Statistics Courses and Competition-Driven Teaching and Learning: Pathways, Implementation, and Reflections on Integrating Mathematical Modeling

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Abstract: Targeting statistics majors, this paper leverages mathematical modeling as a key vehicle to implement a "competition-driven teaching and learning" completion-oriented reform. By reconstructing the course cluster around a "contest problem–course–assessment" closed loop, we build a case library and rubrics, forming an isomorphism between training and assignments and achieving coordination between online and offline learning. An interdisciplinary teaching team is established to embed competition tasks into courses such as Statistical Methods and Data Analysis and Modeling, supported by a provincial first-class course and the Xueyin Online platform. Practice shows that students' engagement, modeling ability, and collaboration improve significantly, and higher-order course performance rises. Meanwhile, a replicable course roadmap and organizational mechanism are formed, and suggestions are offered for optimizing resource allocation and expanding coverage.

Keywords: Statistics; Mathematical Modeling; Competition-Driven Teaching; Competition-driven Learning

1. Introduction

Against the backdrop of the "New Liberal Arts/New Engineering" initiatives and outcome-based education (OBE), transforming competition tasks into routine course practice has become an important lever for improving teaching quality in statistics programmes. Since its launch in 1992, the China Undergraduate Mathematical Contest in Modeling (CUMCM) has, by 2025, involved 68,311 teams from 1,837 institutions/campuses and more than 200,000 participants. It has been included in the official "white list" of discipline competitions and related evaluation catalogues, and exerts a strong pulling effect on students' abilities in data understanding, model-based inference and teamwork. This provides solid institutional and practical soil for classroom reconstruction oriented toward "competition-driven teaching and competition-driven learning".

Research over the past three years shows a gradual move from concepts and pathways toward more systematic evidence. Chen Cang (2023), in "Research on the Application of a Competition-Driven Practical Teaching Model in Advanced Mathematics", took in-course competitions and project review as the core and reported improvements in learning initiative and classroom effectiveness [1]. Cheng Lijuan, Guo Juxi and Zhou Xiuxiang (2024) summarised pain points in mathematical modeling teaching such as "single content, insufficient practice, and unbalanced assessment", and proposed reform highlights combining task-driven approaches with process-based assessment [2,3]. Han Zhen (2024) introduced competition–teaching integration into Biostatistics, constructing a progressive training scheme of "in-class tiered tasks – in-class competition – extracurricular competition" [4]. Liu Changbiao (2025) emphasised the design of a "Why–What–How–Do" question chain to strengthen practical ability and innovation awareness [5]. At the same time, practice reports from multiple universities around statistics and statistical modeling competitions show that organisational mechanisms, case libraries and systematic training are key guarantees for improving both competition performance and teaching effectiveness [6-8]. Together, these studies sketch out a feasible pathway for a "contest problem–course–assessment" closed loop and "classroom–competition" linkage [9-11].

However, existing literature is still insufficient with respect to systematic reconstruction at the level of course clusters, the implementation of assessment rubrics, and mechanisms for cross-disciplinary collaboration; in particular, completion-oriented evidence and replicable practices specifically for statistics majors remain relatively fragmented. In response, this paper builds on an ongoing teaching reform at our university and provides a completion-oriented account of “competition-driven teaching and competition-driven learning”. First, we construct an alignment system and course map linking contest problems, course units and assessment rubrics, using OBE and constructive alignment as the methodological underpinning. Second, we form a progressive training and resource platform of “classroom cases – university-level competition – national competition”. Third, we report multi-source evidence on student engagement, competence performance and course outputs, and reflect on areas for improvement and conditions for broader implementation. Theoretically, the paper introduces constructive alignment and self-determination theory to explain the causal chain from “authentic tasks and supportive environments → motivation and engagement → performance”, providing a verifiable framework and practical reference for course reconstruction and continuous improvement in statistics programmes.

2. Overall Framework of the Teaching Reform

To transform the high-level tasks of competitions into routine mechanisms in regular teaching, this study constructs an overall “competition problem–course–assessment” closed-loop framework, which is shown in Figure 1. The overarching idea is to take constructive alignment as the guiding principle (ensuring a coherent evidence chain among course objectives, teaching activities, and learning outcomes) and use the competency elements embedded in competition problems to drive the reconstruction of the course cluster and unit tasks. Specifically, we first extract a five-stage competency chain—“problem identification, model construction, algorithm implementation, validation and interpretation, report presentation” —from past mathematical modeling contest problems, and then map it onto measurable learning outcomes and classroom tasks in course units such as Probability and Mathematical Statistics, Regression Analysis, Time Series and Forecasting, Optimization Methods, and Statistical Computing and Visualization (Python/R), thereby forming an isomorphic relationship in which “classroom tasks ≈ competition tasks.” On the assessment side, rubrics are used to connect course objectives with competition-oriented competencies, ensuring alignment between teaching, learning, and assessment.

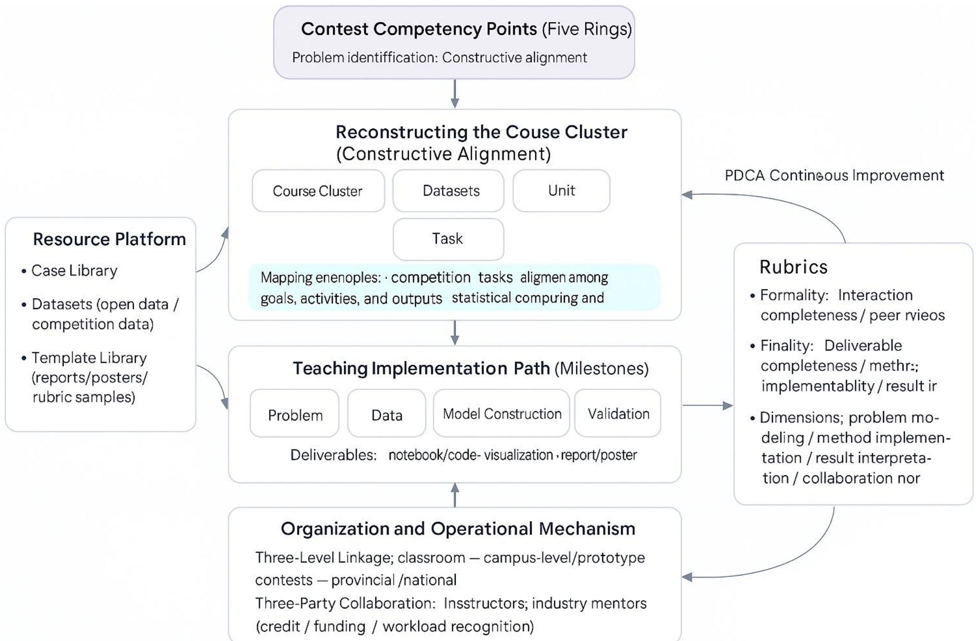

Figure 1. Overall Framework of the Teaching Reform

At the course and resource level, we adopt a four-tier design of “course cluster–course–unit–task.” At the course-cluster level, we clarify the foundations of cross-disciplinary collaboration and software skills; at the course level, we embed competition-style cases and phased milestones (problem posing, data, modeling, validation, presentation); at the unit level, we provide replaceable competition prototypes and datasets covering common modeling paradigms such as statistical inference, optimization, differential-equation modeling, simulation, and machine learning; and at the task level, we implement concrete, submitable learning outputs (Jupyter notebooks, reports, posters, presentations). On the resource side, we build four categories of assets—"case library, data warehouse, template library, and code snippets"—and rely on an online platform to support material submission, version management, and process recording, so that process data are traceable and outcome evidence can be archived.

At the assessment and quality-assurance level, we develop a diversified system that combines formative and summative assessment. Formative assessment focuses on the learning process (classroom interaction, interim presentations, code style, and peer review), while summative assessment emphasizes the completeness and interpretability of problem solving (modeling correctness, robustness checks, visual communication, and reproducible experiments). The rubric is decomposed into dimensions such as "problem modeling, method implementation, result interpretation, and collaboration norms," and three layers of evidence—course grades, performance in school-level/provincial competitions, and learning process data—are established to drive continuous improvement (PDCA). Based on rubric results and process data, we diagnose bottlenecks and iteratively adjust case difficulty, teaching-assistant support, and toolchains, thus achieving iterative optimization.

In terms of organization and operational mechanisms, we adopt a three-tier linkage of "classroom–school competition–national competition" and a tripartite collaboration of "teachers–industry mentors–teaching assistants." Within each semester, weekly milestones are used to advance classroom progress; mid-semester, in-house contests or thematic competitions are organized for stress testing and post-hoc review of student work, and outstanding teams are then connected to provincial and national competitions. Teachers are responsible for course design and academic integrity, industry mentors provide real-world scenarios and implementable constraints, and teaching assistants support data preparation and tool services. Through institutional arrangements such as financial and credit incentives, workload recognition, and outcome recognition, we ensure that the reform operates as a normalized routine and can be sustainably scaled up.

3. Reconstruction of the Course Cluster and Implementation Pathways

3.1 Mapping Competition Competency Points onto the Course Cluster

Using past mathematical modeling contest problems as "competency anchors," we extract a six-stage capability chain—"problem identification, data acquisition and cleaning, model construction, algorithm implementation, robustness verification, and result presentation"—to build a five-level alignment of "competency points–course–unit–task–evidence." The corresponding mapping is as follows: Probability and Mathematical Statistics → statistical inference and characterization of uncertainty; Regression Analysis/Multivariate Statistics → model diagnostics, variable selection, and interpretation; Time Series and Forecasting → modeling of trend/seasonality/residual structure; Optimization Methods → linear/nonlinear/integer programming and constraint handling; Statistical Computing and Visualization (R/Python) → data engineering and reproducible experiments; Survey and Experimental Design → sampling, questionnaire design, and causal identification. Each competency point is linked to at least one measurable Course Learning Outcome (CLO) and one submittable task, thereby forming a course map.

3.2 Construction of the Case Library and Data Resources

The case library adheres to the principles of "authentic, accessible, reproducible, and extensible." Its sources include publicly released competition problems, industry scenarios, and open data (such as government data and data from competition platforms). For each case, we create a metadata card (including topic, competency points, methodological hints, data fields, difficulty level, estimated class hours, reference solutions, and common pitfalls), and provide a package of "dataset + starter code + visualization templates + report templates." Cases are stratified by topic (transportation/finance/culture & tourism/ecology), by method (statistical inference/optimization/simulation/machine learning), and by difficulty (L1–L3), so as to facilitate cross-course reuse and iterative upgrades.

3.3 Isomorphism between In-Class Tasks and Assignments

Classroom teaching follows a milestone-based progression: Week 1 focuses on topic framing and background reading; Weeks 2–3 on data acquisition and cleaning; Weeks 4–6 on model building and comparison; Week 7 on robustness and sensitivity analysis; Week 8 on visualization and report writing; the final week is devoted to public presentation and defense. Each stage includes tangible deliverables (notebooks/code, methodological memos, visualization sketches, posters and slide decks), supported by a closed loop of peer review, instructor feedback, and TA-led technical checks. In this way, "classroom tasks ≈ competition tasks," achieving an isomorphic relationship between training activities and graded assignments.

3.4 Assessment Rubrics and the Evidence Chain

The rubric is organized around four dimensions with suggested weights: (1) Problem modeling (20%): contextual understanding, reasonableness of assumptions, and the formulation of indicators and constraints; (2) Methods and implementation (35%): appropriateness of models, algorithmic rigor, code quality, and reproducibility; (3) Result interpretation and communication (25%): statistical interpretation, visual storytelling, and practical applicability; (4) Teamwork and norms (20%): division of labor, version control and management, and academic integrity. Formative assessment runs through each milestone (scores for process documentation, peer evaluation, and in-class contribution), while summative assessment focuses on "a complete, reproducible work." The evidence chain consists of process data (submission and revision logs), objective performance (course grades and school-level competition results), and qualitative materials (interviews/reflection), serving the dual purpose of classroom grading and quality improvement.

3.5 Organizational and Operational Mechanisms

We establish a structure of "three-layer support and tripartite collaboration": a three-level linkage of classroom–school competition–national competition, and a three-party collaboration among teachers, industry mentors, and teaching assistants. The classroom provides methods and academic norms; school-level competitions serve as mid-term stress tests and occasions for post-hoc review of student work; outstanding teams further advance to provincial and national contests. Industry mentors contribute real-world constraints and data interfaces, while teaching assistants are responsible for toolchain support and reproducibility checks. Credit incentives, workload recognition, and outcome recognition are used to institutionalize these practices and ensure the reform operates on a regular and sustainable basis.

4. Outcomes and Evidence of Implementation

4.1 Scope of Implementation and Data Sources

This reform covers the core course cluster of the Statistics major, including Probability and Mathematical Statistics, Regression Analysis, Time Series and Forecasting, Optimization Methods, and Statistical Computing and Visualization (R/Python). It runs throughout a full academic year and involves multiple cohorts and parallel classes. The data sources (see Table 1) fall into four categories: (1) process data from online platforms (logs of assignment and project submissions and version iterations, records of in-class interaction and peer assessment); (2) formative and summative scores based on a four-dimensional rubric of "problem modeling, method implementation, result interpretation, and collaboration norms"; (3) course final grades and performance in school-level/provincial (or thematic) competitions; and (4) questionnaires on learning engagement, learning motivation, and satisfaction, as well as interviews with teachers and students. Together, these data form a multi-evidence closed loop of "process–output–

perception," providing a traceable basis for quality diagnosis and continuous improvement.

Table 1. Data Sources

Course	Number of Classes	Number of Students	Total Submitted Logs	Avg. Version Iterations per Student	Classroom Interactions +PeerReviews (entries)	Total Rubric Score (Mean ± SD, % scale)	Final Score (Mean ± SD)	Participation Rate in School/Thematic Contests	Award Rate	Questionnaire Response Rate	Interview Sample (persons)
Probability and Mathematical Statistics	2	92	2304	5.8	680	82.4 ± 6.8	84.1 ± 7.2	43%	12%	96%	16
Regression Analysis	2	88	2056	5.1	620	83.7 ± 6.2	85.6 ± 6.7	47%	14%	94%	15
Time Series and Forecasting	2	84	1987	5.6	590	85.1 ± 5.9	87.2 ± 6.1	52%	17%	92%	14
Optimization Methods	1	46	982	5.0	310	81.5 ± 7.1	82.8 ± 7.4	38%	9%	91%	8
Statistical Computing and Visualization (R/Python)	2	98	2650	6.2	760	86.3 ± 5.6	88.3 ± 5.8	55%	18%	95%	18

4.2 Learning Engagement and Learning Outcomes

The results (see Table 2) show improvements in students' behavioral, emotional, and cognitive engagement . On-time submission rates and the average number of iterations per student increased, interactions and peer assessment became more active, and students' learning interest and value identification were enhanced, with deep-learning strategies and self-monitoring used more frequently.

The mean scores on all four rubric dimensions rose, with the most pronounced gains in "methods and implementation" and "result interpretation." Pass rates on higher-order comprehensive problems and the reproducibility of student work improved in parallel. At the competition level, both participation and award rates in school- and provincial-level contests exceeded those of comparable historical cohorts.

For robustness, we compared with historical cohorts and parallel classes and controlled for covariates such as grade level, prior achievement, and whether teams were formed across majors. Regression analyses indicate that "competition-oriented teaching" has a significant effect on total rubric scores, course grades, and competition performance. These findings remain stable under robustness checks such as reweighting, trimming outliers, and using cluster-robust standard errors, while threats to internal validity are mitigated through common exam problems, unified rubrics, and cross-grading.

Table 2. Effect Sizes of Learning Engagement and Learning Outcomes

Indicator	Historical Cohort	Reform Semester	Difference Δ	Effect Size d	Significance (p)
Behavioral Engagement – On-time Submission Rate (%)	78	91	+13 pp	—	<0.001
Behavioral Engagement – Avg. Version Iterations per Student	3.9	5.7	+1.8	1.03	<0.001
Behavioral Engagement – Classroom Interactions + Peer Reviews (entries/student)	6.4	11.1	+4.7	1.17	<0.001
Emotional Engagement – Learning Interest (1–5)	3.33	3.92	+0.59	0.90	<0.001
Emotional Engagement – Value Identification (1–5)	3.41	4.02	+0.61	0.98	<0.001
Cognitive Engagement – Deep Learning Strategies (times/week)	1.8	3.1	+1.3	1.18	<0.001
Cognitive Engagement – Self-monitoring (times/week)	2.2	3.5	+1.3	1.08	<0.001
Learning Outcomes – Total Rubric Score (0–100)	82.3	85.9	+3.6	0.56	0.002
Learning Outcomes – Method Implementation Dimension (0–100)	80.1	85.5	+5.4	0.78	<0.001
Learning Outcomes – Result Interpretation Dimension (0–100)	79.4	84.8	+5.4	0.77	<0.001
Learning Outcomes – Pass Rate on Higher-order Comprehensive Items (%)	62	74	+12 pp	—	0.008
Learning Outcomes – Pass Rate on Reproducibility of Student Work (%)	68	86	+18 pp	—	<0.001
Competition Performance – Participation Rate (%)	28	47	+19 pp	—	<0.001
Competition Performance – Award Rate (%)	8	15	+7 pp	—	0.030

5. Conclusion

Taking mathematical modeling as the entry point, this study implements an outcome-oriented teaching reform that uses competitions to enhance both teaching and learning. Around a closed loop of competition problems–courses–assessment, we reconstruct the course cluster and unit tasks, build a case library and rubrics, and establish a three-level linkage of "classroom–school competition–national competition" together with a PDCA-based continuous improvement mechanism. Practice shows that students' behavioral, emotional, and cognitive engagement have all improved; scores on key dimensions such as “methods and implementation” and “result interpretation” have increased; and the reproducibility of student work and competition performance have improved in parallel, while reusable course maps, case–data–template resources, and organizational mechanisms have been accumulated. The key elements of the reform lie in fine-grained curriculum alignment driven by mapping competition competency points, task design that makes training activities and graded assignments isomorphic, quality assurance through rubric-based assessment and process traceability, and long-term operation supported by cross-disciplinary mentor collaboration and institutionalized incentives. Constrained by the implementation period and sample coverage, the current evidence still has room for improvement in terms of comparison strength and longitudinal tracking; future work will extend the reform to non-modeling courses and cross-faculty collaboration, enrich open cases and data warehouses, promote inter-institutional recognition of assessment standards and the application of learning analytics/causal inference techniques, and conduct long-term tracking along the chain of “courses–competitions–practice–employment” to further examine the transfer effects and educational value of the reform.

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References

[1] Chen Cang, Pan Yingxue, Zhao Zhiqin. Application of a competition-driven practical teaching model in the College Mathematics course. Educational Progress, 2023, 13(9): 6343-6346.

[2] Cheng Lijuan, Guo Juxi, Zhou Xiuxiang. Research on the teaching reform of mathematical modeling. Educational Progress, 2024, 14(12): 502-508.

[3] Zhou Yang, Du Haiting, Liu Guosheng, Gu Chenyang, He Junhong. Teaching research on interdisciplinary integration and competition-driven instruction under the background of New Liberal Arts: A case study of the course “Brand Management and Communication”. Educational Progress, 2024, 14(12): 1256-1261.

[4] Han Zhen, Feng Shijing. Teaching reform and practical exploration of “integration of competition and teaching” in Biostatistics under the background of curriculum ideological and political education. Innovative Education Research, 2024, 12(1): 190-194.

[5] Liu Changbiao, Weng Ming. Exploration of an integrated “learning-competition-research-innovation” training model for innovative talents in Statistics majors. Educational Progress, 2025, 15(5): 1059-1066.

[6] Li Yuanyuan, Du Mintong, Jia Jiyuan. The “empowering” effect of innovation competitions on the quality of undergraduate education: Empirical evidence from 106 universities in Sichuan Province. Journal of Chengdu University of Technology (Social Sciences), 2025-06-25.

[7] Wu Bin, Zhang Mengsi, Zhai Li, Song Ye, He Yanan. The influence of learning support services on satisfaction with blended learning: The chain mediating roles of learning alienation and learning engagement. Journal of Xinyang Normal University (Philosophy and Social Sciences), 2024, 44(3): 81-88.

[8] Organizing Committee of the China Society for Industrial and Applied Mathematics

National Undergraduate Mathematical Contest in Modeling. National Undergraduate Mathematical Contest in Modeling. [2025-11-12].

[9] Expert Working Group on the Evaluation and Management System of University Competitions, China Association of Higher Education. Release of the 2023 National General University Student Competition Analysis Report. 2024-03-22.

[10] Biggs J. B., Tang C. S. Teaching for Quality Learning at University. 4th ed. Maidenhead: McGraw-Hill/Open University Press, 2011.

[11] Ryan R. M., Deci E. L. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 2000, 55(1): 68-78.