OPEN ACCESS
Journal of Advances in Education and Philosophy
Abbreviated Key Title: J Adv Educ Philos
ISSN 2523-2665 (Print) |ISSN 2523-2223 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Review Article

A Dynamic Evaluation System for Applied Regression Analysis in Graduate Applied Statistics Education

Junjie He[1]*, Han Yang[1], Zhonggui Li[1]

[1]School of Mathematics and Statistics, Xinyang Normal University, Xinyang 464000, China

DOI: https://doi.org/10.36348/jaep.2026.v10i05.002 | **Received:** 09.03.2026 | **Accepted:** 06.05.2026 | **Published:** 08.05.2026

***Corresponding author:** Junjie He
School of Mathematics and Statistics, Xinyang Normal University, Xinyang 464000, China

Abstract

Applied Regression Analysis is a core course in Master of Applied Statistics programs. It consolidates students' statistical modeling foundations and develops their ability to analyze real-world data. Yet conventional course evaluation relies on final exams, lab reports, and project scores--emphasizing results over process and technique over problem-solving. Instructors struggle to identify where students struggle: data governance, model construction, diagnostics, communication. This design article proposes a dynamic evaluation system that uses a regression modeling competency map and process-oriented assessment to capture evidence from quizzes, code submissions, model outputs, case reports, presentations, and online behavior. The system converts this evidence into actionable feedback: problem localization, diagnostic attribution, and modeling prescription. Supported by automated code analysis, model diagnostics extraction, text analysis, and AI-assisted feedback, it is designed to evaluate students' modeling competencies throughout the full regression workflow. The system is intended to improve evaluation timeliness, specificity, and interpretability; support instructors in evidence-based teaching adjustments; and help students refine their modeling strategies.

Keywords: Applied Regression Analysis, statistical modeling competency, competency map, dynamic evaluation, process-oriented assessment, learning analytics.

INTRODUCTION

Master of Applied Statistics programs train professionals to solve real problems–economic forecasting, market analysis, policy evaluation. Applied Regression Analysis is central to this training. Students need to understand linear regression, multiple regression, diagnostics, variable selection, and generalized linear models (James et al., 2021; Montgomery *et al.,* 2012; Weisberg, 2014). Crucially, they must complete the full modeling process in authentic data contexts: identifying research problems, constructing variables, specifying models, estimating parameters, diagnosing assumptions, revising models, interpreting results, and writing reports.

Course evaluation should therefore focus on how students develop statistical modeling competency, not on formula derivation, software operation, or one-time exam scores. In practice, several persistent problems emerge. Evaluation is delayed. Final exams and end-of-course projects show only staged outcomes. Instructors cannot identify where students struggle–variable selection, assumption testing, outlier handling, interpretation–until it is too late. Evaluation is incomplete. Traditional assessment asks: Does the model run? Are coefficients significant? It ignores problem transformation, data governance, diagnostic reasoning, and communication. Feedback lacks personalization. Different students fail at different stages: data preprocessing, code implementation, statistical inference, contextual interpretation. Uniform feedback does not help. Learning data go unused. Students generate rich process data through code submissions, lab revisions, classroom interactions, case discussions, and presentations. These data rarely become evidence for teaching decisions.

With advances in artificial intelligence, learning analytics, and educational data mining, evaluation is shifting from single-result assessment to full-process, evidence-based, intelligent evaluation (Long & Siemens, 2011; Ferguson, 2012; Lang et al., 2025). For graduate statistics courses, the value of digital-intelligence tools lies not in replacing teacher judgment but in helping instructors capture key evidence in students' modeling processes and provide more fine-grained, interpretable, targeted feedback.

Outcome-based education emphasizes that curriculum design should begin with the learning outcomes students are expected to demonstrate, and that teaching activities and assessment tasks should be aligned with those outcomes (Biggs, 1996; Davis, 2003; Harden et al., 1999). For a graduate Applied Regression Analysis course, this perspective implies that assessment should not stop at whether students remember formulas or operate software. It should examine whether students can transform applied questions into statistical problems, construct models, diagnose assumptions, interpret results, and communicate evidence-based conclusions. Formative assessment and feedback research further suggests that assessment should support learning while it is happening, not merely judge learning after completion. Effective feedback clarifies goals, identifies the gap between current and expected performance, and guides the next learning action (Hattie & Timperley, 2007; Nicol & Macfarlane-Dick, 2006; Shute, 2008). This is particularly relevant to regression modeling because students' weaknesses often occur in intermediate reasoning steps, such as variable construction, model diagnosis, or contextual interpretation, rather than only in final numerical results.

Learning analytics provides a technical basis for collecting and interpreting learning process data. Prior studies show that digital traces, dashboards, and analytics-supported feedback can help instructors understand student progress and make teaching decisions more evidence-based (Ferguson, 2012; Long & Siemens, 2011; Matcha *et al.,* 2020). Recent work also connects learning analytics with feedback design and class-wide intervention, highlighting the need to make analytics actionable for both teachers and students (Er *et al.,* 2021). Studies on generative artificial intelligence and intelligent feedback further indicate that AI can support automated feedback, adaptive assessment, learning analytics, and AI-assisted grading in higher education (Lampou *et al.,* 2026; Lang *et al.,* 2025; Lee & Moore, 2024; Saez *et al.,* 2026). However, these tools also raise concerns about feedback quality, transparency, fairness, and the boundary between machine assistance and teacher judgment. Overall, existing studies provide theoretical and technical foundations for outcome alignment, formative feedback, learning analytics, and AI-assisted feedback, but much of this work remains at a general pedagogical or technological level. This gap motivates a course-specific evaluation design for Applied Regression Analysis.

This design article therefore proposes a dynamic evaluation system for Applied Regression Analysis and explores how process data, task performance, and intelligent feedback can integrate into graduate teaching. Unlike evaluation approaches that remain at the level of summative scoring or general learning analytics, this system emphasizes continuous, process-oriented feedback grounded in a course-specific competency map. Its contribution lies in translating outcome-based education, process-oriented assessment, learning analytics, and AI-assisted feedback into an integrated design for Applied Regression Analysis.

1. Theoretical Foundations and Course Objective Reconstruction

1.1 Clarifying Competency Objectives through Outcome-Based Education

In this course, the outcome-based perspective is operationalized by asking what Master of Applied Statistics students should be able to do with regression methods. The outcomes of Applied Regression Analysis should extend beyond "master regression theory" or "use statistical software" and become observable, assessable modeling competencies (Biggs, 1996; Davis, 2003).

This design article identifies seven competency elements: Problem transformation: Convert practical problems (economics, finance, education, health care, market research) into analyzable statistical modeling problems. Data governance: Clean data, handle missing values, identify outliers, encode variables, construct features. Model construction: Select appropriate regression models for the data structure and research purpose; estimate parameters correctly. Model diagnosis: Examine linearity, residual normality, heteroscedasticity, multicollinearity, autocorrelation, influential observations. Model optimization: Conduct variable selection, model comparison, robustness checks, necessary revision. Result interpretation: Interpret coefficients, significance levels, confidence intervals, predictions in disciplinary context. Practical communication: Produce standardized data analysis reports; clearly explain modeling logic, evidence chains, decision recommendations in presentations.

These competency elements guide course evaluation and process data collection. In the competency map, they are further grouped into four integrated dimensions for operational assessment, linking course objectives, learning tasks, evidence sources, diagnostic indicators, and feedback actions.

1.2 Supporting Modeling Competency Development through Process-Oriented Assessment

Regression modeling competency is inherently process-oriented. In real data analysis, students' problems do not always manifest as wrong final answers. More often: insufficient justification for variable selection, neglect of assumptions, weak interpretation of diagnostic plots, confusion between statistical significance and practical importance, conclusions disconnected from context.

Course evaluation must cover the entire modeling process. This design article divides Applied Regression Analysis learning into five stages: data understanding and problem definition, data preprocessing and variable construction, model estimation and statistical inference, model diagnosis and revision, result interpretation and report writing. Each stage has observable evidence and feedback indicators.

In data preprocessing, evaluation asks: Are missing values handled appropriately? Are categorical variables encoded correctly? In model diagnosis: Do students calculate variance inflation factors? Draw residual plots? Interpret heteroscedasticity tests? In report writing: Do conclusions answer the research question? Do students distinguish statistical association from causation?

Process-oriented assessment converts a single score into a competency profile. It helps instructors see where students struggle and helps students understand how to improve their next modeling attempt.

1.3 Enabling Targeted Feedback through Digital-Intelligence Technologies

Digital-intelligence tools support the course in three ways. First, learning platforms, code repositories, and lab systems collect process data and form an evidence base for students' learning behaviors and modeling performance. Second, automated analysis tools extract model outputs, diagnostic indicators, and code features, reducing instructors' workload in repetitive checking. Third, AIGC generates preliminary feedback, supplementary exercises, and report revision suggestions, with the potential to improve timeliness and personalization (Lang *et al.,* 2025; Lee & Moore, 2024; Saez *et al.,* 2026).

Accordingly, this system treats digital tools as decision support under teacher leadership, especially for higher-order judgments such as model appropriateness, substantive interpretation, and possible overclaiming.

2. Design of the Dynamic Evaluation System

The dynamic evaluation system has three layers: data collection, intelligent diagnosis, and feedback application. Together they form a loop: learning tasks generate data, intelligent tools analyze evidence, teachers and students use feedback to improve. The overall architecture is shown in Figure 1.

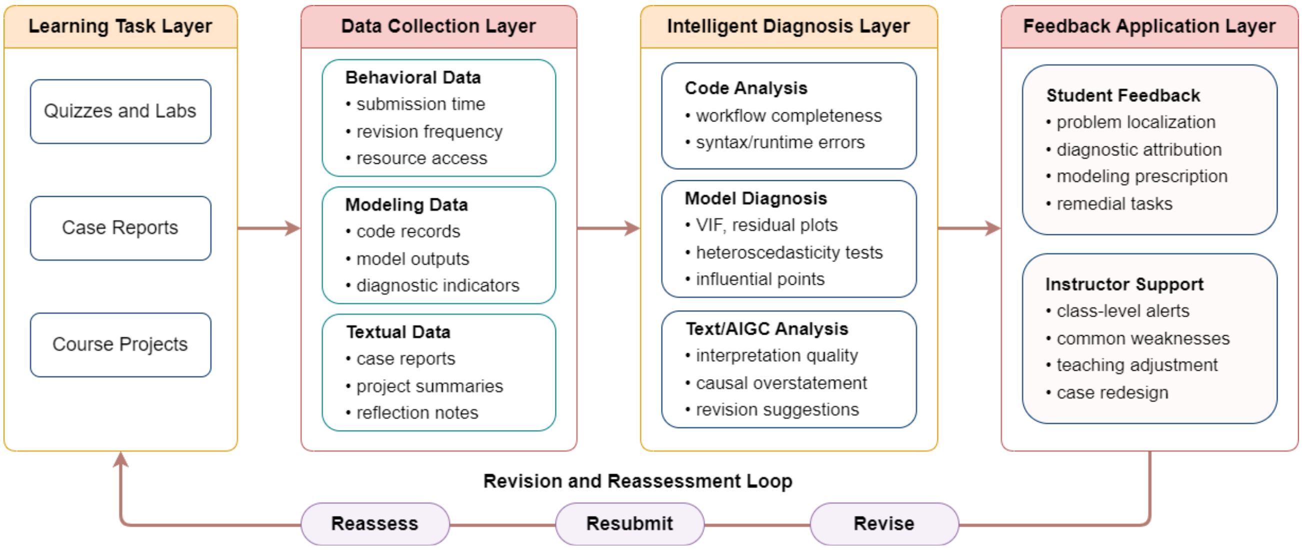

Figure 1: Architecture of the dynamic evaluation system

2.1 Multi-Source Learning Data Collection

The data collection layer centers on actual learning activities, not isolated assessment events. Students' modeling competency shows up not just in final answers but in how they understand a problem, prepare data, write code, diagnose assumptions, revise models, communicate results. The system collects evidence from multiple scenarios: classroom quizzes, programming assignments, model outputs, case reports, project presentations, online learning behaviors. These sources describe students' cognitive understanding, technical operation, statistical reasoning, and engagement.

Classroom quizzes provide direct evidence of mastery: model assumptions, parameter interpretation, diagnostic methods, case-based judgment. Unlike final exams, quiz data accumulate continuously and reveal conceptual misunderstandings early. Programming assignments record how students implement regression analysis in R, Python, SPSS, or Stata. Submission time, revision frequency, running results, error types, and function use reveal whether students have formed a complete modeling workflow or just produced a number.

Model output data constitute another key source. The system extracts coefficients, standard errors, t tests, F tests, R-squared, adjusted R-squared, AIC, BIC, variance inflation factors, residual test results, and other diagnostics. These indicators show whether students move beyond model estimation to necessary diagnostic and comparative procedures. A student might obtain statistically significant coefficients but skip multicollinearity diagnostics or residual checks. That omission is hard to catch in a final score but visible in structured model output analysis.

Case reports and project presentations evaluate higher-order competencies that code and numbers cannot fully capture. In case reports, students explain research background, define variables, justify modeling choices, present diagnostic evidence, compare models, derive decision-oriented conclusions. Text analysis checks report structure, terminology, interpretive completeness, logical consistency. Project presentations reveal students' ability to explain modeling logic, respond to questions, transfer regression methods to new contexts. Online learning behavior--resource access, discussion participation, feedback viewing, remedial task completion--is not a substitute for learning outcomes but auxiliary evidence for understanding engagement and improvement trajectories.

By integrating these heterogeneous data, the system shifts focus from static scores to process evidence. It builds a comprehensive competency profile where knowledge mastery, software implementation, diagnostic reasoning, report communication, and learning improvement can be analyzed together. This integrated evidence base enables subsequent intelligent diagnosis and targeted feedback.

2.2 Regression Modeling Competency Map

To avoid a fragmented checklist of assessment points, this design article constructs a regression modeling competency map following the logic of the regression modeling workflow. The map groups the seven competency elements into four integrated dimensions. The goal: evaluate not just whether students know particular methods but whether they can organize these methods into a coherent analytical process. The map connects course content, learning tasks, process evidence, diagnostic indicators, and feedback actions with the professional competencies expected of Master of Applied Statistics students.

First dimension: Problem transformation and data governance.

Evaluation asks: Can students translate an applied question into a statistically analyzable problem? Define dependent and independent variables appropriately? Formulate reasonable research hypotheses? Can they clean data, handle missing values, identify outliers, encode variables, transform variables, conduct descriptive analysis? These indicators emphasize that regression analysis begins before model estimation. A vague research question or poorly constructed variables means subsequent results may be technically correct but substantively meaningless.

Second dimension: Model construction and statistical inference.

Do students select regression models that match the data structure and research purpose? Estimate parameters correctly? Interpret overall model significance and individual variable significance? Do they understand what regression coefficients, standard errors, confidence intervals, and goodness-of-fit measures mean, or just report software output? This dimension links theoretical understanding with technical implementation.

Third dimension: Model diagnosis and optimization.

This marks advanced modeling competency. Students should examine linearity, residual distribution, heteroscedasticity, multicollinearity, autocorrelation, influential observations. More importantly, they should propose revision strategies based on diagnostic evidence: transform variables, use robust standard errors, compare alternative specifications, reconsider variable selection. Evaluation focuses not just on whether diagnostic tests are performed but whether diagnostic results are meaningfully used to improve the model.

Fourth dimension: Result interpretation and communication.

In applied statistics, regression results must become understandable, responsible analytical conclusions. Do students interpret coefficients in context? Distinguish statistical significance from practical importance? Avoid presenting association as causation? Produce reports with complete structure, standardized tables and figures, coherent logic, usable recommendations? This dimension reflects the professional requirement that applied statistics graduates communicate quantitative evidence to decision makers.

Together, these dimensions form a progressive map from problem definition to data processing, model estimation, diagnostic revision, and result communication. The map covers Applied Regression Analysis content while highlighting the practical, integrative, communicative competencies required in professional graduate education. It also provides a structural basis for intelligent diagnosis: each observed learning problem can be located on the map, traced to a possible cause, and connected to a corresponding feedback action. The operational structure of the competency map is provided in Appendix A.

The relationship between the competency map and the diagnosis-prescription feedback loop is illustrated in Figure 2.

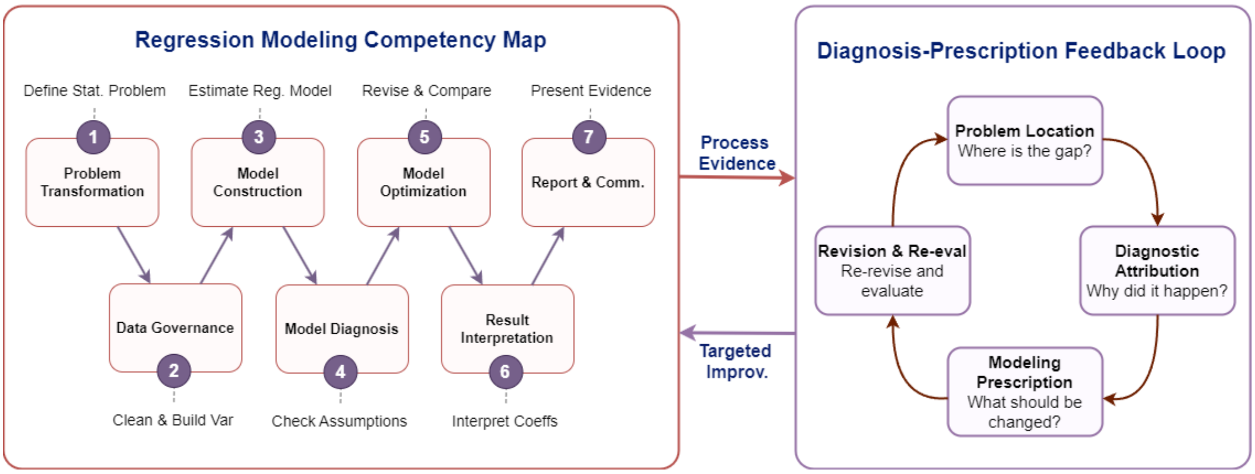

Figure 2: Regression modeling competency map and diagnosis-prescription feedback loop

2.3 Intelligent Diagnosis and Feedback Mechanism

The intelligent diagnosis layer consists of code analysis, model diagnosis, text analysis, and AIGC-assisted feedback. Its core function is not just error detection but transforming process evidence into a diagnosis-prescription feedback loop. In this loop, feedback identifies where the student's modeling process is incomplete or weak, analyzes why the problem occurred, and provides an actionable modeling prescription for revision. This responds to the need for feedback to move beyond simple scoring or general comments toward structured guidance for self-regulated learning.

Specifically, the system first extracts diagnostic evidence from code submissions, model outputs, and written reports. Code analysis checks whether students completed key steps: data import, variable processing, model estimation, diagnostic plotting, model comparison. If a student only runs a linear regression command without residual analysis, the system marks the submission as missing a model diagnosis step. Model diagnosis then extracts key indicators from regression outputs. High variance inflation factor? Possible multicollinearity. Significant heteroscedasticity test? Consider robust standard errors, variable transformation, or model respecification. Influential observations detected? Examine data sources and assess model robustness. Text analysis complements these numerical checks by identifying problems in written reports: whether the report explains the sample source, defines variables clearly, avoids overstating statistical significance, and does not interpret predictive results as causal effects.

On this basis, AIGC-assisted feedback organizes diagnostic results into student-facing and instructor-facing messages. Student-facing feedback emphasizes specificity and actionability: "please add a residual plot and explain whether there is evidence of nonlinearity" or "the current conclusion lacks interpretation of the substantive meaning of the core independent variable." Instructor-facing feedback supports teaching decisions: "most students can complete model estimation, but many struggle with heteroscedasticity tests; a follow-up case on robust standard errors is recommended."

The feedback need structure is summarized in Table 1. It reflects the transition from locating a modeling gap to explaining its cause to prescribing the next modeling action.

Table 1: Feedback need structure in Applied Regression Analysis

Feedback need	Meaning in regression learning	Typical feedback action
Problem localization	Identifying which modeling step is missing or weak	Mark missing residual analysis, unclear variable definition, or incomplete model comparison
Diagnostic attribution	Explaining why the problem may have occurred	Link the problem to misunderstanding of model assumptions, weak statistical inference, or confusion between significance and practical meaning
Strategy guidance	Suggesting the method or reasoning path needed for improvement	Recommend VIF analysis, robust standard errors, variable transformation, or alternative model specification
Modeling prescription	Providing a concrete next revision task	Ask the student to add a diagnostic plot, revise coefficient interpretation, compare candidate models, or rewrite the conclusion
Rubric alignment	Connecting the student's work with course objectives	Indicate the gap between current performance and expected competency in diagnosis, interpretation, or communication

Through this structure, feedback is no longer a terminal judgment after task completion. It becomes an embedded learning support mechanism that helps students understand "where the problem is," "why it occurs," and "what should be revised next." For instructors, aggregated feedback reveals class-level patterns--frequent omission of diagnostic tests, widespread overinterpretation of statistical significance--supporting targeted classroom intervention.

3. Course Implementation Path

3.1 Designing a Task Chain for Applied Regression Analysis

To embed evaluation into teaching, the course is organized as a progressive task chain, not disconnected chapters. The chain follows the developmental logic of modeling competency: students first acquire basic regression concepts and software operations, then learn to diagnose and revise models, then complete comprehensive case analyses, then conduct an independent course project. Each task produces process data that feed into the dynamic evaluation system.

At the beginning, foundational training tasks consolidate essential knowledge: simple linear regression, multiple linear regression, parameter estimation, hypothesis testing, interpretation of standard regression outputs. These tasks are relatively structured, letting students become familiar with modeling procedures and statistical software. Evaluation focuses on whether students can correctly implement basic models and explain core indicators: coefficients, standard errors, t tests, F tests, goodness-of-fit measures.

After students gain basic operational competence, diagnostic and revision tasks are introduced. These tasks center on common modeling problems: multicollinearity, heteroscedasticity, autocorrelation, outliers, influential observations. Students do not just identify these problems--they revise models according to diagnostic evidence. This design prevents students from treating regression analysis as a mechanical process of running commands and reporting significance levels. Instead, it encourages them to view model construction as an iterative process of evidence-based judgment.

Comprehensive case tasks then connect regression methods with real application scenarios. Datasets come from regional economic development, household consumption, financial risk, educational input, health care, market surveys. In these tasks, students complete the full process: problem definition, data preparation, model estimation, diagnosis, comparison, interpretation, report writing. The evaluation focus shifts from isolated technical operations to the coherence of the whole analytical process.

The course project is the culminating task. Students work individually or in groups to select a real problem, obtain or construct a dataset, develop a regression modeling strategy, interpret results, present findings. The project is evaluated not just by final report and presentation but by the revision trajectory recorded during the project process. In this way, the course project becomes both summative assessment and an opportunity for sustained formative feedback. Overall, the task chain guides students from solving textbook-style exercises to conducting applied statistical modeling, and from operating software to producing evidence-based analytical conclusions.

3.2 Supporting Instructor Decision-Making

The instructor dashboard is designed to summarize students' weekly learning performance: knowledge mastery, laboratory completion, omission rates in model diagnostics, report quality, completion of remedial tasks. Instructors can use these results to adjust teaching pace and case design.

For example: If most students can run multiple linear regression models but cannot explain the difference between R-squared and adjusted R-squared, add a focused discussion on model comparison. If students commonly ignore heteroscedasticity, introduce a cross-sectional economic data case to train students in residual plot analysis, Breusch-Pagan testing, robust standard errors. If reports frequently contain causal overstatements, supplement the course with a discussion of the limits of causal interpretation in observational data.

Through instructor-facing feedback, course teaching shifts from experience-based adjustment to evidence-supported precision teaching.

3.3 Providing Personalized Learning Support for Students

Student-facing feedback reports are designed to include competency radar charts, task completion trajectories, key problem alerts, remedial learning suggestions. Based on students' performance at different stages, the system can generate personalized task lists.

For students with weak data governance competency, the system recommends exercises on missing-value treatment, outlier identification, variable encoding. For students with insufficient model diagnosis competency, the system recommends cases on residual analysis, VIF calculation, heteroscedasticity testing, influential point detection. For students with weak result interpretation competency, the system recommends exemplary report segments, expression templates, exercises in contextual interpretation.

Students revise laboratory reports and course projects according to feedback, while instructors evaluate improvement through revision trajectories. In this way, evaluation transforms from a one-time judgment into a continuous mechanism for learning improvement.

4. Expected Effects, Implementation Considerations, and Future Validation

As a design-oriented teaching reform framework, the proposed dynamic evaluation system is expected to support course improvement in the following ways, which also provide directions for future classroom validation.

Timeliness.

The system is designed to transform laboratory submissions, case tasks, model outputs, and report drafts into process evidence. It is expected to help instructors identify common difficulties before the final project stage: missing diagnostic tests, weak variable justification, incomplete interpretation of coefficients. Students are expected to receive more concrete revision suggestions soon after completing tasks, reducing the risk that modeling problems accumulate until course end.

Specificity.

Compared with traditional total-score evaluation, the competency map is intended to help instructors distinguish students' performance in data governance, model construction, diagnostic revision, result interpretation, and report communication. One student may be proficient in software operation but weak in substantive interpretation; another may understand the theoretical logic but produce incomplete code or diagnostic evidence. Such differentiated competency profiles are expected to support more targeted guidance.

Continuous development.

The diagnosis-prescription feedback loop is designed to support continuous development of modeling competency. Through repeated feedback and revision, students are expected to develop a stronger awareness of regression modeling as an iterative process rather than a mechanical procedure of running commands and reporting significance levels. The hypothesized learning shift is from "obtaining a regression output" to "constructing, diagnosing, revising, and explaining a defensible model."

Evidence-based teaching.

Aggregated feedback is expected to help instructors adjust case difficulty, add topic-based explanations, optimize laboratory design, and track alignment between learning tasks and course objectives. Classroom intervention is therefore designed to become more precise: instead of responding only to final mistakes, instructors can intervene when recurring patterns appear in students' modeling processes, such as weak problem formulation, insufficient diagnostic reasoning, and overstatement of causal conclusions.

Implementation considerations.

Several caveats apply. First, the accuracy of intelligent feedback depends on the quality of evaluation rules, course cases, and training materials. Automated tools can identify missing diagnostic steps, abnormal indicators, textual overstatements, but they cannot independently determine whether a model is substantively appropriate for a research question or whether a conclusion is meaningful for a specific decision context. The system should be understood as an intelligent enhancement of teacher judgment, not a replacement.

Second, the human-machine collaboration boundary must be clearly defined. AIGC and automated diagnosis are suitable for evidence organization, preliminary error detection, repetitive feedback generation, class-level pattern summarization. Instructors remain responsible for evaluating model appropriateness, substantive interpretation, ethical use of data, educational value of feedback. This boundary is especially important in Applied Regression Analysis, where the same statistical output may lead to different interpretations depending on data quality, research design, application context.

Third, collecting process data may increase the platform operation burden for both students and instructors. A balance between data granularity and usability is necessary. AIGC-generated feedback should avoid being overly generic or template-based. Future development should improve prompt strategies by incorporating course case libraries, high-quality report samples, discipline-specific evaluation rubrics. Finally, the system involves student learning data, so data use boundaries, privacy protection, academic integrity mechanisms must be clearly established.

CONCLUSION

For Master of Applied Statistics programs, Applied Regression Analysis should center on real problem solving and statistical modeling competency. This design article proposes a digital-intelligence-enabled dynamic evaluation system built around a regression modeling competency map and a process-oriented diagnostic feedback loop.

The proposed system is intended to address the limitations of traditional evaluation, which emphasizes final results while neglecting learning processes. It provides a design framework for diagnosing students' competency weaknesses across the full regression modeling workflow and supporting instructors in precision teaching. Future classroom implementation and empirical validation are necessary to examine the actual effectiveness of the system.

Acknowledgments

This study was supported by the 2024 Henan Province Graduate Education Reform and Quality

Improvement Project (No. YJS2024ZX34).

REFERENCES

- Biggs, J. (1996). Enhancing teaching through constructive alignment. *Higher Education*, 32(3), 347-364. https://doi.org/10.1007/BF00138871
- Davis, M. H. (2003). Outcome-based education. *Journal of Veterinary Medical* Education, 30(3), 258-263. https://doi.org/10.3138/jvme.30.3.258
- Er, E., Dimitriadis, Y., & Gasevic, D. (2021). Collaborative peer feedback and learning analytics: Theory-oriented design for supporting class-wide interventions. *Assessment & Evaluation in Higher Education*, 46(2), 169-190. https://doi.org/10.1080/02602938.2020.1764490
- Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, 4(5/6), 304-317. https://doi.org/10.1504/IJTEL.2012.051816
- Harden, R. M., Crosby, J. R., Davis, M. H., & Friedman, M. (1999). AMEE Guide No. 14: Outcome-based education: Part 5 - From competency to meta-competency: A model for the specification of learning outcomes. *Medical Teacher*, 21(6), 546-552. https://doi.org/10.1080/01421599978951
- Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81-112. https://doi.org/10.3102/003465430298487
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An introduction to statistical learning: With applications in R* (2nd ed.). Springer.
- Lampou, R., Noor, M., Vivekanantharasa, R., & Patnaik, S. (2026). AI-driven educational ecosystems: Integrating learning analytics, adaptive assessment, and intelligent feedback for sustainable student performance. *Qubahan Techno Journal*, 5(1). https://doi.org/10.48161/qtj.v5n1a80
- Lang, Q., Wang, M., Yin, M., Liang, S., & Song, W. (2025). Transforming education with generative AI (GAI): Key insights and future prospects. *IEEE Transactions on Learning Technologies*, 18, 230-242. https://doi.org/10.1109/TLT.2025.3537618
- Lee, S. S., & Moore, R. L. (2024). Harnessing generative AI (GenAI) for automated feedback in higher education: A systematic review. *Online Learning*, 28(3). https://doi.org/10.24059/olj.v28i3.4593
- Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30-40.
- Matcha, W., Uzir, N. A., Gasevic, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies*, 13(2), 226-245. https://doi.org/10.1109/TLT.2019.2916802
- Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). *Introduction to linear regression analysis* (5th ed.). Wiley.
- Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, 31(2), 199-218. https://doi.org/10.1080/03075070600572090
- Saez, Y., Garcia, L. M., Mochon, A., & Isasi, P. (2026). Evaluating large language models for AI-assisted grading: A framework and case study in higher education. *Scientific Reports*. https://doi.org/10.1038/s41598-026-48656-3
- Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research*, 78(1), 153-189. https://doi.org/10.3102/0034654307313795
- Weisberg, S. (2014). *Applied linear regression* (4th ed.). Wiley.

Appendix A. Regression Modeling Competency Map

Table A1. Regression modeling competency map for Applied Regression Analysis

Key indicators	Evidence sources	Diagnostic and feedback focus	Performance levels
Competency dimension I: Problem transformation and data governance			
Problem definition; Variable definition; Hypothesis formulation; Data cleaning; Missing-value treatment; Outlier identification; Variable encoding; Descriptive analysis	Case proposal; Data preprocessing code; Data dictionary; Descriptive statistics; Classroom discussion records	Diagnose: vague research questions, unclear variables, or missing preprocessing steps; Guide students to revise problem statements, variable definitions, and data-processing justifications	Basic: completes partial data preparation; Developing: defines variables and handles common data issues; Proficient: connects problem framing, data governance, and modeling purpose coherently
Competency dimension II: Model construction and statistical inference			
Model selection; Parameter estimation; Standard errors, confidence intervals; T tests, F tests;	Programming assignments; Model output files; Quiz answers; Lab reports	Diagnose: model-choice mismatch or unexamined statistical output; Guide students to justify model selection, explain key estimates,	Basic: runs a regression model; Developing: interprets main statistical outputs;

Key indicators	**Evidence sources**	**Diagnostic and feedback focus**	**Performance levels**
R-squared, and adjusted R-squared		and compare alternative specifications	Proficient: justifies model choice and explains results in context
Competency dimension III: Model diagnosis and optimization			
Residual analysis; Linearity checking; Normality assessment; Heteroscedasticity testing; Multicollinearity diagnosis; Autocorrelation checking; Influential-point analysis; Robustness check; Model comparison	Diagnostic plots; VIF values; Residual test outputs; Model comparison tables; Revision records	Diagnose: omitted or unused diagnostic evidence; Guide students to conduct residual analysis, VIF analysis, heteroscedasticity tests, robustness checks, or model respecification	Basic: performs isolated diagnostic tests; Developing: identifies common model problems; Proficient: revises and compares models based on diagnostic evidence
Competency dimension IV: Result interpretation and communication			
Contextual interpretation; Statistical and practical significance; Avoidance of causal overstatement; Standardized tables and figures; Report structure; Presentation and response to questions	Case report; Project presentation; Peer questioning; Report revision history; Instructor comments	Diagnose: software-output copying, disconnected conclusions, or causal overstatement; Guide students to rewrite interpretations, align conclusions with questions, add limitations, and standardize reporting	Basic: reports numerical results; Developing: explains findings with partial contextualization; Proficient: communicates defensible conclusions and limitations to decision makers

