

Dynamic Evaluation and Incentive Mechanism Framework for Postgraduates' Academic Performance Stability

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Abstract: Against the backdrop of the Party and the state's emphasis on promoting educational evaluation reform and implementing process-based evaluation, this paper combines the process optimization concept of Industrial Engineering (IE) and data-driven thinking to construct a dynamic evaluation system covering the entire student learning process. In response to the shortcomings of the traditional "30/70" rigid scoring system, such as insufficient discrimination, inability to dynamically assess students' learning stability, and difficulty in guiding learning enthusiasm through scientific rewards and punishments, this paper designs a stability quantification method based on indicators such as average scores and trend slopes, and formulates segmented incentive and punishment strategies. This model can effectively enhance the discrimination of high-score segments while protecting the learning enthusiasm of underperforming students, providing a feasible approach for the digital and scientific reform of educational evaluation.

Keywords: Industrial Engineering; Statistical Process Control; Teaching Scoring System

1. Introduction

Student academic performance is crucial as a key indicator of their educational experience[1]. With the ongoing transformation of modern higher education governance, it is of great timeliness and necessity to revisit the core characteristics of service quality in tertiary educational institutions[2]. Research on the rank-order stability of student academic performance carries important implications for educational research and instructional practice[3]. Traditional evaluation models focus only on final scores, making it difficult to reflect fluctuations and changes in students' learning processes. In the context of modern information technology and the demand for teaching to cultivate students' multi-dimensional abilities, the current "30/70" rigid scoring system, which relies on small differences in regular scores and simple average scores as the basis for assessment, and fails to dynamically capture students' learning stability and guide learning enthusiasm through scientific rewards and punishments, has shown limitations. Therefore, this paper introduces Industrial Engineering (IE) methods to construct a dynamic evaluation system covering the entire learning process, incorporating changes in scores during the learning process, and implementing targeted incentives through dynamic assessment of learning stability. This approach not only enhances the discrimination of high-score segments to reflect the value of effort but also effectively protects and encourages students' learning enthusiasm. This paper aims to propose a dynamic evaluation method, providing theoretical basis and practical ideas for educational evaluation reform and incentive mechanism design.

2. Construction of Dynamic Academic Performance Stability Indicators

2.1 Evaluation and Design of Learning Stability

Research findings indicate that artificial intelligence tools can enhance learning motivation through timely, low-risk feedback and flexible practice arrangements[4]. While IT-enhanced education has gained prominence, traditional grading still lacks the capacity to reflect learning stability[5]. The openness of Internet content and the application of Information Technology (IT) in education have provided new and better learning methods[6]. This research addresses this gap by

modeling the learning process as a controllable system. We utilize longitudinal assessment data to calculate trend slopes and score variability, constructing a multidimensional stability index. Unlike static models, our framework quantifies learning progress and regression trends through data-driven indicators, offering a scientific basis for assessing student performance and implementing precise incentive mechanisms.

2.2 Incentive and Punishment Mechanism Oriented to Stability

To balance the dynamic changes in students' academic performance and their learning enthusiasm, this study adopts process capability analysis and trend analysis methods to quantitatively judge the learning status and implement segmented incentives. Classroom-level incentives can foster positive peer effects and incentivize students across all achievement levels, unlike individual-level incentives that primarily reward top performers[7].

Calculate the trend slope: Extract the student's second lowest test scores and the corresponding time.

$$k_{trend} = \frac{\sum_{i=1}^n (t_i - \bar{t})(s_i - \bar{s})}{\sum_{i=1}^n (t_i - \bar{t})^2} \quad (1)$$

Calculate the stability bonus situation: Segment evaluation based on the mean, standard deviation, target benchmark, and tolerance:

$$c_{stab} = \begin{cases} \frac{\beta_1 \cdot \mu}{(\sigma + 1.5)^2} & \sigma \leq \sigma_{limit} \text{ 且 } \mu \geq S_{threshold} \text{ (High-Score Controlled Zone)} \\ 0 & \sigma \leq \sigma_{limit} \text{ 且 } \mu < S_{threshold} \text{ (Systemic Deviation Zone)} \\ \beta_2 \cdot k_{trend} & \sigma > \sigma_{limit} \text{ 且 } k_{trend} > 0 \text{ (Beneficial Variation Zone)} \\ -\beta_3 \cdot (\sigma - \sigma_{limit})^2 \cdot (1 + |k_{trend}|) & \sigma > \sigma_{limit} \text{ 且 } k_{trend} \leq 0 \text{ (Out-of-Control Decline Zone)} \end{cases} \quad (2)$$

Situation A (High Score/Stable): If $\sigma \leq \sigma_{limit}$ and $\mu \geq S_{threshold}$, reward stability and excellence with $\beta_1 \cdot \mu / (\sigma + 1.5)^2$.

Situation B (Low Score/Stable): If $\mu < S_{threshold}$, it is considered a "systematic deviation", and the student is not punished, $c_{stab} = 0$.

Situation C (Improvement/Fluctuation): If $\sigma > \sigma_{limit}$ and $k_{trend} > 0$, it is regarded as the "Kaizen stage", and the improvement trend is rewarded with $\beta_2 \cdot k_{trend}$.

Situation D (Out of Control): If $k_{trend} \leq 0$, the process is "unstable", and it is punished with $-\beta_3 \cdot (\sigma - \sigma_{limit})^2 \cdot (1 + |k_{trend}|)$.

To verify the model's effectiveness, this paper compared the final score distributions before and after the improvement. The optimized scores maintained the overall trend while enhancing the discrimination in the high-score range. The heterogeneous reward and penalty mechanism for the stability contribution value achieved a multi-dimensional assessment of academic quality.

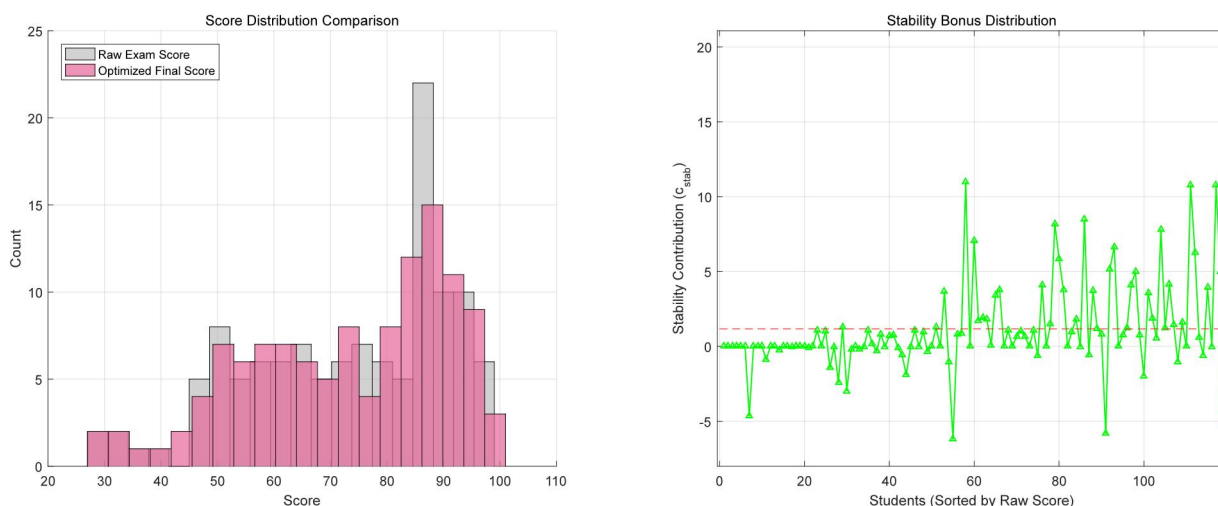


Figure 1 Comparison of Score Distribution Before and After Improvement

3. Practical Value and Innovation Points

This study, based on the process optimization ideas of Industrial Engineering (IE), combines data-driven and dynamic statistical methods to construct an "IE Concept + Dynamic Evaluation" integrated model. This provides experimental support for the theory of dynamic and precise evaluation in the teaching process and offers a new perspective for the cross-integration of industrial engineering in the field of higher education evaluation. Research demonstrates that artificial intelligence tools can enhance learning motivation through timely, low-stakes feedback and flexible learning exercises[8].

In addition, this study has developed a stability contribution value calculation model, which, in combination with the data-driven concept, customizes personalized guidance plans for students in different learning states, effectively enhancing the precision of academic evaluation and management. Studies have shown that artificial intelligence tools can effectively enhance students' learning motivation through timely, low-pressure feedback and flexible learning exercises[9].

4. Conclusion

Based on the policy requirements for educational evaluation reform and the implementation of process-based evaluation, this study deeply integrates IE ideas into the evaluation system, constructing a student evaluation system that includes learning stability assessment and segmented reward and punishment incentives. Research shows that artificial intelligence tools can boost learning motivation through timely, low-risk feedback and flexible learning practices[10]. This provides a practical solution to the real-world problems of insufficient discrimination in traditional rigid scoring systems and the inability to dynamically assess learning states. In the future, the model parameters and evaluation rules can be further optimized, and cross-disciplinary and cross-grade application scenarios can be expanded to inject new impetus into the digital and scientific development of higher education evaluation. In the future, we need to further explore more efficient dynamic screening algorithms to adapt to application scenarios with larger datasets, and incorporate more external information such as learning paths and behavioral characteristics to enhance the utilization value of uninteracted information.

Acknowledgements

This work was supported by National Social Science Foundation of China (Grant No.20BGL025) and Teaching Reform Project for Graduate Education at Nanjing Tech University (Grant No.YJG2507).

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