Groups	Name	Variance	Std.Dev
Cont_Tret	(Intercept)	0.1202	0.3467
Residual		0.1568	0.3959

The variance value for the Cont_Tret group is 0.1202, which is the estimated variance of the random intercepts across the clusters.

$ICC = \frac{Cluster\ Level\ Variance}{Total\ Varience} = 0.1202/0.1568$

where,

The Cluster-Level Variance obtained from the Random effects.

Total Variance = Scaling Factor^2 *X Cluster-level Variance*

The total variance is the overall variability observed in the outcome variable across all individuals in the study, without initially considering how individuals are grouped.)

Scaling Factor = $\sqrt{\frac{\text{Residual Variance}}{\text{Residual Scale Factor}}}$

An ICC of 0.7668 suggests that approximately 76.68% of the total variance in the outcome variable is attributable to differences between clusters. At the same time, the remaining 23.32% of the variance is due to differences within clusters. An ICC closer to 1 indicates a high similarity within clusters, and this high-value ICC implies a substantial degree of homogeneity within clusters and indicates that individuals within the same cluster tend to have more similar responses compared to individuals from different clusters.
In our research, a high ICC is advantageous. It implies that addressing factors at the cluster level could lead to significant impacts on the outcome variable across individuals within those clusters. In such cases, targeting the cluster directly will be more efficient and effective than individual-level interventions. Any interventions or treatments applied at the cluster level could substantially impact the outcomes measured within those clusters.
Once we confirmed the ICC, signifying significant variance at the cluster level, we proceeded with our empirical investigation using a logistic regression model. This model was selected due to its appropriateness for analyzing binary outcome variables and its ability to incorporate individual and cluster-level predictors. In addition to the primary variables of interest, we included demographic variables to capture their potential

influence on the outcome. By employing logistic regression, we explored the nuanced connections between various factors, including our demographic characteristics and the likelihood of event completion. The logistic model outputs are as follows:Logistic regression model output:

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	Odds Ratio
Intercept	5.3262	1.1729	-4.541	5.59e-06***	0.005
Cont_TretT	3.1925	0.6759	4.723	2.32e-06***	24.35
GenderM	0.8850	0.5000	1.770	0.0767 .	2.42
Class_Sopho	2.4612	1.0539	2.335	0.0195 *	11.72
Class_Junior	2.1289	0.9046	2.353	0.0186 *	8.41
Class_Senior	1.8395	0.9050	2.033	0.0421 *	6.29

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

In the logistic regression analysis and the outputs from the output table, we can infer that the intercept represents the log odds of the response variable when all other predictors are zero. For instance, when Cont_TretT (Treatment Group) is 0, GenderM (Male) is 0 (indicating female), and the student is classified as a Freshman, the intercept estimates the log odds under these conditions. Moving on to the coefficients, the value associated with Cont_TretT (3.1925) signifies a positive coefficient, implying that being in the treatment group is linked with higher log odds of the response.

Regarding GenderM, the coefficient (0.8850) reflects the estimated change in log odds for males compared to females, the reference category. While the positive coefficient suggests that being male is associated with increased log odds, the p-value (0.0767) is not highly significant, so we may not differentiate between male and female students. Similarly, coefficients for classifications, such as Junior, Senior, and Sophomore, compared to the reference category Freshman, assess how each classification affects the log odds of the response variable. A coefficient of 2.4612 for the Sophomore, 2.1289, and 1.8395 for the Senior classification suggests that being in these groups increases the log odds of the response compared to being a freshman. This output suggests that students other than first-year students have a high chance of completing the task.

Further examining significance through p-values, a significant intercept underscores varying outcomes even when all predictors are zero, especially for Freshmen. Meanwhile, a significant and positive coefficient for Cont_TretT indicates heightened odds of the response within the treatment group. However, the less pronounced significance associated with the GenderM coefficient warrants careful consideration, suggesting a potential trend rather than a definitive effect. Notably, significant coefficients for different classifications shed light on how diverse student categories influence the response variable, offering nuanced insights into the impact of demographic factors on outcomes.

When we interpret logistic regression results, looking at the odds ratio over log odds is crucial. Log odds provide valuable information about the relationship between predictor variables and outcomes. In contrast, odds ratios directly quantify the change in the odds of the outcome variable associated with a one-unit increase in the predictor variable.

Based on the odds ratios from the logistic regression model, it is evident that the treatment variable (Cont_TretT) significantly influences the outcome, with individuals in the treatment group having approximately 24.35 times higher odds of the outcome compared to those in the control group. This indicates a substantial positive effect of the treatment on the outcome variable. Additionally, gender (GenderM) also plays a role, with males having approximately 2.42 times higher odds of the outcome compared to females. Furthermore, classification level (Freshmen, Sophomore, Junior, and Senior) significantly impacts the odds of the outcome, with juniors, seniors, and sophomores exhibiting approximately 8.41, 6.29, and 11.72 times higher odds, respectively, compared to first-year students.

After running the logistic regression model, we must ensure that we have employed the best-fitting model and rigorously assessed its validity through various tests. These tests include diagnostics for model assumptions, such as checking for multicollinearity. Additionally, we need to conduct goodness-of-fit tests to evaluate how well the model explains the variability in the data and compare different models using information criteria like AIC (Akaike Information Criterion). We also employed a confusion matrix to assess the accuracy of the model. This involved using a machine learning algorithm to evaluate the goodness of fit, supporting the model's validity.

Multicollinearity test:

	GVIF	Df	GVIF^(1/(2*Df))
Cont_Tret	1.090925	1	1.044474
Gender	1.179313	1	1.085962
Classification	1.232611	3	1.035470

The Generalized Variance Inflation Factor (GVIF) values provide insights into multicollinearity among the predictors in the logistic regression model. For the predictor Cont_Tret (Treatment Group), the GVIF value of approximately 1.09 indicates a low level of multicollinearity, as a GVIF close to 1 suggests that the predictor does not exhibit strong multicollinearity with other predictors. Similarly, for the predictor Gender, the GVIF value is approximately 1.18, indicating a relatively low level of multicollinearity. The predictor classification, however, has a slightly higher GVIF value of around 1.23 but is within an acceptable range (VIF more than 5 indicates a severe multicollinearity). Overall, the GVIF values for all predictors are relatively low, indicating that multicollinearity is not a significant concern in the model.

Furthermore, we test for the goodness-of-fit tests to evaluate how well the model explains the variability in the data and compare different models using information criteria like AIC and the Hosmer-Lemeshow test. The analysis model was the best based on the AIC compared to other reduced models. Secondly, Based on the Hosmer-Lemeshow test, the p-value (0.1426) is more significant than the standard alpha level of 0.05, which means that we fail to reject the null hypothesis, which implies that the logistic regression model we used appears to fit the data well. Finally, from the confusion matrix (a popular machine learning algorithm for binary classification tasks), we derived the model's accuracy, and we found that the model's accuracy is 75% (11% more than the baseline accuracy). The model accuracy can be calculated by adding true positive and negative values divided by the total observations in the data set.

Hosmer and Lemeshow goodness of fit:

Measure	**Value**
Chi-squared (X^2)	12.197
Degrees of Freedom (df)	8
P-value	0.1426

Confusion Matrix:

Actual	**Predicted 0**	**Predicted 1**
Actual 0 (Not Completed)	69 (TN)	19 (FP)
Actual 1 (Completed)	18 (FN)	23 (TP)

Conclusion:

The findings of this study highlight the substantial impact of integrating technological interventions into traditional classroom settings, fostering increased student engagement, and extending learning beyond the confines of the classroom. Moreover, the recognition garnered by students upon certification acquisition from industries underscores the value of such integration in enhancing academic achievements and preparing students for the evolving workforce landscape. Our conclusions are underpinned by a robust statistical methodology, incorporating a clustered randomized controlled trial, contingency table analysis, and logistic regression. This comprehensive analytical approach enhances the reliability and validity of our study's findings, offering nuanced insights into integrating technological interventions in educational settings. These insights contribute significantly to ongoing educational practice discussions, providing valuable guidance for educators, administrators, and policymakers.

Limitations and potential for future research:

The study's findings, rooted in a specific university context, may need more generalizability to institutions with different characteristics. To bolster the generalizability of these findings, future research efforts could explore a broader array of institutions and their engagement with technological interventions. Moreover, longitudinal studies that track students' progress post-graduation could shed light on the lasting impacts of integrating additional technological interventions beyond conventional classroom environments.

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