Article

Comparative Study of Gamification Interventions for Enhancing Statistics Learning in AI-Focused Education

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Abstract

Statistical education is a crucial yet often overlooked aspect of AI in higher education. However, traditional approaches usually focus heavily on procedural knowledge, leaving students anxious about statistics and less confident in applying concepts to real-world problems. This study examines a method that enhances statistical learning outcomes by integrating data visualization and gamification strategies. Students were randomly assigned to either a control group (CG) or an intervention group (IG), and each group was further divided into teams. The curriculum was enhanced in a college statistics course offered for both engineering and math majors. IG students applied data visualization and gamification in a hands-on group project aimed at solving a real-world problem and competed as they presented their results. The effectiveness of this approach was assessed through statistical analyses comparing the performance of IG and CG in surveys, final grades, and project grades. The results from evaluation methods indicated that IG students outperformed CG students, demonstrating a positive impact of gamification on statistics education.

Keywords: data visualization; gamification; active learning; AI education

1. Introduction

Statistics education is vital for preparing students for data-driven fields like artificial intelligence (AI) and engineering. However, traditional statistics teaching often focuses on procedural problem-solving and memorizing formulas, which can increase anxiety and limit students' ability to apply concepts in real-world situations (Beurze et al., 2013). A survey about undergraduate research experiences (UREs) distributed to statistics faculty members at various types of institutions shows that 31% of participants believe their statistics program is not robust enough to prepare students for statistics research (Nolan et al., 2020). Despite advice from organizations such as the American Statistical Association, lecture-based teaching remains the dominant approach in higher education (Jones & Palmer, 2022). To address this issue, educators are increasingly employing active learning methods that foster visualization, participation, and teamwork.

Gamification—the use of game-like elements such as competition, teamwork, and rewards in non-game settings—has been shown to boost student engagement, motivation, and perseverance (J. J. Lee & Hammer, 2011; McGonigal, 2011; Hamari et al., 2014). In STEM education, gamified strategies have enhanced collaboration and facilitated the development

of soft skills (Subhash & Cudney, 2018; Fernandez-Antolin et al., 2021; Sanz-Angulo et al., 2025). Despite rising interest, limited research exists on how gamification, combined with data visualization, impacts student achievement and engagement in statistics courses within AI-focused education.

Research Question: This study aims to answer the main research question:

How does integrating gamification methods in statistics courses impact the learning experience (players vs. non-players) among Hispanic Engineering and Mathematics students?

Motivation and Contribution

Several studies have incorporated gamification strategies into STEM courses; however, their effects on student success in acquiring knowledge or performing data analytical evaluations through hands-on, real-world problem projects have not yet been thoroughly assessed. A notable gap exists in the understanding of the impact of teaching statistics via visual learning and the application of data visualization combined with gamification in addressing real-world problems, particularly concerning its influence on students' overall performance in the statistics course. This has motivated us to address this gap through the proposed intervention and to conduct comparative statistical analyses both with and without its implementation.

While increasing evidence suggests that gamification and AI-enhanced tools can enhance engagement and performance in STEM education, most existing studies either focus on general STEM courses or prioritize platform design over rigorous learning outcomes. For example, Trinh (2024) gamified a graduate-level statistics course and observed increased motivation and performance, but the course was situated in management education and did not include AI-focused visual analytics. Jack (2025) found that gamification in a flipped undergraduate statistics class enhanced behavioral and emotional engagement, yet the study did not incorporate AI tools or compare results to a non-gamified, visualization-rich control group. Similarly, recent research on gamified STEM and calculus instruction (e.g., Ortiz-Rojas et al., 2025) highlights the potential of leaderboard-based gamification but rarely examines statistics learning within AI-oriented curricula or with randomized group assignment. Building on this emerging evidence, our study offers a randomized controlled comparison of visual learning with and without gamified competition in an AI-focused statistics course at a Hispanic-Serving Institution, using real CO_2 time-series data and Python-based modeling to connect statistical concepts, data visualization, and AI-style prediction tasks.

In this paper, data visualization was incorporated into statistics teaching. Compared to the common practice in the college curriculum, including the previous classes taught in our institute, this intervention prepared students not only with the theories of data analysis but also with practical skills to analyze specific datasets. This project combined data visualization and gamification approaches, which have not been used in previous studies, to enhance statistics teaching as an instructional strategy, applying the learning to solve real-world problems in a project. Figure 1 illustrates the conceptual framework that links our in situ intervention in statistics to solving complex real-world problems. This longitudinal in situ intervention employed a randomized controlled trial to select cohorts, and by comparing cohorts with and without intervention, it generated knowledge and an opportunity to understand how visualization and gamification can be combined to improve statistics teaching. The group receiving intervention will have teams compete to solve a real-world problem by applying the data visualization techniques learned in the statistics course.

The subsequent sections of this paper are organized as follows: Section 2 reviews the literature, Section 3 describes the methodology, including the experimental design and data

analysis, and Section 4 presents the main results. Section 5 discusses the data analysis, and Section 6 provides the conclusion.
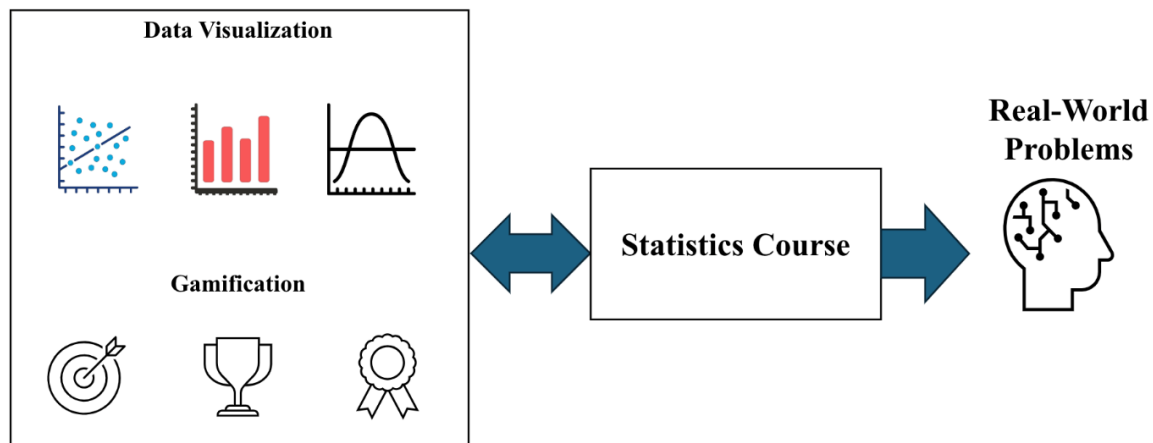

Figure 1. The Conceptual Framework Linking our Intervention.

2. Literature Review

Recent research in statistics and AI-related education has emphasized the need to transform traditional lecture-based teaching into more interactive, learner-centered experiences. This section reviews relevant research on data visualization, gamification, and their combined impact on learning outcomes, forming the basis for the conceptual framework of this study.

2.1. Data Visualization

A study by Yuan et al. (2024) employs ECharts, a powerful data visualization tool, to generate statistical analysis charts. This integration helps present educational data insights clearly and concisely, making them more accessible to educators and stakeholders. Using visualization tools, such as concept maps, in teaching has been shown to assist learners in externalizing their thought processes and improve students' understanding. While statistical analysis and methods provide insightful explanations of the available data, data visualization can offer insights that cannot be drawn from statistical methods (Malik & Ünlü, 2011). Interactive graphic visualization benefits data analysis by providing new insights compared to traditional static graphics methods. Therefore, data visualization is a key complement to data exploration and understanding. In our current teaching approach, engineering and math instructors often deliver lectures based on textbooks that use complex equations and mathematical operations to explain engineering and mathematical concepts and principles. Students typically learn how to solve textbook problems using equations and rules, but they often need help connecting their learning to real-world engineering applications. Interactive visual examples can help learners understand concepts without the need to memorize equations or formulas. Students are generally expected to receive information passively from instructors and textbooks rather than actively engage in their learning process.

Recent advances have strengthened the link between AI-based learning analytics and gamified visualization, indicating a shift toward adaptable, data-driven education. For example, Xu et al. (2025) demonstrated that incorporating AI feedback loops into gamified dashboards significantly enhanced student motivation and retention in STEM learning settings. Similarly, Morales and Han (2024) examined visual analytics in AI education and discovered that interactive visualization tools, which show students' progress in real-time, help promote greater self-efficacy in data interpretation.

Furthermore, Kao et al. (2025) found that using augmented reality (AR) for immersive visualization in math classes led to a 23% increase in conceptual retention compared to traditional methods. These results build on earlier findings (Yuan et al., 2024) and confirm that carefully designed visual learning environments, incorporating cognitive load principles, can enhance both understanding and practical skills.

2.2. Gamification as a Pedagogical Strategy

Gamification refers to the integration of game mechanics—such as points, leaderboards, challenges, and rewards—into educational settings to boost motivation and engagement (McGonigal, 2011; J. J. Lee & Hammer, 2011; Hamari et al., 2014). McGonigal (2011) and J. J. Lee and Hammer (2011) highlight that gamification transforms routine academic tasks into goal-driven experiences that sustain student interest. Empirical studies across various disciplines have found that gamified courses promote persistence, collaboration, and higher achievement levels (Kiryakova et al., 2014; Palacios et al., 2022). In STEM education, gamification has been applied in engineering (Fernandez-Antolin et al., 2021), mathematics (J. Y. Lee et al., 2023; Sanz-Angulo et al., 2025), flow theory (Kapp, 2012), and chemistry (Candel et al., 2022), consistently showing improvements in learning performance and positive emotional responses.

2.3. Integrating Gamification in AI Education

While data visualization and gamification have each proven effective independently, their integration remains underexplored, particularly in AI-oriented and statistics-focused courses. Legaki et al. (2020) found that challenge-based gamification enhanced conceptual mastery in statistics, yet few studies have examined how such strategies interact with visual learning. Fernandez-Antolin et al. (2021) and Sanz-Angulo et al. (2025) demonstrate that gamified, team-based environments foster soft skills like communication and problem-solving, which are vital in data analytics and AI education. Building on this research, our study uniquely integrates both methods in a statistics course that involves real-world data analysis and competition-based presentation.

In gamification research, Ochoa and Liu (2025) reviewed recent meta-analyses and noted that post-2023 implementations increasingly combine machine learning personalization with traditional game mechanics, creating adaptive challenges that sustain engagement longer than static leaderboard systems. In higher education, Serrano et al. (2024) observed that students engaged with AI-supported gamified systems demonstrated enhanced persistence, suggesting that challenge-based gamification (Legaki et al., 2020) remains effective but gains additional power when combined with predictive AI feedback. Recent studies from 2024 to 2025 further clarify how gamification and AI intersect in higher education. Trinh (2024) demonstrated that a points- and badge-based system in a graduate statistics course improved students' perceived relevance and mastery of statistical concepts, although the design focused on management students and did not compare gamified and non-gamified conditions. Jack (2025) found that adding leaderboards and challenges in a flipped statistics classroom increased engagement, especially for students who were initially less confident in mathematics. In STEM fields more broadly, Ortiz-Rojas et al. (2025) showed that leaderboard-based gamification in a university calculus course improved exam performance but warned that design choices can differently impact subgroups of learners. At the same time, Gómez Niño (2024) summarized evidence on AI-driven gamified systems and argued that personalization and data-driven feedback are essential for developing 21st-century skills, while Marengo (2025) proposed an AI-supported gamification framework that uses learning analytics to adjust challenge levels and feedback in real time. Collectively, these studies highlight the potential of AI-supported gamified learning but also identify a

gap: few works systematically examine gamification in statistics courses within AI-focused engineering curricula, with randomized group assignments and detailed analyses of both project and overall course performance.

3. Method

3.1. Participants and Recruitment Process

Participation in the study was entirely voluntary, and informed consent was obtained from all students under the oversight of the Institutional Review Board (IRB). This experimental design involved two groups, randomly assigned: the control group (CG) and the intervention group (IG), as illustrated in Figure 2. In Fall 2024, twenty-eight students were recruited through a randomized controlled trial approach for the cohort and divided into two groups: the control group (CG), comprising fifteen students, and the intervention group (IG), comprising thirteen students. Cross-listed courses in Engineering and Mathematics (Statistical Analysis (MATH 3360) and Engineering Statistics (ENGR 2372)) were chosen for the research experiment. The comparison groups were set up as follows:

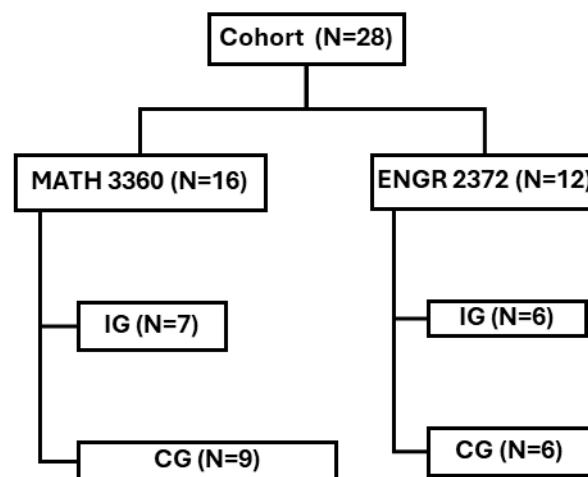- IG: Visual Learning (VL) + Gamification
- CG: VL

Figure 2. Allocation of Cohort Participants into two comparison groups within the Cohort.

Furthermore, each of the two comparison groups (i.e., IG and CG) was further divided into teams of 2 to 4 randomly selected participants. Both IG and CG were expected to complete the project. The project was based on a real-world problem that incorporated what they had learned in class, including data visualization and the use of a simple AI algorithm for prediction. Additionally, IG presented their project findings as part of the gamification activity or intervention before a panel of judges and competed. Additionally, teams in both IG and CG groups meet with faculty members who have expertise in AI and data analytics to seek additional support with their projects. The IG group classification teams convened outside the class on the day of presentations and competed. Presentations were evaluated based on time management, content depth, preparedness, enthusiasm, creativity, and clarity of delivery (each category was graded on a 4-point Likert scale (1 = Strong Disagree, 4 = Strongly Agree)). Judges assessed the presentations, selected the top three teams, and awarded prizes accordingly. These two team-based creative presentation projects and activities are described below, juxtaposed, and summarized in Table 1.

Table 1. Details of Comparison Groups: Control Group (CG) vs. Intervention Group (IG).

	Parameters	Control Group (CG)	Intervention Group (IG)
1	Curriculum and Courses	Intra-curricular, course-based;	Intra-curricular, course-based;
2	Components	Visual Learning	Visual Learning; Gamification
3	Duration	One Cohort (One semester (fall)), 14 weeks long	One Cohort (One semester (fall)), 14 weeks long
4	Team-based Real-world project with gamification	Pick a real-world problem with the dataset, visualize it, and build AI algorithms to solve it.	Pick a real-world problem with the dataset, visualize it, and build AI algorithms to solve it + Gamification (points, leader board, and trophy) competition among teams.

3.2. Interactive Visualization and Gamification

The course was developed in accordance with the principles of Cognitive Load Theory (CLT) to enhance students' conceptual understanding and minimize their reliance on rote memorization. Instructional materials integrated interactive, web-based visualizations and Python-generated figures created by the instructor to facilitate active engagement with statistical concepts.

For instance, during instruction on the normal distribution, a Python-generated visualization illustrated the probability density curve along with the regions corresponding to one, two, and three standard deviations from the mean ($\mu \pm \sigma$, $\mu \pm 2\sigma$, $\mu \pm 3\sigma$), as shown in Figure 3. By interacting with the figure, students could explore the approximate probabilities associated with these intervals, fostering an intuitive understanding of distributional behavior. This visualization-driven approach encouraged conceptual reasoning and reduced extraneous cognitive load, aligning with evidence-based practices in statistical education.
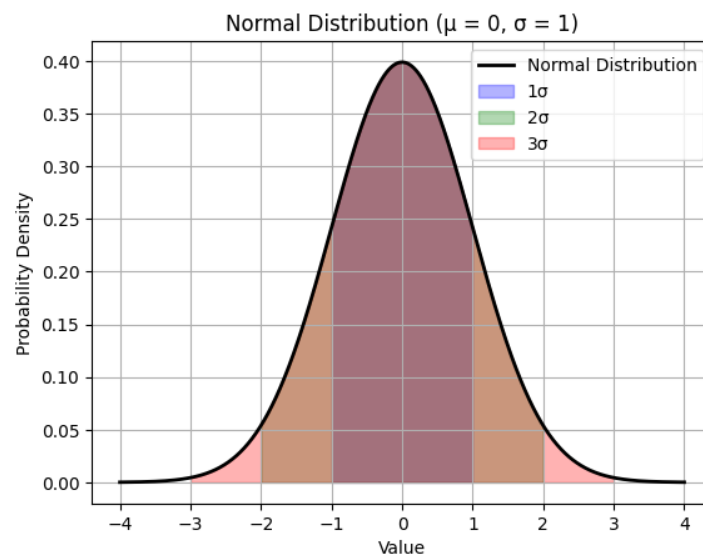

Figure 3. Interactive Visualization using Python for Normal Distribution. Overlapping shaded regions produce blended colors (for ex. brown in the center) due to the transparency-based color mixing of the 1σ, 2σ, and 3σ intervals.

Additionally, visual learners acquired knowledge of various topics through alternative methods (Table 2), employing visualization of meaning rather than rote memorization of equations. Table 2 illustrates the descriptive and inferential statistics discussed in class, presenting these topics in a visual format for the visual learner. Students received training

in data analysis using Python. For instance, in the context of normal distributions, all statistical analyses were conducted within a programming environment to illustrate the execution of specific statistical tests and the interpretation of the resultant data. Fundamental programming commands were imparted during class sessions, encompassing procedures to import, read, and visualize data utilizing box plots, histograms, and heat maps. By carefully considering cognitive load theory, data visualization designers can create visualizations that are not only visually appealing but also highly effective in conveying information and promoting understanding. Students were instructed in differentiating between linear and nonlinear data. For linear data, they were educated on constructing a simple linear regression model and interpreting its implications through graphical representation. This innovative methodology was adopted in preparing the chapter on simple linear regression within the context of this course.

Table 2. Details of Selected Topics in statistics vs. the similar topic taught with visualization.

Topic	Visual Learner
Box Plot	Visualize the meaning of the Box Plot through a five-number summary.
Histogram	Visually observe the changes in the frequency table through a plot.
Normal Distribution	Visually observe how the bell-shaped curve changes.
Confidence Interval	What changes make the confidence interval wider (i.e., less precise) or narrower (i.e., more accurate)?
Q-Q Plot	Visual check for normality in a dataset.
Counting Probability	Visually observe the Tree Diagram in Bayes Rule.
The Exponential and Gamma Distribution	Visualize the comparison of the shapes of gamma functions with different parameters.
Simple Linear Regression	Fitting a line using the least squares and visually observing the changes in the fit.

Gamified elements were incorporated into statistical learning through a competitive framework, where students from the IG group applied statistical concepts and visualized data to solve real-world challenges. The dataset includes records of atmospheric CO_2 levels, which must be monitored to maintain a safe environment. The dataset is publicly available on Kaggle, featuring daily atmospheric CO_2 concentrations from February 2014 to October 2024. Specifically, students in the IG employed Python-based machine learning tools, such as linear regression modeling, correlation visualization, and trend prediction, to analyze and forecast real-world datasets. These AI-driven analyses constituted the primary challenge of the gamified competition. Teams were awarded points and rankings based on the accuracy, interpretability, and creativity of their predictive models, thereby transforming AI-supported data analysis into an engaging, game-based educational experience.

This analysis scrutinizes CO_2 concentration data over time, emphasizing the visualization of cycles and trends, conducting correlation analyses between variables, and constructing and evaluating a predictive model. This experiential, project-based approach can enhance engagement and motivation while reinforcing educational objectives. Teams participating in projects were also assigned points and standings, striving to maximize their potential during oral presentations, with the top three positions receiving awards. Figure 4 displays samples selected from the assignments of a team of IG students. The data was partitioned into testing and training datasets. The data visualization in Figure 4 reveals a correlation of 0.96 between the cycle and trend. A value approaching 1 indicates a positive relationship between the two variables being analyzed. An R^2 value of 0.998 from Figure 5 accounts for 99.8% of the variance in the trend data, signifying an exceptional fit.

This value represents the degree to which the regression model elucidates the variance in the target variable. Additionally, future trends can also be predicted using AI algorithms.
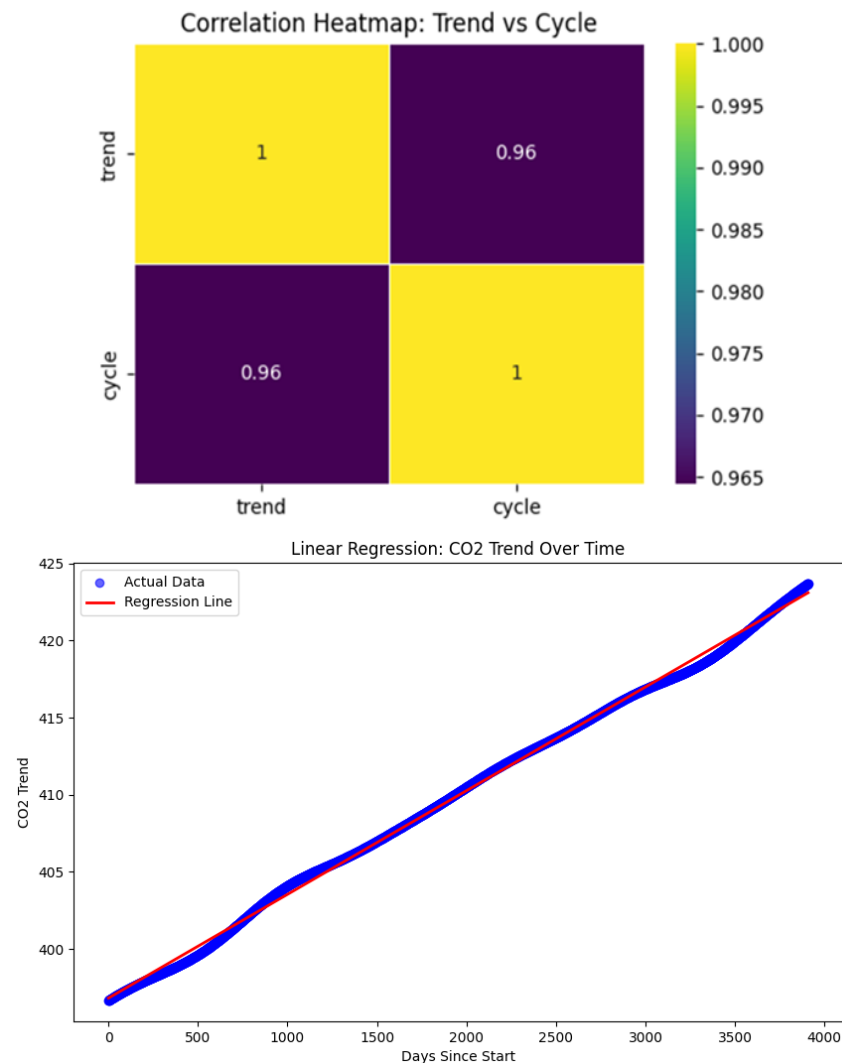

Figure 4. Samples from student project: (**top**) Heat map showing the correlation between Trend and Cycle, (**bottom**) Prediction of the long-term CO_2 trend over time using a simple linear regression AI model.
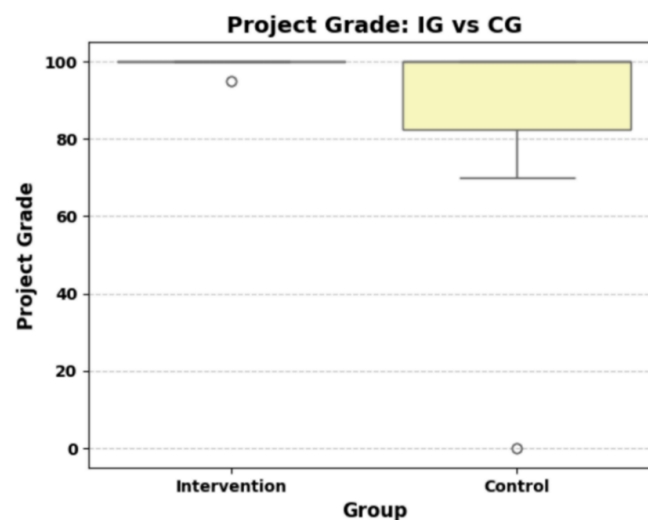

Figure 5. Visualization of the Summary Statistics for Project Grade between IG and CG in a Box plot.

3.3. Analysis Methods

The data analysis was conducted utilizing Python version 3.10. The data preprocessing steps included selecting appropriate variables for evaluating student performance; specifically, the project grade and final class grade were selected for analysis. Data visualization methods, such as histograms and distribution graphs, were employed to visually evaluate the data. Furthermore, an independent *t*-test was applied to evaluate the significance of several variables. Various data analysis techniques were employed to achieve the specified objectives. For example, histograms were created and analyzed based on the scores from the final project and the overall class grade. An independent *t*-test was performed to ascertain whether the differences between the groups were statistically significant, with a significance level established at $p \leq 0.05$. Additionally, an odds ratio test was conducted to determine whether students in the IG are more likely to achieve a higher score in the course compared to those in the CG. Moreover, heat maps were utilized to investigate any correlation between a student's project grade and their final class grade.

4. Results

Data Analysis

The data analysis results were used to determine whether gamification enhances student grades and engagement in the statistical course. Table 3 summarizes the descriptive statistics results for the data collected for the project grade. The summary statistics were calculated for the project grade, and a histogram was used to analyze the data, as shown in Figure 5.

Table 3. Summary Statistics for Project Grade Between IG and CG.

Group	Count	Mean	STD	MIN	Q1	Q2	Q3	MAX
IG	13	99.62	1.39	95	100	100	100	100
CG	15	87.13	26.49	0	82.5	100	100	100

Figure 5 presents a visualization of the summary statistics table from Table 3 using a box plot to illustrate the performance differences between the two groups in the course.

In addition, Figure 6 illustrates the distribution of project grades for both the IG and CG. The blue bars indicate the frequency of students achieving specific grades. From Figure 6a, it is evident that the majority of students attained a perfect score of 100 for their project grade. The red line denotes the density estimate, which approximates the distribution. This representation reveals that the density is skewed to the right, indicating that most grades are concentrated in this region, with a mean of 99.62. Conversely, Figure 6b highlights a greater diversity in the grades. This density line is likewise skewed to the right, indicating that most grades are concentrated between 95 and 100. The peak of the density line represents the mean value, which is 87.13.

Similarly, Table 4 summarizes the descriptive statistics for the final course grade between IG and CG. The final course grade includes class activity participation as extra credit, assignments, tests, and the project; therefore, there is more diversity within this dataset. Grades exceeded 100 because students participated in various class activities, earning bonus points and extra credit that contributed to their overall grades. Here, the mean for the IG is 103.80, and the control group's mean is 93.21, showing a 10.59-point difference. We also observe the differences between Q1, Q2, and Q3.

Figure 7 illustrates the data from Table 4 in a boxplot. We can observe that the data for both groups is more widespread.
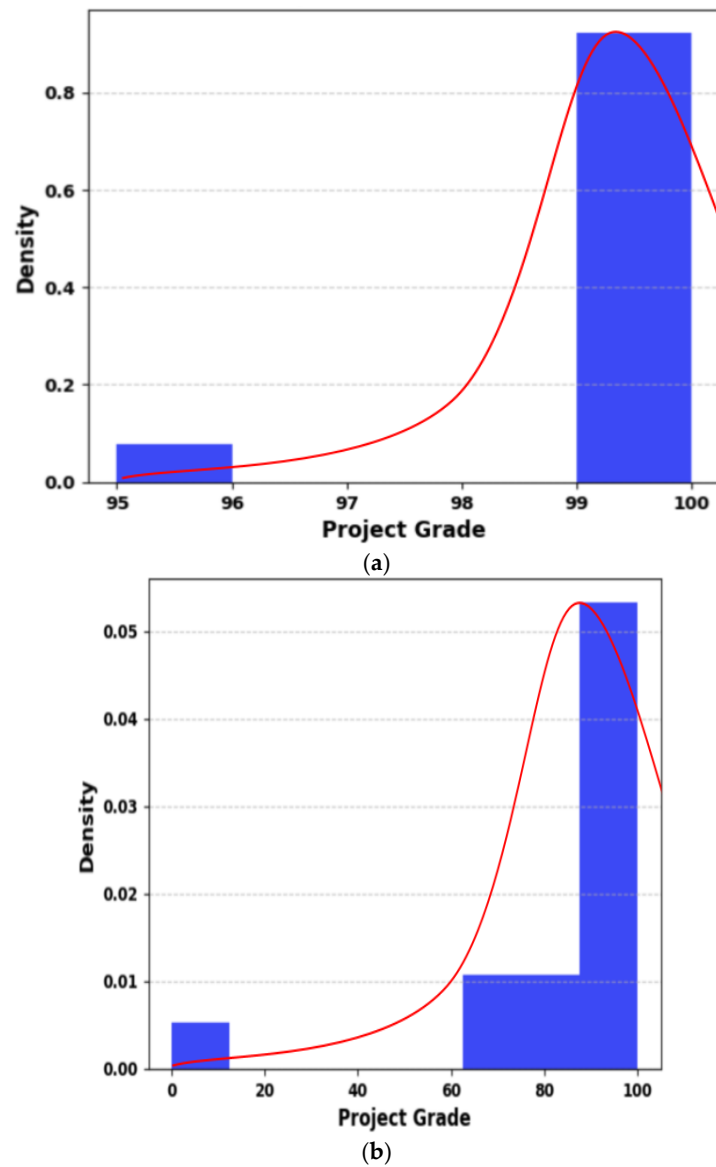
(**a**)

(**b**)

Figure 6. The distribution of the project grade and the density line for: (**a**) the IG, and (**b**) the CG.
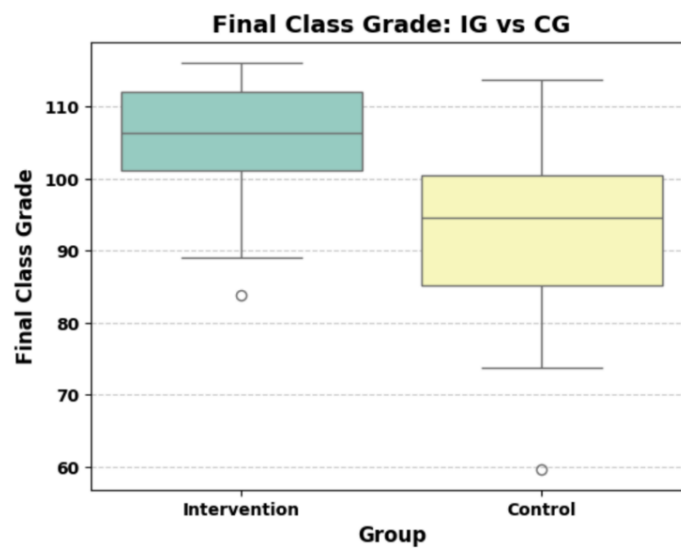

Figure 7. Box plot Visualization of Summary Statistics for Final Class Grade between IG and CG.

Table 4. Summary Statistics for Final Course Grade Between IG and CG.

Group	Count	Mean	Std	Min	Q1	Q2	Q3	Max
IG	13	103.8	10.51	83.79	101.1	106.3	112.0	116.13
CG	15	93.21	14.85	59.58	85.18	94.54	100.17	113.84

Figure 8 displays the final class grade distribution for the IG and the CG. Figure 8a shows the distribution and density line for the final class grade for the IG. Here, we can see that the lowest grade from this dataset is between 80 and 90. According to Table 4, the minimum is 83.79. We can also see that the maximum is between 110 and 120. We can also observe that the point of the density curve corresponds to the mean of the dataset, which is 103.80. Figure 8b visualizes the distribution of and the density line for the final class grade from the CG, showing that the data is more widespread. We can observe that the minimum is between sixty and seventy, while the maximum is between 110 and 120. We can also observe that the highest point of the red density line falls between 90 and 100, with a mean of 93.21.
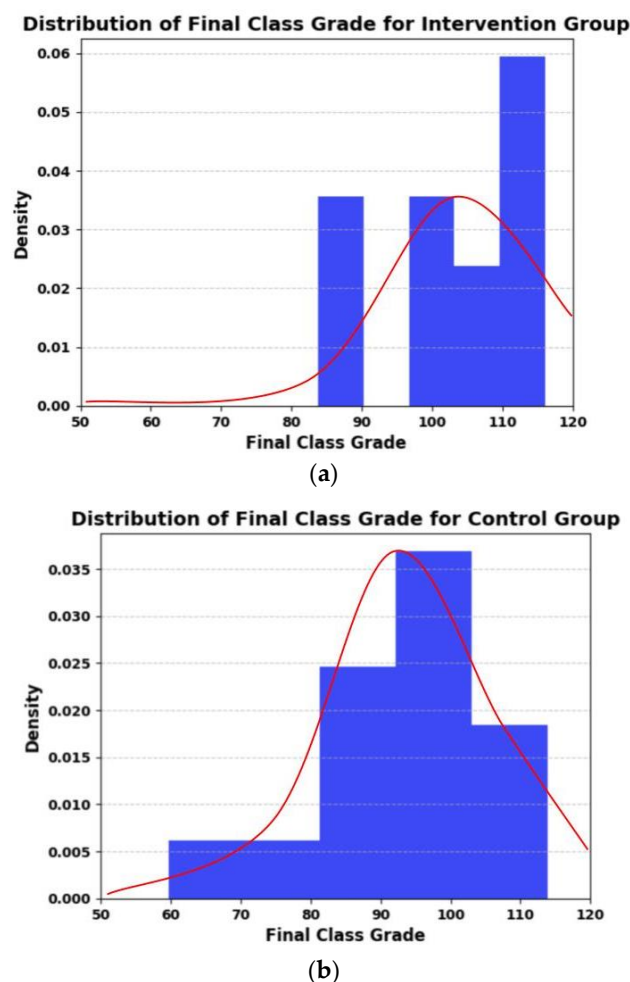

(**a**)

(**b**)

Figure 8. The distribution of the final grade and the density line for: (**a**) the IG, and (**b**) the CG.

Table 5 shows the inferential statistical results between the project grade and final grade for IG and CG. We conducted an independent *t*-test to determine if the difference was statistically significant. The *p*-value was 0.102; therefore, the project grade was not statistically significant in determining the final grade. Similarly, an independent *t*-test revealed that the difference in final grades between the intervention groups and the control groups is statistically significant ($p = 0.042$), indicating that students who received the intervention treatment achieved better course outcomes than those who did not.

**Table 5.** Group Statistics Summary for IG and CG for Project Grade and Final Grade.

	Group	N	Mean	Std	*p*-Value
Project Grade	IG	13	99.62	1.39	0.102
	CG	15	87.13	26.49	
Final Grade	IG	13	103.80	10.51	0.042
	CG	15	93.21	14.85	

Furthermore, the contingency table of odds ratios for grades 90 and 97 is shown in Table 6.

Table 6. Contingency Table of Odds Ratio When $\alpha = 90$ and $\alpha = 97$.

	Group	False	True	Odds Ratio	*p*-Value
$\alpha = 90$	IG	3	10	1.667	0.686
	CG	5	10		
$\alpha = 97$	IG	3	10	6.667	0.030
	CG	10	5		

Results from the Heatmap (Figure 9) show that there was no correlation between a student's project grade and their final class grade. In other words, a student's performance in a specific project cannot predict how well they will do in the class overall, regardless of whether they received that intervention or not.
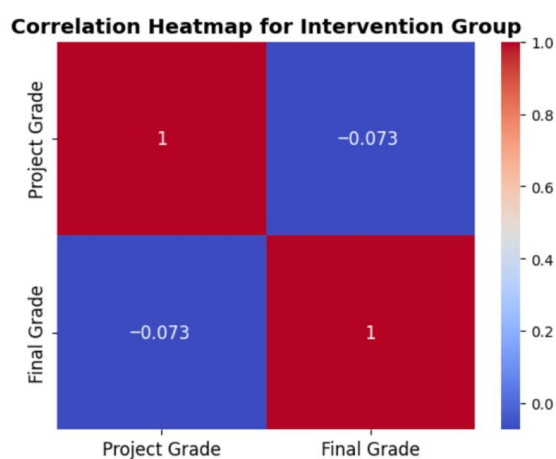
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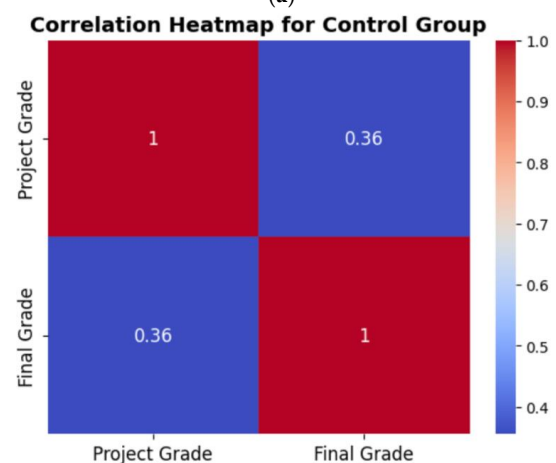
(b)

Figure 9. Correlation heatmap for the project grade and final grade for the: (**a**) IG, and (**b**) CG.

5. Discussion

From Table 3, we can see that the IG's project mean was 99.62, which was 12.49 points higher than the CG's mean. Most of the IG grades were 100 because students from IG received additional feedback after the gamification to ensure everything was on track before submission. Additionally, IG teams were competing for the final project presentation, which was judged by a team of three faculty members. Grades were assessed based on three main criteria: the quality of the presentation content, the rigor of the data analysis, and the clarity and professionalism of delivery. There is a significant disparity between the minimum scores of both groups. IG's minimum score is 95, while CG's minimum is 0. This suggests that one participant from the control group (CG) did not submit their project. Quartile 1 (Q1) shows a 17.5-point difference between the two groups, whereas the second (Q2), third quartiles (Q3), and the maximum scores are the same for both groups. Figure 5 also shows that almost all the grades from the IG are in the hundreds, as IG students received feedback and comments on their presentation. As a result, we observe what appears to be a line at one hundred since the majority of the grades are concentrated there. Additionally, we can see that the box plot for the CG is more diverse, as not all participants received hundreds. These results indicate that the IG performed better with gamification than the CG. From Figure 7, we can also note the differences between the minimum, maximum, Q1, Q2, and Q3. First, the average is higher for the IG than the CG by 10.75%. Our results partially align with the results from Rodrigo (Smiderle et al., 2020), which show that the impact of gamification increased engagement for some students. Additionally, we can see that the maximum and minimum values were higher by 1.99% and 33.77%, respectively, for the IG as well.

These findings align with previous research indicating that gamification can boost engagement and learning in statistics and STEM fields, while expanding this work into an AI-focused course design. Trinh (2024) reported that gamifying a graduate statistics course improved students' perceptions of relevance and mastery, and Jack (2025) demonstrated that gamification in a flipped undergraduate statistics class increased engagement metrics such as participation and time-on-task. Our results agree with these studies by showing that competition-based gamification can enhance performance in statistics; however, our approach differs in three key ways. First, we implement gamification within a randomized controlled comparison between IG and CG rather than relying solely on pre–post comparisons. Second, we incorporate discipline-specific AI tasks (time-series prediction of CO_2 levels using Python) into the gamified project, placing statistics within a clearly AI-related context. Third, our sample includes Hispanic engineering and mathematics majors at a Hispanic-Serving Institution, a group that remains underrepresented in the gamification and AI-education literature.

Table 5 is in good agreement with Legaki's results; we can see that gamification can help students learn material more effectively overall, rather than just in the moment (Legaki et al., 2020; Kiryakova et al., 2014). Similar results were shown in the study by Nouri (2019) and Tan et al. (2023), which examined the effectiveness of a digital learning strategy designed to enhance student performance and engagement in university-level statistics courses. Students who engaged in the frequency-building practice demonstrated significantly higher scores compared to those in the self-directed learning group. As previously mentioned, the main goal was to analyze the impact of visualization and gamification on student success in a statistics course. After analyzing the results, we can see that it impacted the final course grade, not just as a specific class project (Table 5).

Table 6 represents the odds of success in the IG compared to the CG. We initially observe a positive association, indicating that a student in the intervention group is 1.67 times more likely to achieve an A in the course; however, a *t*-test reveals that this finding is

not statistically significant (p = 0.69). Nevertheless, when the threshold for success is increased to 97, the results show greater statistical significance. With a p-value of less than 0.05 (p = 0.030), we can conclude that students in the IG who received the intervention are 6.67 times more likely to earn a high A (97+) than those who did not receive the intervention. Additionally, students from the IG communicated more frequently than those in the CG, which boosted their motivation and engagement.

This increase in test scores is in good agreement with the literature from the Chans and Portuguez Castro group (Chans & Portuguez Castro, 2021). Students reported that gamification made the classes more dynamic and helped maintain focus and interest. Post-intervention surveys indicated that 90% of students felt more motivated and challenged compared to traditional teaching methods. The average pre-test score was 57%, which increased to 79% in the post-test, resulting in a pass rate rise from 24% to 76% (Chans & Portuguez Castro, 2021). This further demonstrates that using gamification as a pedagogical tool can help new generations of students achieve greater success, not only in a statistics course but also in any course where they can compete in a friendly environment with their peers and learn simultaneously (Legaki et al., 2020; Kiryakova et al., 2014).

Figure 9a shows a correlation heatmap between the project grade and final grade for the IG. The red color in the heatmap indicates a stronger correlation between the two variables. In this case, we can see that the intersection of the project grade on the x-axis and the project grade on the y-axis is one. Since the intersection is the same variable itself, it will always correlate with one. The same can be said for the intersection between the final grade on the x-axis and the final grade on the y-axis. The blue color signifies minimal or no correlation between the variables at the intersection. In this instance, a correlation coefficient of -0.073 is observed between the project grade and the final grade, indicating a weak negative correlation. Therefore, we can conclude that a student's performance on the project grade does not guarantee their success in the final grade.

Figure 9b illustrates a correlation heatmap between the project grade and the final grade for the CG. In this instance, it is evident that the intersection of the project grade on both the x and y axes is one. Given that the intersection represents the same variable, it will invariably correlate with one. A parallel observation may be drawn regarding the intersection between the final grades represented on both the x and y axes. The blue color denotes minimal to no correlation between the variables at the junction. In this context, a correlation coefficient of 0.36 is observed between the project grade and the final grade, indicating a weak positive correlation. Hence, it can also be concluded that if a student from the control group performs well on the project grade, there will only be a marginal improvement in their final grade. The difference in correlation coefficient between the IG and CG groups mainly results from the fact that the entire IG group has high project and final grade scores compared to the CG group, which has a broader range of scores.

The findings from this study support the growing body of research from 2024 to 2025, highlighting the effectiveness of AI-enhanced gamification in promoting sustained engagement. Xu et al. (2025) and Ochoa and Liu (2025) both confirm that real-time data visualization and gamified feedback significantly boost motivation and reduce cognitive overload, aligning with the improvements seen in the intervention group (IG). This convergence strengthens the case that interactive, competition-based visual learning fosters deeper conceptual reasoning rather than surface-level memorization.

Furthermore, Kao et al. (2025) observed similar effects in engineering statistics courses, where gamified visual analytics enhanced group collaboration and data-driven problem-solving. The strong performance gains in our IG cohort mirror Morales and Han's (2024) findings, which suggest that adaptive visualization tools help close the gap between mathematical abstraction and practical AI contexts. Additionally, Serrano et al. (2024)

emphasize that integrating gamified simulations into AI courses develops essential 21st century skills—communication, teamwork, and digital literacy—all of which are reflected in our students' post-survey responses and presentation evaluations.

The effect size, calculated as Cohen's d, of 0.81 indicates that the IG achieved significantly higher grades, further confirming that the IG had a stronger impact on students' overall performance in class. In comparison, the effect size of 0.64 for IG indicates a moderate to strong influence on the project grades. Overall, the results suggest that the gamification intervention was effective in improving educational outcomes compared to traditional teaching methods.

Limitations and Future Research Directions

This study has several limitations to consider when interpreting the findings. First, the sample size was relatively small (n = 28) and was drawn from a single Hispanic-Serving Institution, which limits the generalizability of the results to other institutional types, disciplines, and student populations. Second, the study was conducted in one course taught by the same instructor, so instructor effects and the novelty of the intervention may have influenced the differences observed between groups. Third, while course grades and project scores are meaningful indicators of achievement, they do not fully capture changes in students' attitudes toward statistics, perceived relevance of AI, or long-term retention of concepts. Additionally, as noted earlier, a baseline survey was not administered at the start of the course, which prevents direct pre–post comparisons of motivation and self-efficacy.

Future research will build on this initial cohort by expanding the intervention to a second cohort and increasing participant enrollment to boost statistical power. We plan to add baseline and follow-up surveys that assess statistics anxiety, AI-related self-efficacy, and perceived usefulness of gamification and visualization, allowing for more detailed modeling of attitudinal changes. Collecting learning analytics data (e.g., Python log files, platform interaction traces, and presentation rubrics) will help us analyze how students' behaviors within the visual and gamified environment relate to their performance, in line with recent work on AI-driven learning analytics in STEM education. Future studies could also compare different gamification designs—such as cooperative versus competitive formats (Caponetto et al., 2014), or adaptive versus fixed challenge levels—and explore how these configurations differentially impact various student subgroups. Finally, applying this visual learning and gamification framework to other AI-related courses (e.g., machine learning, data science, or engineering design) could provide a way to scale AI-ready statistics education across STEM curricula.

6. Conclusions

In conclusion, the visual learning and gamification approach has improved student learning outcomes. This improvement is evident through higher performance, indicated by both project and final grades, of students who participated in the gamification intervention compared to those who did not. This hands-on approach, which incorporates gamification, fosters teamwork, problem-solving, and critical thinking skills, thereby reinforcing statistical concepts. The products and techniques developed through this project can be easily scaled and adapted for use in other STEM fields, such as chemistry and physics.

For instructors, the study presents a pedagogical model that strikes a balance between motivation and understanding. Gamification elements—such as leaderboards, peer reviews, and team competitions—can be implemented using commonly available learning management system features or free online platforms (e.g., Kahoot, Canvas, or GitHub Classroom). Visualization-based instruction should be deliberately aligned with course outcomes to reduce cognitive overload and improve knowledge transfer. Faculty pro-

fessional development workshops that focus on these strategies can promote innovation across departments.

Overall, this study offers insights into how a more hands-on approach to problem-solving in a project addressing a real-world issue, combined with data visualization, can positively affect student learning, particularly in college statistics courses. In other words, students will be better prepared to enter the professional data analytics or AI workforce after graduation. They will have gained experience working in a group environment that promotes healthy competition, leading to the creation of the best possible product for the company or organization they join.

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