Integrating Statistical Process Control and Capability Analysis to Diagnose Pedagogical Variation in an Engineering Statistics Course

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Abstract

Higher education engineering programs require graduates to possess strong statistical literacy for evidence-based decision-making. However, disparities in student achievement often obscure whether the pedagogical delivery is operating under stable conditions or if specific factors are introducing detrimental variation into the learning process. This study evaluates the stability and capability of the learning process within an Industrial Statistics course by applying a Quality Management System (QMS) framework to educational assessment data. The research analyzed the grades of 216 students across three evaluation instruments: quizzes, case studies, and examinations. Data was categorized according to Course Learning Outcomes (CLOs) to form consistent subgroups of n=3. Process stability was assessed using Statistical Process Control (SPC) with $\overline{X}$-R control charts. Subsequently, a Process Capability Analysis (PCA) was conducted to determine whether the learning process could consistently yield outcomes meeting the defined minimum passing threshold (LSL = 50,01). The SPC analysis indicated that while the examination component achieved a state of statistical control, the quiz and case study assessments exhibited significant out-of-control variations. Furthermore, the PCA revealed systemic pedagogical deficiencies across all metrics. Both the potential (Cp) and actual (Cpk) capability indices for all evaluation instruments fell entirely below the acceptable industry threshold of 1,0. Critically, the case study component demonstrated a negative capability index (Cpk = -0.093), signifying that the mean class performance had shifted completely below the specification limit. Additionally, the examination component displayed extreme statistical variance ($\hat{\sigma}$=32,794), highlighting a substantial disparity in cognitive comprehension among the cohort.

Keywords: *Education; Process Capability Analysis; Quality Control in Education; Quality Management System; Statistical Process Control*

1. Introduction

Higher education institutions are expected to produce graduates equipped with competencies that meet industry standards. Within engineering programs, students' statistical proficiency is crucial, serving as an analytical foundation for advanced coursework specific to their chosen engineering disciplines. Statistical literacy is essential for interpreting, critically evaluating, and communicating statistical arguments and reports [1]. In the professional realm, higher education graduates are required to possess the ability to critically interpret data and engage in evidence-based decision-making [2]. Without a robust foundation in statistical understanding, students will struggle with the complexities of real-world, data-driven decision-making, leaving them underprepared for the transition into the workforce [3]. Consequently, the learning process within statistics courses constitutes a fundamental component of engineering curriculum.

Based on the assessment results of the statistics course conducted over one semester, the final grades indicate that the proportion of students failing to achieve the minimum passing threshold (50.01) was 10% for quizzes, 68% for case studies, and 29% for examinations. These findings reveal disparities in student achievement across the learning evaluation components, with the assessment of case study

problem-solving emerging as the most significant area of underperformance. Furthermore, this situation suggests that the learning process exhibits variations impacting student outcomes, which necessitates further evaluation to identify the underlying characteristics of these variations.

Although the final grade percentages across the assessment components are substantial, they do not inherently indicate whether the learning process operated under stable conditions or if specific factors introduced variation. Therefore, a statistical approach is required to objectively analyze process stability and variation. In this context, the learning process is conceptualized as a system that generates student grades as its output. This output is influenced by multiple factors within the educational system, including students' cognitive abilities, instructional methods, learning materials, student characteristics, the learning environment, the evaluation system, and the pedagogical delivery by the lecturer. Excessive or negligible grade variations produce unnatural extreme values, which indicate the presence of special cause variation such as assessment items being excessively difficult or trivially easy. Consequently, a Quality Management System (QMS) approach can be employed to analyze whether the implemented learning process generates a stable output that fulfills the targeted learning outcomes.

Statistical Process Control (SPC) is a Quality Management System (QMS) methodology developed to monitor and control variation within manufacturing production processes. It is utilized to evaluate process outcomes by comparing them against predetermined standards. Upon the detection of deviations or nonconformities, corrective actions can be implemented to control and improve the process. Furthermore, SPC is employed to assess process capability in yielding products that conform to specified requirements or specifications [4]. SPC analyzes the output variation of a process, categorizing it into common cause variation and special cause variation. Although initially applied within the manufacturing sector, the application of this methodology has expanded in recent years to encompass other sectors, including healthcare [5],[16],[17],[25], agriculture [6],[18],[19], the food industry [7],[22], ship loading [20], and education [8],[9],[21].

The $\overline{X}$ - R control chart, a fundamental tool within SPC, was selected for this study due to its suitability for continuous variable data (student grades) collected in small subgroups (n = 3, comprising quizzes, case studies, and examinations). The $\overline{X}$ chart evaluates the stability of the process mean across subgroups, while the R chart monitors the stability of the variation (range) within each subgroup [4],[10],[23]. By employing $\overline{X}$ - R control charts, the analysis extends beyond merely reporting average student performance, it systematically determines whether these grades were generated by a learning process operating in a state of statistical control.

However, achieving a state of statistical control does not inherently guarantee that a process is capable of producing outputs that meet expected standards or targets. A process may be 'in control' yet remain 'incapable' this condition arises when the inherent process variation is stable, but the process spread or the position of the process mean fails to satisfy the established specification limits. Therefore, following the SPC evaluation, a process capability analysis is conducted to determine whether the implemented learning process consistently yields student grades within the specification boundaries defined by the study program (i.e., falling between the Lower Specification Limit (LSL) and the Upper Specification Limit (USL)). In a previous study by Gessa et al. [8], Statistical Process Control (SPC) was utilized to assess students' academic progress by analyzing the variability of performance rates across courses. Furthermore, it was employed as a decision-making tool to support the Quality Assurance System. SPC can effectively address the limitations of traditional evaluation methods such as conventional descriptive statistics or benchmarking performance against rigid, arbitrary averages [24], which are often deemed subjective, lack contextual relevance, and disregard the inherent variability naturally present in educational processes. However, the study also recommended the incorporation of capability analysis in future research.

Following the previous research on the use of SPC in educational sector, this study employs SPC and Process Capability Analysis, which subsequently enable a comprehensive evaluation of the learning process quality and the formulation of actionable recommendations for continuous improvement in teaching the statistics course. Ultimately, this study seeks to address the central research question: How stable and capable is the learning process within the Statistics course? Consequently, the primary objective of this research is to comprehensively evaluate the learning process of this course.

2. Method

The data collected consists of primary data regarding student academic performance in the Industrial Statistics course over one semester, involving a total of 216 students. Each student was assessed using three evaluation instruments: quizzes, case studies, and exams. Each instrument involved three assessment repetitions aligned with the course's three Course Learning Outcomes (CLOs). These repetitions formed subgroups of size n = 3 for each student across each instrument, serving as the basis for calculating $\overline{X}$ - R Control Chart in the SPC analysis.

Consequently, the total dataset analyzed comprised 216 students × 3 instruments × 3 repetitions (CLOs) = 1,944 score data points. These were grouped into 216 × 3 = 648 subgroups, each with a size of n = 3 for the purpose of calculating $\overline{X}$ - R Control Chart for each assessment instrument.

2.1 Statistical Process Control (SPC)

Fundamentally, Statistical Process Control (SPC) is a systematic approach for comparing the outputs of a process or service against established standards [10],[14],[15]. It is utilized to evaluate whether a process is capable of yielding products that conform to desired specifications or requirements. Within the SPC framework, control charts are employed to assess process performance. A control chart serves as a graphical tool for monitoring ongoing process activities over time. A standard control chart comprises three primary reference lines: the center line (CL), which typically represents the process mean of the observed characteristic; the upper control limit (UCL); and the lower control limit (LCL). These limits are critical for making informed decisions regarding the condition of the process. If all plotted observation points fall strictly within these control limits and exhibit no identifiable non-random patterns, the process is deemed to be operating in a state of statistical control. Conversely, if these conditions are not met, the process is considered out of statistical control. The primary advantages of utilizing control charts include identifying the necessity and specific type of corrective actions, distinguishing inherent common-cause variation from special-cause variation that necessitates intervention, evaluating process capability to satisfy requirements, and establishing a baseline for continuous process monitoring and quality improvement [4].

2.2 $\overline{X}$ - R Control Chart

The $\overline{X}$ - R control chart is a primary type of variables control chart employed concurrently to monitor the process mean and range (R) of a quantitative quality characteristic [4],[10],[23]. These control charts are utilized to control characteristics that are numerically measurable on a continuous scale, such as dimensions, weight, or time. $\overline{X}$ chart serves to monitor process centering, tracking shifts in the quality mean over time, whereas the R chart is designed to monitor process variability, or dispersion, based on the range within each subgroup [10].

2.3 Process Capability Analysis

Process Capability Analysis (PCA) is defined as the uniformity or performance of a process when it operates in a state of statistical control [11],[12]. This performance is determined by the total variability resulting from inherent common causes within the system, a condition attained only after all special causes have been identified and eliminated. The objective of PCA is to assess process capability, which involves estimating the process mean and standard deviation, as well as projecting the percentage of nonconforming outputs, provided that the specification limits are known. Consequently, process capability is evaluated against these established boundaries [11],[13], specifically the Upper Specification Limit (USL) and the Lower Specification Limit (LSL) [4].

2.4 Research Stages

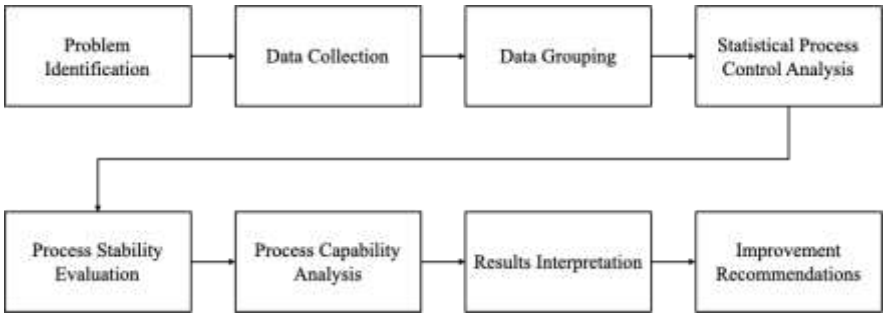

Figure 1. Research Stages

Figure 1. Research Stages illustrates the methodological stages of this research, which commences with problem identification regarding the final grades in the statistics course. This step is followed by comprehensive data collection encompassing all scores across various course topics. Subsequently, data grouping is performed, wherein each score is categorized based on its specific assessment component (i.e., quizzes, examinations, and case studies). Once the data preparation is complete, Statistical Process Control (SPC) calculations are executed utilizing $\overline{X}$ - R control charts to evaluate current process stability. This is immediately followed by a process capability analysis to determine whether the implemented learning process for the statistics course is statistically capable. In the final stage, the analytical results are interpreted to formulate actionable recommendations for continuous improvement.

3. Results and Discussion

This study utilizes the statistics course grades from 216 students. Each assessment component consists of quizzes, examinations, and case studies comprise the number of evaluations corresponding to the defined Course Learning Outcomes (CLOs). Consequently, this alignment establishes a consistent subgroup size of n = 3 for the statistical process control analysis. To provide an initial descriptive overview of score distribution prior to the SPC and capability analysis, boxplots were constructed for each assessment instrument: Quiz, Case Study, and Exam with scores following their respective Course Learning Outcomes (CLO1, CLO2, and CLO3), as presented in Figure 2.

These boxplot distributions provide preliminary visual evidence of the uneven and inconsistent performance patterns across CLOs within each assessment instrument patterns that are quantified through the $\overline{X}$ - R Control Chart and process capability analysis presented in the following sections.

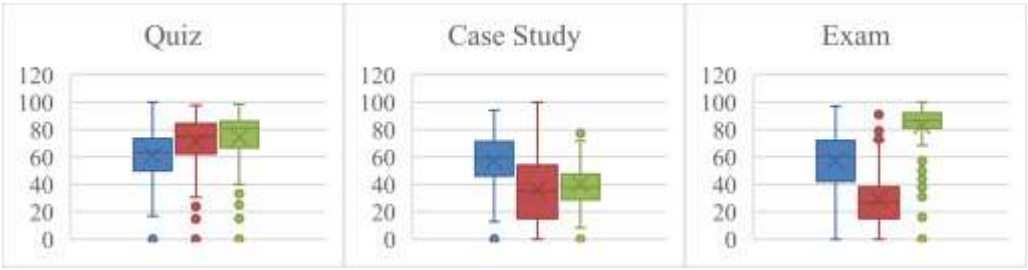

Figure 2. Boxplot Assessment Components

3.1 Data Grouping

The initial step following data collection involves categorizing the scores from quizzes, case studies, and examinations according to their respective Course Learning Outcomes (CLOs). Table 1. Data Grouping illustrates a representative sample of this data categorization process (where Q=Quiz; S=Case Study; and E=Examination).

Table 1. Data Grouping

Student ID	Q1	Q2	Q3	S1	S2	S3	E1	E2	E3
1	43,33	28,57	41,66	22,5	68	70,18	90	65	94,5
2	86,66	88,57	87,71	23,16	30	29,01	42	10	92
3	43,33	54,28	87,5	63,41	86	47,78	61	40	84
...	...	...	...	...	...	...	...	...	...
216	63,34	71,91	80,21	57,09	19	39,78	48	17	77

3.2 Statistical Process Control Analysis

This study employs the $\overline{X}$ - R control chart, which is optimally suited for the specific characteristics of this dataset. This selection is justified by the utilization of continuous variable data (student grades) and a constant subgroup sample size of n=3 (comprising quiz, examination, and case study scores). The calculations for the control limits and central tendencies were performed using the standard $\overline{X}$ - R equations as follows:

$\overline{X}$ Chart

$$\text{Center Line (CL)} \quad \overline{\overline{X}} = \frac{\sum \overline{X}}{k} \tag{1}$$

$$\text{Upper Control Limit (UCL)} = \overline{\overline{X}} + A_2 * \overline{R} \tag{2}$$

$$\text{Lower Control Limit (LCL)} = \overline{\overline{X}} - A_2 * \overline{R} \tag{3}$$

R Chart

$$\text{Center Line (CL)} \quad \bar{R} = \frac{\sum R}{k} \tag{4}$$

$$\text{Upper Control Limit (UCL)} = D_4 \times \overline{R} \tag{5}$$

$$\text{Lower Control Limit (LCL)} = D_3 \times \overline{R} \tag{6}$$

Where:

$\overline{X}$ = The mean of the observations within a single subgroup.

R = The range, defined as the difference between the maximum and minimum values within a single subgroup.

$\overline{R}$ = The grand average of the range values across all subgroups.

A_2 = A statistical constant, value is dependent on the subgroup sample size (n = 3; A_2 = 1,023)

D_4 = A statistical constant, value is dependent on the subgroup sample size (n = 3; D_4 = 2,574)

D_3 = A statistical constant, value is dependent on the subgroup sample size (n = 3; D_3= 0)

3.2.1 $\overline{X}$ - R Quiz

The $\overline{X}$ control chart was employed to monitor the stability of the mean student quiz scores in the Statistics course throughout the semester. Based on the data analysis, the established control limits are as follows: CL = 69,09; UCL = 96,26; and LCL = 41,91. Concurrently, the R control chart was utilized to monitor the stability of the variation (range) in student quiz scores within each subgroup. The analysis yielded the following control limits for the range: CL = 26,57; UCL = 68,38; and LCL = 0. Figures 3 and 4 demonstrate that several data points fall beyond these established limits, indicating that the current learning process is out of control.

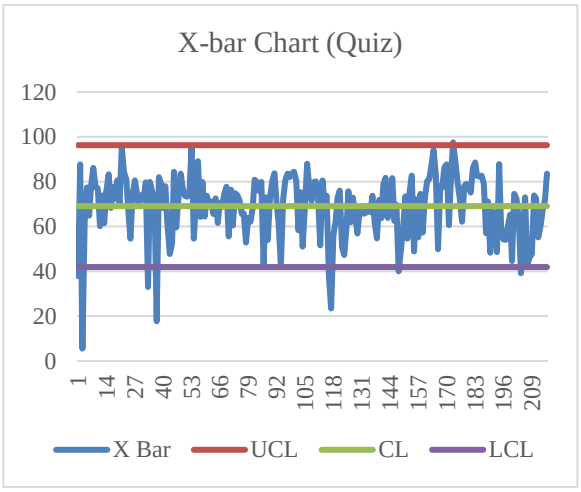

Figure 3. X-Bar Chart (Quiz)

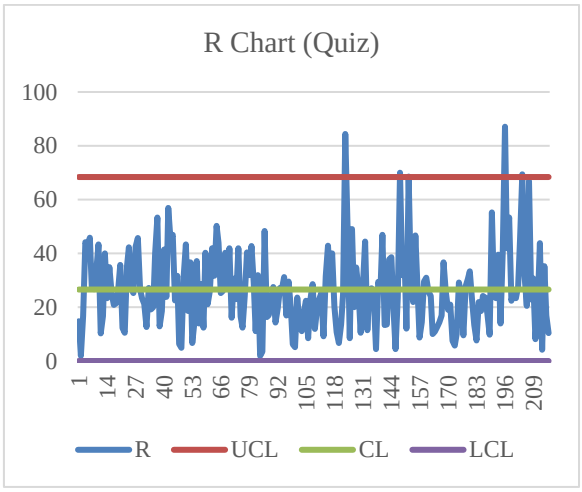

Figure 4. R Chart (Quiz

3.2.2 $\overline{X}$ - R Case Study

Based on the data analysis, the established control limits for the The $\overline{X}$control chart are as follows: CL = 44,47; UCL = 81,09; and LCL = 7,86. Similarly, the data analysis for the R control chart yielded the following limits: CL = 35,79; UCL = 92,12; and LCL = 0. Figures 5 and 6 illustrate that several data points fall beyond the established boundaries, indicating that the current learning process is out of control.

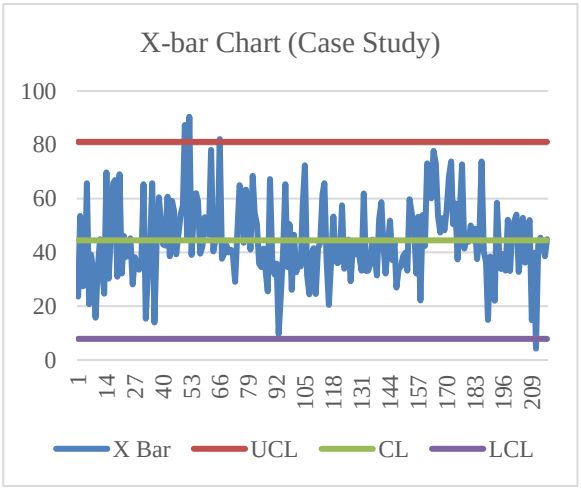

Figure 5. X-bar Chart (Case Study)

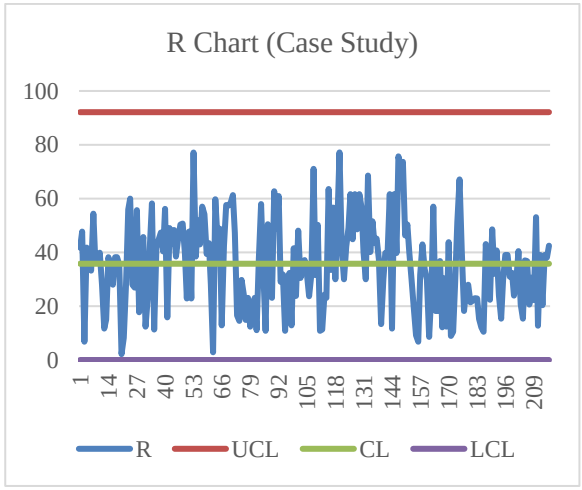

Figure 6. R Chart (Case Study)

3.2.3 $\overline{X}$ - R Exam

Based on the data analysis, the established control limits for the $\overline{X}$ control chart are as follows: CL = 56,27; UCL = 113,064; and LCL = -0,53. Correspondingly, the data analysis for the R control chart yielded the following limits: CL = 55.52; UCL = 142.91; and LCL = 0. Figures 7 and 8 illustrate that no data points fall beyond the established boundaries, indicating that the process is in control.

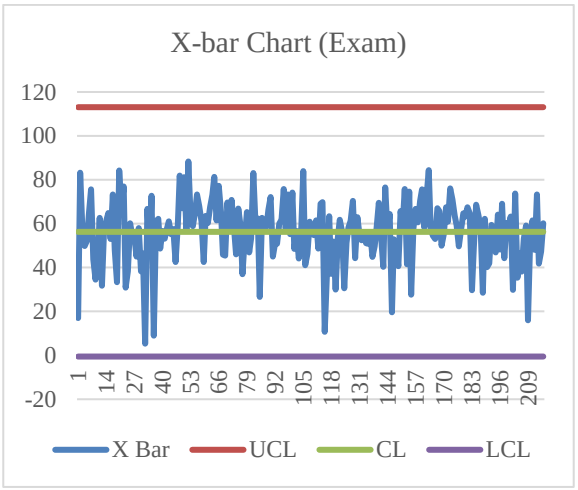

Figure 7. X-bar Chart (Exam)

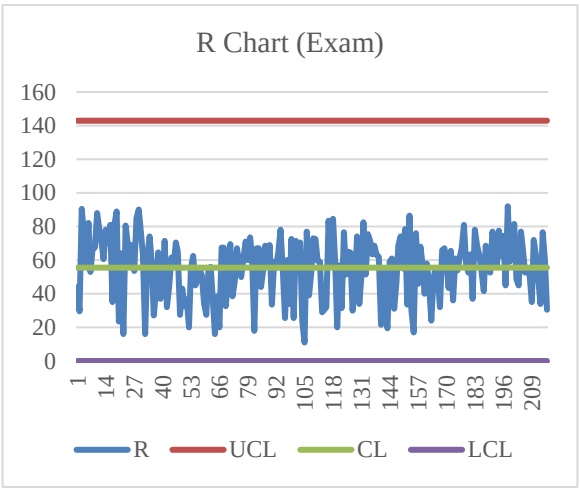

Figure 8. R Chart (Exam)

3.3 Process Capability Analysis

Based on the SPC calculations, only the examination component has achieved a state of statistical control, whereas the quiz and case study components remain out of control. Nevertheless, these findings alone do not provide a definitive conclusion regarding whether the current learning process for the statistics course is capable of meeting established standards. Therefore, a Process Capability Analysis (PCA) is conducted to evaluate the current performance of the educational process. The following equations were utilized for this analysis:

$$\text{Process Mean} = \bar{\mu} = \bar{\bar{X}} \quad (7)$$

$$\text{Estimated Process Standard Deviation} = \hat{\sigma} = \frac{\bar{R}}{d2} \quad (8)$$

$$\text{Potential Process Capability Index} = Cp = \frac{USL - LSL}{6\hat{\sigma}} \quad (9)$$

$$\text{Actual Process Capability Index} = Cpk = \min(CPU, CPL) \quad (10)$$

$$\text{Upper Process Capability Index} = CPU = \frac{USL - \bar{\bar{X}}}{3\hat{\sigma}} \quad (11)$$

$$\text{Lower Process Capability Index} = CPL = \frac{\bar{\bar{X}} - LSL}{3\hat{\sigma}} \quad (12)$$

Table 2. Process Capability Calculation

	Quiz	Case Study	Exam
$\bar{\mu}$	$\bar{\bar{X}} = 71{,}309$	$\bar{\bar{X}} = 44{,}067$	$\bar{\mu} = \bar{\bar{X}} = 56{,}27$
$\hat{\sigma}$	$\frac{\bar{R}}{d2} = \frac{25{,}02}{1{,}693} = 14{,}78$	$\frac{\bar{R}}{d2} = \frac{21{,}33}{1{,}693} = 21{,}339$	$\hat{\sigma} = \frac{\bar{R}}{d2} = \frac{55{,}52}{1{,}693} = 32{,}794$
Cp	$\frac{USL - LSL}{6\hat{\sigma}} = \frac{100 - 50{,}01}{6 * 14{,}78}$ Cp = 0,564	$\frac{USL - LSL}{6\hat{\sigma}} = \frac{100 - 50{,}01}{6 * 21{,}34}$ Cp = 0,781	$\frac{USL - LSL}{6\hat{\sigma}} = \frac{100 - 50{,}01}{6 * 32{,}79}$ Cp = 0,254
CPU	$\frac{USL - \bar{\bar{X}}}{3\hat{\sigma}} = \frac{100 - 71{,}31}{3 * 14{,}78}$ CPU = 0,647	$\frac{USL - \bar{\bar{X}}}{3\hat{\sigma}} = \frac{100 - 44{,}07}{3 * 21{,}34}$ CPU = 0,874	$\frac{USL - \bar{\bar{X}}}{3\hat{\sigma}} = \frac{100 - 56{,}27}{3 * 32{,}79}$ CPU = 0,444
CPL	$\frac{\bar{\bar{X}} - LSL}{3\hat{\sigma}} = \frac{14{,}78 - 50{,}01}{3 * 14{,}78}$ CPL = 0,480	$\frac{\bar{\bar{X}} - LSL}{3\hat{\sigma}} = \frac{44{,}07 - 50{,}01}{3 * 21{,}34}$ CPL = -0,093	$\frac{\bar{\bar{X}} - LSL}{3\hat{\sigma}} = \frac{56{,}27 - 50{,}01}{3 * 32{,}79}$ CPL = 0,064

	Quiz	Case Study	Exam
Cpk	min (0,647; 0,480) Cpk = 0,480	min (0,781; -0,093) Cpk = -0,093	min (0,444; 0,064) Cpk = 0,064

Table 2. showed the result of the process capability calculation. Based on the process capability analysis of the statistics course grades, it can be concluded that the current evaluation system is incapable of yielding student outcomes that satisfy the minimum passing standard (LSL = 50,01). All three assessment instruments quizzes, case studies, and examinations exhibited potential process capability (Cp) and actual process capability (Cpk) indices well below the acceptable industry threshold of 1,0 (Cp < 1,0 and Cpk < 1,0). The most critical condition was identified within the case study component, which yielded a negative Cpk value of -0,093. This indicates a systemic deficiency, as the mean class performance ($\bar{\mu}$= 44,067) has entirely shifted below the lower specification limit. Furthermore, the examination component demonstrated extreme variability ($\hat{\sigma}$ = 32,794) with the lowest Cp index of 0,254, reflecting a substantial disparity in cognitive comprehension among the students. Consequently, these findings empirically demonstrate that the targeted learning competencies have not been achieved consistently or uniformly across the cohort.

3.4 Recommendations for Improvement

Based on the Statistical Process Control (SPC) analysis, the presence of out-of-control points within the quiz and case study assessment results indicates that the implemented learning process for the statistics course remains unstable. Furthermore, the Process Capability Analysis (PCA) calculations reveal that all Cp and Cpk indices fall below the acceptable threshold of 1,0. This signifies that the current process is incapable, resulting in a substantial proportion of student grades falling outside the established specification limits. Consequently, comprehensive pedagogical improvements within the statistics course are imperative. Recommended continuous improvement strategies include:

a. Conducting student profiling via cluster analysis: This enables the design of tailored instructional strategies that align with students' inherent cognitive abilities, characteristics, and learning styles. This approach is anticipated to bridge comprehension gaps and minimize statistical variance in student assessment outcomes.
b. Utilizing visual media to reduce conginitive load: By integrating visual learning aids, student engagement can be enhanced, thereby facilitating a more intuitive comprehension of complex instructional materials.
c. Implementing statistical modeling with real-world data: This allows students to practically bridge theoretical course materials and raw data with authentic, real-world contexts.
d. Adopting Project-Based or Problem-Based Learning: These active learning frameworks have been empirically proven to enhance conceptual understanding, enabling students to critically analyze given problems and apply the theoretical concepts they have acquired.
e. Cultivating critical thinking-based statistical literacy: This can be achieved by employing a structured literacy framework grounded in the FRISCO critical thinking elements (Focus, Reason, Inference, Situation, Clarity, Overview).

4. Conclusion

This study comprehensively evaluated the learning process within a Statistics course utilizing Statistical Process Control (SPC) and Process Capability Analysis (PCA). The SPC findings revealed that while the examination component operated in a state of statistical control, both the quiz and case study assessments exhibited significant out-of-control variations, indicating underlying process instability. Furthermore, the capability analysis demonstrated a systemic deficiency across all evaluation metrics, with all potential (Cp) and actual (Cpk) capability indices falling well below the acceptable industry threshold of 1,0. Notably, the case study component presented a critical negative capability

index (Cpk = -0,093), while examinations showed extreme statistical variance. These results empirically confirm that the current pedagogical framework is incapable of consistently meeting the minimum academic passing standards. To rectify these disparities and enhance educational quality, this study strongly recommends the implementation of targeted continuous improvement strategies. These include adopting student profiling via cluster analysis, integrating visual media to alleviate cognitive load, utilizing real-world statistical modeling, shifting towards Problem-Based Learning (PBL), and cultivating statistical literacy through the FRISCO framework. By applying these Quality Management System principles to the educational sector, institutions can systematically reduce performance variations and ensure that targeted learning outcomes are achieved.

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