Research on the Evaluation Mechanism of College Counselor Work Performance Empowered by Artificial Intelligence

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Abstract: With the expansion of higher education and the increasing complexity of student affairs, the performance evaluation of college counselors needs to become more scientific, dynamic, and evidence-based. Traditional evaluation methods often rely on periodic reports, subjective judgment, and fragmented data, which may weaken fairness and timeliness. This study develops an artificial intelligence-enabled evaluation mechanism for college counselor work performance. Based on public higher education statistics, policy requirements, and an institutional case from Sichuan Vocational College of Culture and Communication, the paper proposes a multidimensional evaluation framework covering workload, responsiveness, student feedback, professional development, and ethics control. A weighted index model is designed to support process-based evaluation and decision feedback. The study argues that AI can improve evaluation accuracy and efficiency, but it should function as a supportive tool rather than a substitute for human judgment. A human-machine collaborative mechanism is therefore necessary for fair and developmental counselor evaluation.
***Keywords*:** artificial intelligence; college counselor; performance evaluation; higher education governance; student affairs

1. Introduction

College counselors play an important role in ideological guidance, student management, psychological support, employment assistance, and campus stability. In Chinese higher education, they are also a key part of the ideological and political education team. Therefore, how to evaluate their work fairly and scientifically has become an important issue in university governance.

With the expansion of higher education, counselor work has become more complex. China had more than 47.63 million higher education students in 2023, and the gross enrollment rate reached 60.2%, which means that student affairs work now faces greater pressure and more diverse demands [1]. However, many existing evaluation methods still rely on annual reports, administrative records, superior ratings, and simple student surveys. These methods often emphasize final results rather than daily work processes, and they may fail to reflect responsiveness, student feedback, crisis intervention, and professional development.

Artificial intelligence offers a possible way to improve this situation. Through data integration, text analysis, learning analytics, and decision-support tools, AI can help collect multidimensional evidence and support dynamic evaluation. Based on public data and the case materials of Sichuan Vocational College of Culture and Communication, this study constructs an AI-enabled counselor performance evaluation framework. It argues that AI should support, rather than replace, human judgment in counselor evaluation.

2. Literature Review

College counselors are closely involved in student development, ideological guidance, psychological support, campus management, and educational governance. In China, they are not only administrative workers but also front-line educators who participate in students' daily growth and value formation. With the expansion of higher education, counselor work has become more complex. China had more than 47.63 million higher education students in 2023, which places student affairs work in a large-scale governance environment [1].

Traditional counselor evaluation often depends on annual assessment, superior evaluation, peer review, student satisfaction surveys, and work summaries. These methods are useful but may produce delayed feedback and excessive dependence on subjective judgment. Since counselor work is continuous and interactive, final outcomes alone cannot fully reflect emotional support, crisis intervention, student communication, or professional responsibility.

Learning analytics provides a useful basis for improving this situation. Siemens and Long argue that educational data can support better decision-making, resource allocation, and institutional improvement [2]. Similarly, educational data mining research shows that computational methods can extract useful patterns from educational data and support more evidence-based educational decisions [3]. These studies suggest that counselor evaluation can move from static assessment to process-based analysis.

Artificial intelligence further expands this possibility. OECD notes that AI, learning analytics, and other smart technologies are changing both teaching and the management of educational organizations [4]. Holmes, Bialik, and Fadel also point out that AI can support personalized learning, feedback, and educational decision-making [5]. In counselor evaluation, AI may assist text analysis, risk warning, feedback classification, and workload monitoring.

However, AI-based evaluation must be used carefully. UNESCO emphasizes that AI in education should follow a human-centered approach with attention to ethics, privacy, and regulation [6]. Slade and Prinsloo also warn that learning analytics involves issues of surveillance, consent, transparency, and data interpretation [7]. Therefore, AI should support rather than replace human judgment in counselor evaluation.

3. Methodology and Evaluation Model

3.1 Research Design

This study adopts a model-oriented qualitative and analytical research design. Its purpose is to construct an artificial intelligence-enabled evaluation mechanism for college counselor work performance rather than to conduct a large-scale statistical test. The research combines policy analysis, public data interpretation, institutional case information, and index construction. This design is suitable for the topic because the evaluation of counselor work involves both measurable work records and educational judgment that cannot be fully quantified.

The study follows three steps. First, it identifies the main problems in traditional counselor performance evaluation, including subjective judgment, fragmented data, delayed feedback, and insufficient use of evaluation results. Second, it analyzes how artificial intelligence can support counselor evaluation through data integration, text analysis, response tracking, risk warning, and decision feedback. Third, it develops a multidimensional evaluation model that can be applied by higher education institutions according to their own student scale, counselor responsibilities, and management conditions.

This research does not treat artificial intelligence as a substitute for human evaluators. Instead, AI is regarded as a technical support tool that can improve the accuracy, timeliness, and transparency of evaluation. Final judgment should still be made through human review, institutional discussion, and educational interpretation. This design is consistent with the nature of counselor work, because counselor performance is not only reflected in task completion, but also in student guidance, emotional support, ideological education, crisis response, and professional responsibility.

3.2 Data Collection Logic

The data logic of this study is based on three types of sources. The first type is public higher education statistics, which provide the macro background for understanding the growing scale and pressure of student affairs work. The second type is policy and institutional documents, which provide the normative basis for counselor team construction and performance evaluation. The third type is institutional case information, which helps connect the proposed model with a real college management scenario.

In practical application, the evaluation data can be collected from multiple internal sources, including counselor work logs, student affairs management systems, class activity records, student interview records, employment guidance records, psychological support records, training records, and student feedback surveys. These data sources can be integrated through an AI-supported platform. Before being used for evaluation, all indicators should be cleaned, standardized, and reviewed to ensure data accuracy and ethical compliance.

Since counselor work involves sensitive student information, data collection should follow the principles of necessity, anonymization, restricted access, and secure storage. The purpose of data use should be clearly defined. Student feedback and personal records should not be used mechanically or punitively. Instead, they should be used to identify work patterns, support counselor development, and improve student service quality.

3.3 Construction of the Evaluation Model

To make counselor performance evaluation more systematic, this study proposes an Artificial Intelligence-Enabled Counselor Performance Evaluation Index, abbreviated as ACPEI. The model includes five dimensions: workload and task completion, responsiveness and student support efficiency, student satisfaction and feedback, professional development, and ethics and fairness control.

The model is expressed as follows:

$$ACPEI = \alpha W + \beta R + \gamma S + \delta D + \theta E \quad (1)$$

where ACPEI represents the overall evaluation result of counselor work performance. W refers to workload and task completion. R refers to responsiveness and student support efficiency. S refers to student satisfaction and feedback. D refers to professional development. E refers to ethics and fairness control. The weights satisfy the following condition:

$$\alpha + \beta + \gamma + \delta + \theta = 1 \quad (2)$$

In this model, workload and task completion reflect the basic responsibilities of counselors. Responsiveness and student support efficiency reflect the timeliness and effectiveness of counselor services. Student satisfaction and feedback reflect the student experience. Professional development reflects the long-term growth of counselors. Ethics and fairness control reflect privacy protection, equal treatment, and responsible use of AI.

Before calculation, each indicator should be standardized to a 0–100 scale. Positive indicators, such as training participation, student satisfaction, and task completion rate, can be scored directly after normalization. Negative indicators, such as delayed response rate, unresolved case rate, or complaint rate, should be converted through reverse scoring. In this way, all indicators can be compared within the same evaluation framework.

3.4 Human-Machine Collaborative Evaluation Procedure

The proposed evaluation mechanism follows a human-machine collaborative procedure. In the first stage, AI systems collect and organize multidimensional work data from different platforms. In the second stage, the system standardizes the data and calculates preliminary scores based on the ACPEI model. In the third stage, AI tools generate visual reports, trend analysis, abnormal data warnings, and improvement suggestions. In the fourth stage, human evaluators review the results, interpret the context, and make final judgments.

This procedure is important because counselor work contains many elements that are difficult to measure directly. For example, a counselor may spend a large amount of time handling a serious student crisis, but this work may not be reflected by the number of routine activities. Similarly, student satisfaction may decline temporarily when counselors enforce necessary discipline or intervene in risky behavior. Therefore, AI-generated scores should not be used as the only basis for evaluation.

The role of AI is to provide evidence, reduce repetitive manual statistics, and help managers identify trends and problems. The role of human evaluators is to understand educational context, examine fairness, and make responsible decisions. Through this procedure, the evaluation mechanism can avoid both pure subjective judgment and excessive technical dependence.

4. Data Sources and Model Application

4.1 Data Sources

This study uses three types of data: public statistics, policy information, and institutional case materials. First, public data show that China had more than 47.63 million higher education students in 2023, indicating the growing pressure of student affairs governance [1]. Second, policy-related information shows that counselor work covers ideological education, student management, psychological support, employment guidance, and campus stability. Therefore, evaluation should include not only workload but also service quality and ethical responsibility. Third, the case materials from Sichuan Vocational College of Culture and Communication show that the institution had 17,174 students, and the project leader served 200 students. These data support the construction of a mechanism-oriented evaluation model.

4.2 Model Application Framework

Based on the above data sources, the proposed AI-enabled evaluation model can be applied to college counselor performance evaluation through five dimensions. These dimensions are workload and task completion, responsiveness and support efficiency, student satisfaction and feedback, professional development, and ethics and fairness control. To make the structure of the model clearer, Table 1 summarizes the major dimensions, symbols, suggested weights, main indicators, and AI-supported functions.

Table 1. Structure of the AI-Enabled Counselor Performance Evaluation Index

Dimension	Symbol	Suggested Weight	Main Indicators	AI-Supported Function
Workload and task completion	W	0.25	Number of students served; class meetings; student interviews; activity organization; employment support; emergency cases	Data integration; workload classification; abnormal workload detection
Responsiveness and support efficiency	R	0.20	Response time; follow-up rate; case completion rate; early-warning intervention efficiency	Real-time monitoring; delay warning; case tracking
Student satisfaction and feedback	S	0.20	Student survey results; anonymous feedback; service experience; open-ended comments	Sentiment analysis; keyword extraction; feedback clustering
Professional development	D	0.15	Training participation; research output; work innovation; case writing; competition guidance	Growth record analysis; personalized training recommendation
Ethics and fairness control	E	0.20	Privacy protection; complaint records; equal treatment; data compliance; risk control	Bias detection; risk alert; compliance review

As shown in Table 1, the proposed evaluation mechanism does not assess counselor performance through a single administrative indicator. Instead, it divides counselor work into five connected dimensions. Workload and task completion form the foundation of performance evaluation because counselors must first complete basic responsibilities. Responsiveness and student support efficiency reflect whether counselors can respond to student needs in a timely and effective way. Student satisfaction and feedback provide evidence from the student perspective. Professional development reflects the counselor's long-term growth and capacity improvement. Ethics and fairness control ensures that AI-supported evaluation does not ignore privacy, equity, or responsible governance.

The suggested weights are designed to balance work results, service quality, developmental value, and ethical responsibility. Workload receives the highest weight of 0.25 because basic task completion remains the foundation of counselor work. Responsiveness, student feedback, and ethics control each receive a weight of 0.20, showing that the model values service efficiency, student experience, and responsible use of data. Professional development receives a weight of 0.15, reflecting its supportive role in long-term counselor growth. These weights are not fixed and may be adjusted according to institutional type and management priorities.

To further present the internal structure of the model, Figure 1 visualizes the weight distribution across the five dimensions.

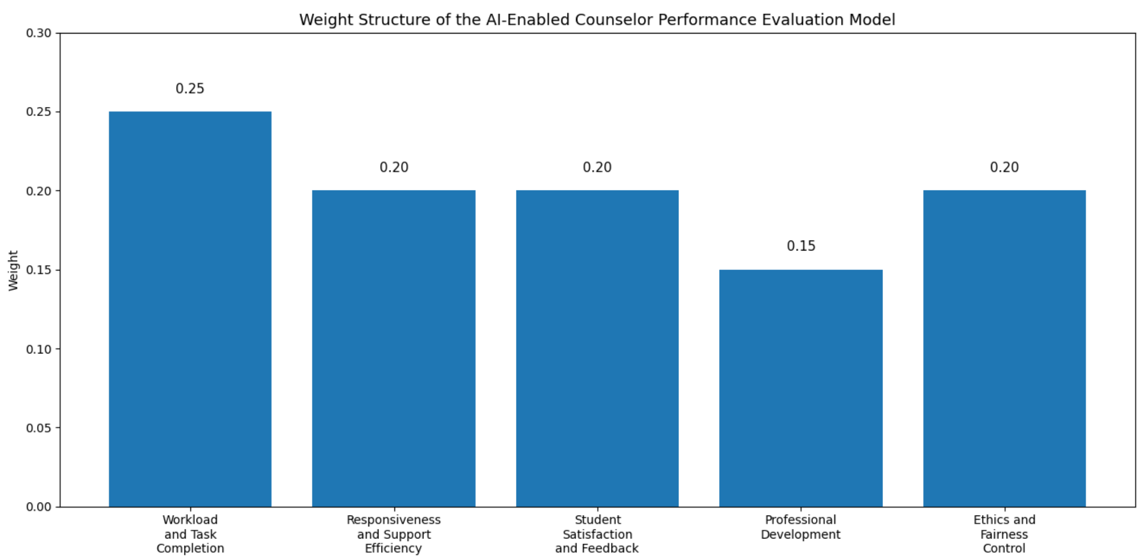

Figure 1. Weight Structure of the AI-Enabled Counselor Performance Evaluation Model

As illustrated in Figure 1, workload and task completion account for the largest proportion, with a weight of 0.25. This indicates that the completion of core responsibilities remains the basic requirement of counselor evaluation. Responsiveness and support efficiency, student satisfaction and feedback, and ethics and fairness control each account for 0.20. This means that the model emphasizes not only work quantity, but also service quality, student experience, and responsible governance.

Professional development accounts for 0.15, showing that the evaluation mechanism also pays attention to the long-term growth of counselors. Overall, the model avoids a single workload-oriented logic and forms a more balanced framework integrating performance, service quality, development, and fairness.

4.3 Application Procedure

In practice, the model can be implemented in four steps. First, colleges collect counselor work data from student affairs systems, class management platforms, counseling records, employment guidance records, activity records, and student feedback channels. Second, all indicators are standardized to a 0–100 scale. Positive indicators are scored directly after normalization, while negative indicators, such as delayed response rate or complaint rate, are converted through reverse scoring.Third, AI tools conduct data cleaning, text classification, keyword extraction, sentiment analysis, trend identification, and abnormal value detection. These functions help identify repeated student concerns, workload pressure, and delayed follow-up. Fourth, human evaluators review AI-generated results in context. Since counselor work involves crisis intervention, emotional support, and ideological guidance, final evaluation should combine AI analysis, qualitative materials, counselor reflection, and departmental review.

4.4 Interpretation of the Model Application

The proposed model helps institutions shift from static assessment to dynamic evaluation. Traditional counselor evaluation is often conducted at the end of a semester or academic year, which may delay feedback. AI-supported evaluation can track work processes more frequently and identify problems earlier, such as delayed responses or repeated student concerns.The model also improves fairness by considering workload, responsiveness, student feedback, professional development, and ethics control together. Counselors with different student numbers or work pressures can therefore be evaluated more appropriately. In addition, the model has a developmental function. It can help counselors identify strengths and weaknesses and support targeted training.However, AI-generated results should not be used as the only basis for rewards, punishments, or promotion. Data quality, privacy protection, and algorithmic bias may affect reliability. Therefore, human review remains necessary in final evaluation decisions.

5. Discussion

The proposed AI-enabled evaluation mechanism can improve counselor performance evaluation in several ways. First, it makes evaluation more evidence-based. Traditional assessment often depends on annual reports, manual summaries, and subjective impressions, which cannot fully reflect the complexity of counselor work. By combining workload, responsiveness, student feedback, professional development, and ethics control, the ACPEI model provides a more balanced evaluation structure.

Second, AI can improve timeliness. Counselor work is process-oriented, and many issues, such as psychological risk, academic difficulty, student conflict, and employment anxiety, require early response. AI-supported systems can provide dynamic feedback and help managers identify problems before they become serious.

Third, the model supports counselor development. It does not only judge past performance, but also shows strengths and weaknesses across different dimensions. For example, a counselor with good task completion but weak student feedback may need communication training, while another with strong student support but weak documentation may need digital management support.

However, the model also has limitations. Data quality may affect evaluation accuracy, especially when records are incomplete or platform data are inconsistent. Algorithmic fairness is another concern, because AI may overemphasize measurable indicators and ignore invisible educational efforts. Privacy protection is also essential, since counselor work involves sensitive student information.

Therefore, AI should be used as a decision-support tool rather than a replacement for human judgment. A reasonable mechanism should combine data analysis with educational interpretation.

6. Conclusion

This study constructs an AI-enabled evaluation mechanism for college counselor work performance. Based on public higher education statistics, policy references, and institutional case materials, the study proposes the ACPEI model, which includes workload, responsiveness, student feedback, professional development, and ethics control. The model can help higher education institutions move from subjective and delayed evaluation toward more dynamic, evidence-based, and development-oriented evaluation.

The main contribution of this study lies in treating AI not as a substitute for counselor evaluation, but as a supporting mechanism for data integration, process monitoring, and decision feedback. The evaluation of counselor work should still respect educational values, human judgment, and institutional context. Future research may further test the model using larger samples, longitudinal data, and comparative evidence from different types of universities. In practice, universities should build a human-machine collaborative evaluation system that improves efficiency while protecting fairness, privacy, and the educational mission of counselor work.

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