



# Practical Implementation of Probability Theory and Mathematical Statistics Curriculum Reform Based on the CDIO Approach

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**Abstract.** Traditional instruction in Probability Theory and Mathematical Statistics (PTMS) often suffers from a disconnect between abstract theory and real-world application, failing to cultivate the systematic engineering thinking demanded by new disciplines. This study addresses this gap by implementing a curriculum reform grounded in the CDIO (Conceive-Design-Implement-Operate) framework. We reconstructed course content around authentic engineering projects, notably a “Bank Wealth Management Team Performance Evaluation” case, guiding students through the full lifecycle of a statistical solution. A quasi-experimental design compared an experimental class ( $n=42$ ) taught with the CDIO model against a control class ( $n=43$ ) using traditional lecture methods. Results demonstrate that the CDIO cohort significantly outperformed their peers on comprehensive application problems (18.7 vs. 13.2,  $p<0.001$ ) and showed markedly higher proficiency in justifying methodological choices (76% vs. 31%). Qualitative data further revealed a paradigm shift among students, from viewing statistics as a set of computational procedures to seeing it as a tool for rational decision-making under uncertainty. This paper provides a replicable, system-oriented model for integrating foundational mathematics courses into the engineering education ecosystem.

**Keywords:** CDIO; Probability Theory and Mathematical Statistics; curriculum reform; engineering thinking; project-based learning.

## 1 Introduction

The persistent gap between theoretical instruction and practical application in Probability Theory and Mathematical Statistics (PTMS) leaves many engineering graduates ill-equipped to handle data-driven challenges. Conventional pedagogy, centered on formula derivation and isolated problem sets, neglects the cultivation of systematic thinking and the ability to translate real-world ambiguity into solvable statistical models<sup>[1-2]</sup>. This “threefold disconnection”—between theory and practice, algorithms and tools, and knowledge and innovation—represents a critical bottleneck in new engineering education.

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To bridge this gap, we propose the CDIO (Conceive-Design-Implement-Operate) framework as a powerful catalyst for PTMS reform. Originally developed for engineering product development, CDIO's core strength lies in its systematic, lifecycle-oriented approach to learning<sup>[3]</sup>. We argue that the “product” in a PTMS course is not a physical artifact, but a defensible *statistical solution* to a complex, open-ended problem. This paper details our practical implementation of this vision, its empirical validation, and its implications for foundational STEM education.

## 2 Designing the Reform: A CDIO-Centric Framework

As a representative framework for modern engineering education reform, the CDIO approach comprises four interconnected phases: Conceive, Design, Implement, and Operate. Its core principle lies in fostering the integrated development of knowledge, skills, and competencies through full-cycle project-based learning<sup>[4]</sup>. Originating from engineering education reforms at institutions like MIT, this philosophy emphasizes establishing a dynamic linkage between curriculum systems and industry demands through the product lifecycle—from development to operation. In higher education, the CDIO model overcomes the traditional disconnect between theoretical instruction and practical application by reconfiguring the relationship between learning and application<sup>[5]</sup>. For probability theory and mathematical statistics courses, the introduction of CDIO provides a systematic reform pathway to address the longstanding “triple disconnect” issues: the disconnect between mathematical theory and engineering practice, the disconnect between algorithm derivation and computational tools, and the disconnect between knowledge acquisition and innovative application<sup>[6-7]</sup>.

Our reform began with a fundamental redefinition of course objectives, shifting from knowledge acquisition to capability development across three integrated dimensions: conceptual understanding of randomness and inference, competency in designing and executing statistical analyses, and the professional attitude of data-driven, critical decision-making.

This new objective directly informed a complete reconstruction of course content. We abandoned the traditional linear progression of topics in favor of a project-centered architecture. The entire syllabus was organized around a central, authentic engineering challenge: evaluating the performance of bank wealth management teams<sup>[8]</sup>. Within this single, rich context, all core concepts found their purpose:

**Conceive:** Students grappled with defining “performance” amidst market noise, leading naturally to random variables and expectation.

**Design:** The need to compare teams introduced sampling distributions, hypothesis testing logic, and the critical importance of verifying assumptions (e.g., homogeneity of variance).

**Implement:** Students executed their analyses using Python (SciPy/statsmodels) in a Jupyter Notebook environment, moving from theory to tangible code.

**Operate:** The final deliverable was a decision report for bank management, requiring clear communication of results, effect sizes, and model limitations.

To support this active learning model, we developed essential resources: a repository of cross-disciplinary cases and a pre-configured online analytics platform. Our teaching methodology shifted to a guided project cycle, where the instructor’s role evolved from lecturer to cognitive coach, posing probing questions rather than providing direct answers<sup>[9-10]</sup>.

This design philosophy is grounded in the principle of cognitive authenticity<sup>[11]</sup>. Rather than fragmenting learning into isolated skill drills—such as calculating a p-value in one exercise and drawing a boxplot in another—we anchor all competencies within a single, coherent professional narrative. This mirrors the cognitive demands of real-world practice, where statisticians must orchestrate multiple concepts and tools in concert to address an ill-defined challenge. By requiring students to produce a unified “statistical solution,” the project compels them to confront the inherent messiness of data: missing values, violated assumptions, and ambiguous interpretations. This integrated approach not only fosters technical proficiency but also cultivates the metacognitive awareness necessary to navigate uncertainty—a core tenet of statistical literacy that is often lost in decontextualized instruction.

### 3 Practice and and Effectiveness Evaluation

#### 3.1 The Bank Performance Evaluation Project in Action

This study uses “Performance Evaluation of Bank Wealth Management Teams” as a cross-cutting case, translating the CDIO four-phase model into actionable teaching activities (see Table 1). The project originates from a real-world business scenario: A bank operates three wealth management teams—A, B, and C—each managing client assets of varying scales over the past year. Management seeks to determine whether “significant performance disparities exist” to guide bonus allocation and resource prioritization. Available data includes each team's monthly return rates (12 months total), though confounding factors such as team size and market volatility remain uncontrolled.

**Table 1.** Mapping of CDIO Four Stages to Course Instruction

CDIO Stage	Learning Objectives	Student Activities	Teacher Support
Conceptualization	Identify statistical requirements in real-world scenarios	Analyze case background, define “what constitutes an excellent team,” and propose quantifiable metrics	Provide multi-source datasets to facilitate discussions on confounding variables
Design	Plan rigorous analytical approaches	Select hypothesis testing methods (e.g., one-way ANOVA), set $\alpha$ level, and design data	Explain methodological prerequisites and provide flowchart templates

		collection/simulation strategy	
		Use Python	
Implementation	Execute and validate using tools	(SciPy/statsmodels) to complete data cleaning, visualization, and test calculations	Offer code script examples and organize “debugging workshops”
Operation	Interpret results and optimize systems	Draft reports for non-technical managers, discuss conclusion robustness, and propose improvement recommendations	Organize peer reviews and introduce “decision-maker” role feedback

During the **Conceive** phase, students moved beyond simple mean comparisons to propose evaluating “market-adjusted excess returns,” demonstrating an early grasp of confounding variables. In **Design**, most groups initially selected ANOVA but were required to validate its assumptions. Upon discovering heteroscedasticity (Levene’s test,  $p=0.032$ ), several groups autonomously pivoted to the non-parametric Kruskal-Wallis test, documenting their rationale in a formal analysis plan. The **Implement** phase saw students write and debug Python code, with a focus on the logic behind each command. Finally, in **Operate**, student reports went beyond stating “Team B is better ( $p=0.018$ )” to discuss practical significance (via effect size  $\eta^2$ ) and the model’s limitations, such as small sample size.

To operationalize the CDIO framework within a foundational mathematics course—traditionally devoid of tangible “products”—we reinterpreted its four phases as a cognitive engineering cycle for statistical problem-solving.

**Conceive:** Students engage with an authentic, open-ended challenge (e.g., “How do we fairly evaluate financial team performance?”), defining the problem’s scope, stakeholders, and success criteria under uncertainty.

**Design:** They select appropriate statistical models (e.g., t-test vs. non-parametric alternatives), justify assumptions, and plan data collection/analysis workflows—treating the analytical strategy as their “design blueprint.”

**Implement:** Using Python or R, they code the analysis pipeline, debug errors, and validate results, mirroring the implementation rigor of engineering prototyping.

**Operate:** Finally, they “deploy” their solution via a professional report or presentation, interpreting findings in context, discussing limitations, and recommending actionable insights—thus closing the loop between technical output and real-world decision-making.

This adaptation preserves CDIO’s systemic integrity while respecting the epistemological nature of statistics as a discipline of inference rather than fabrication.

### 3.2 Empirical Assessment of Learning Outcomes

We employed a quasi-experimental design with a 2023 cohort ( $n=42$ , experimental) and a 2022 cohort ( $n=43$ , control). Both classes were taught by the same instructor,

used identical textbooks and assessments, and had statistically equivalent prior math achievement ( $p > 0.05$ ).

The results were compelling. On a final exam question requiring students to design an A/B test for a new e-commerce algorithm, the experimental class scored significantly higher (18.7/20 vs. 13.2/20;  $t = 5.14$ ,  $p < 0.001$ ). Crucially, 76% of the CDIO group could correctly justify their choice of a chi-square test for categorical click-through data, compared to only 31% in the control group. A post-course survey confirmed these gains, with the experimental class reporting much higher confidence in explaining statistical conclusions to non-experts ( $M = 4.1$  vs.  $M = 2.7$ ).

Qualitative interviews captured a deeper transformation. One student noted, “I now see a p-value not as an endpoint, but as a starting point for asking better questions.” This cognitive shift was further evidenced by students’ autonomous inquiry beyond the syllabus. Several groups, unsatisfied with basic t-tests, independently researched and applied Welch’s correction for unequal variances, citing its robustness in their final reports.

Moreover, project logs revealed iterative refinement: one team revised its initial model three times after discovering outliers skewed their results, demonstrating a nascent but genuine scientific ethos. This shift from a “problem-solver” to a “challenge-addressor” mindset is the true hallmark of the reform’s success. Challenges remain, particularly in managing the time-intensive nature of projects within a standard semester, suggesting a need for more granular scaffolding in future iterations.

The CDIO structure not only organized the workflow but also scaffolded distinct competencies at each phase. The Conceive stage cultivated problem-framing and contextual awareness—skills often neglected in formula-centric curricula. Design demanded methodological justification and critical evaluation of assumptions, moving students beyond mechanical application. Implement honed technical fluency with modern data tools, bridging the gap between theory and digital practice. Most critically, the Operate phase instilled a sense of professional responsibility: students learned that a statistically significant result is merely an intermediate step; its value lies in how clearly and ethically it informs real decisions. This phased progression ensured that learning was not just cumulative, but transformative.

## 4 Conclusions

While the results are promising, this study has limitations that warrant acknowledgment. The intervention was confined to a single course at one institution, and the semester-long timeline offered only a snapshot of long-term skill retention. Furthermore, the success of the model is partly contingent on instructor expertise in both statistics and facilitative pedagogy, which may pose scalability challenges. Nevertheless, these constraints do not diminish the model’s core validity; rather, they delineate a clear pathway for future research. A multi-institutional longitudinal study is currently being planned to assess the durability of these learning gains and to develop standardized faculty training modules that can support broader adoption.

Integrating the CDIO philosophy into the Probability Theory and Mathematical Statistics course fundamentally represents a paradigm shift from “solving problems” to “addressing challenges.” Students no longer passively absorb knowledge but instead internalize engineering thinking and systems concepts throughout the entire process of constructing statistical solutions.

The practical value of this study lies in providing a transferable implementation template for CDIO-based mathematics courses; demonstrating that foundational courses can equally fulfill engineering education missions; and offering micro-level evidence for “mathematics empowering engineering” within the new engineering paradigm. Challenges persist, however: the CDIO model demands high interdisciplinary literacy from instructors, and project timelines require careful balancing. Future directions include developing modular case libraries and exploring vertical integration with specialized courses.

The ultimate goal of education is not to have students memorize the central limit theorem, but to empower them to declare, “Let the data speak,” when confronting the noise and uncertainty of the real world. This is precisely the new life CDIO has breathed into this ancient mathematical discipline.

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