



# A Multidimensional and Process-Oriented Evaluation Framework for Practical Learning in Intelligent Education

Rui Zhang

School of Foreign Studies, Chengdu Neusoft University, Chengdu, 611844, China

zhangrui@nsu.edu.cn

**Abstract.** In intelligent education environments, practical learning is often evaluated through final outcomes, which limits insight into learning processes and underutilizes the multisource data generated during instruction. This issue is particularly pronounced in project-based learning, where learning quality emerges through iterative practice rather than end products alone. To address this gap, this paper proposes a multidimensional and process-oriented evaluation framework from an information science perspective.

The framework integrates four evaluation dimensions—linguistic accuracy, technological competence, communication effectiveness, and social value—across three stages of practical learning: planning, production and guidance, and dissemination. Evaluation evidence is organized into a structured information flow that combines learning platform logs, AI-assisted diagnostics, expert judgment, and dissemination metrics, supporting both formative feedback and summative assessment.

The framework is implemented in a real-world intelligent education setting and examined through a practical learning case. The results suggest improved process transparency, more timely instructional intervention, and more comprehensive representations of learners' practical competence and external impact. Owing to its system-level design, the framework is designed to be transferable to other project-based and practice-oriented learning scenarios and offers a scalable solution for evaluation design in intelligent education systems.

**Keywords:** Intelligent Education; Learning Analytics; Practical Learning; Evaluation Framework; Human–AI Collaborative assessment

## 1 Introduction

With the rapid development of intelligent education technologies, practical and project-based learning has become an important means of cultivating learners' applied competencies. Such learning emphasizes authentic tasks, interdisciplinary integration, and real-world problem solving, and is increasingly supported by digital platforms and intelligent tools. As a result, large volumes of process data are generated throughout plan-

ning, production, and dissemination stages. However, the evaluation of practical learning remains largely outcome-oriented, offering limited insight into learning processes and making insufficient use of available multisource learning data. This misalignment restricts instructional decision-making and weakens formative support during learning activities.

In many instructional contexts, practical learning is still evaluated primarily at the final stage, relying on single-source judgments such as instructor scoring or end-product assessment. While convenient, these approaches provide little visibility into how learning outcomes evolve over time, leaving iterative revisions, interaction records, and tool-assisted feedback underutilized. This limitation is particularly evident in intelligent education environments, where learning analytics is widely recognized as a data-driven means to understand learning processes, yet is not systematically integrated into evaluation practices [2].

From an information science perspective, practical learning evaluation can be viewed as a problem of evaluation information modeling and processing. Learning activities generate heterogeneous data across multiple stages and sources, including learner actions, instructional interventions, and external feedback. Without a structured framework to organize and interpret these data, evaluation outcomes may lack transparency, reliability, and instructional value. The growing use of AI-assisted tools further highlights the need to balance automated analysis with human judgment, as intelligent technologies should support—rather than replace—pedagogical decision-making [10].

Although learning analytics has accumulated a substantial methodological toolkit for tracing learner behavior and engagement, much of the existing research still gravitates toward broad behavioral indicators and dashboard-level visualizations. In practice, such representations often struggle to function as evaluative evidence for complex practical competencies—communication effectiveness or social impact in authentic tasks being typical examples. At the same time, many learning analytics applications remain temporally disjointed, privileging post-hoc or single-stage analysis and offering little in the way of structured mechanisms to align evaluation indicators with the iterative stages of planning, production, and dissemination that shape practical learning as it unfolds. Seen from this angle, the constraint of current work does not arise from any lack of analytical sophistication in learning analytics itself; rather, it reflects the absence of a coherent evaluation framework capable of systematically weaving together multidimensional indicators, stage-aware evidence, and clearly articulated human–AI assessment roles within practical learning evaluation.

To address this issue, this paper proposes a multidimensional and process-oriented evaluation framework for practical learning from an information science perspective. The framework integrates four evaluation dimensions with three sequential evaluation stages and is implemented as a layered evaluation information system supported by learning platforms, AI-assisted tools, and expert participation.

The main contributions of this paper are as follows:

1. A multidimensional evaluation model that represents practical learning outcomes as structured evaluation information attributes.

2. A process-oriented framework that supports stage-aware data collection and analysis across the learning lifecycle.

A real-world case study in an intelligent education environment demonstrating the framework's feasibility and transferability.

## **2 Related Work**

This section reviews related work from three perspectives relevant to practical learning evaluation: data-driven educational evaluation, learning analytics for practical learning, and human–AI collaborative assessment.

### **2.1 Data-Driven Evaluation in Education**

As digital learning tools and platforms have become widely used, data-driven evaluation has received growing attention. Prior studies have developed a range of evaluation frameworks and key quality indicators for learning analytics systems, highlighting evidence-based evaluation and the architectural framework for evaluation information [1]. Despite these advances, many models remain focused on cognitive performance or standardized outcomes, offering limited support for process-oriented evaluation. Recent research on open learning analytics further puts emphasis on synthesizing heterogeneous data across platforms and learning scenarios to foster evaluation transparency and completeness [6].

### **2.2 Learning Analytics for Practical and Project-Based Learning**

Learning analytics research has gradually extended from traditional classroom settings to more complex learning scenarios, including project-based and experiential learning environments. Existing studies primarily emphasize learner-facing dashboards and recommender systems, with relatively limited attention to evaluation design that captures learning processes in practical contexts [3]. Although models such as the RISE framework support data-informed improvement, they typically address specific stages or indicators rather than integrated multidimensional and process-aware evaluation structures [5].

### **2.3 Human–AI Collaborative Assessment**

The increasing integration of AI technologies in education has led to the use of AI-assisted assessment tools to generate feedback and diagnose performance, especially in content production tasks. The promise of these tools is a coin with two sides: despite their promising prospects for efficiency and scale, the concerns about trust, transparency and ethics remain. Consequently, recent research advocates human–AI collaborative assessment models in which AI functions as analytical support rather than an autonomous evaluator. Reviews of learning analytics research consistently highlight

the critical need for systematic evaluation frameworks that bridge technological support, pedagogical principles and expert judgement [4].

### 3 Framework Design

#### 3.1 Multidimensional Evaluation Model

From an evaluation methodology perspective, the proposed framework is centered in evidence-centered design, which emphasizes the architecture of interconnections among evaluation claims, supporting evidence, and data sources [8]. To confront the gap in comprehensive and process-aware evaluation in practical learning, this study develops a multidimensional evaluation model from an information science perspective. Instead of relying on single-outcome indicators, learning performance is mapped as a set of interconnected evaluation information attributes, creating a more complete and structured assessment.

The model defines four complementary evaluation dimensions: linguistic accuracy, technological competence, communication effectiveness, and social value. Linguistic accuracy captures the correctness and professional appropriateness of language use, while technological competence reflects learners' ability to integrate digital tools into content production workflows. Communication effectiveness puts emphasis on the interpretability and dissemination of learning outcomes to target audiences through media platforms. Social value serves as a measure of the external relevance and real-world influence of learning outputs beyond the educational context.

To facilitate practical application, each evaluation dimension may be translated into a set of illustrative quantitative or semi-quantitative indicators, which can be flexibly adjusted in line with disciplinary conventions and instructional objectives. For linguistic accuracy, evaluative evidence might be drawn from patterns of error density across successive drafts, AI-assisted diagnostic scores targeting grammatical control and lexical appropriateness, as well as rubric-based expert judgments that attend to domain-specific language use. Technological competence, by contrast, can be inferred from indicators such as the range and suitability of digital tools adopted, the frequency of tool-supported revisions, and expert-assigned technical quality scores that speak to workflow integration and production standards.

When considering communication effectiveness, quantitative signals often emerge most clearly at the dissemination stage. These may include measures of audience reach, engagement metrics—such as view counts or interaction frequency—and ratings of clarity or interpretability provided by external evaluators. Social value, finally, can be approached through a combination of expert endorsement scores, evidence of reuse or reference in authentic contexts, and relevance ratings that capture how learning outputs are perceived to contribute beyond the immediate instructional setting.

It is worth underscoring that these indicators are intended as configurable exemplars rather than fixed measurement instruments. Within the proposed framework, their function is not to prescribe uniform metrics, but to support the structured mapping of heterogeneous data onto evaluation dimensions, thereby strengthening transparency, comparability, and stage-aware interpretation in the evaluation of practical learning.

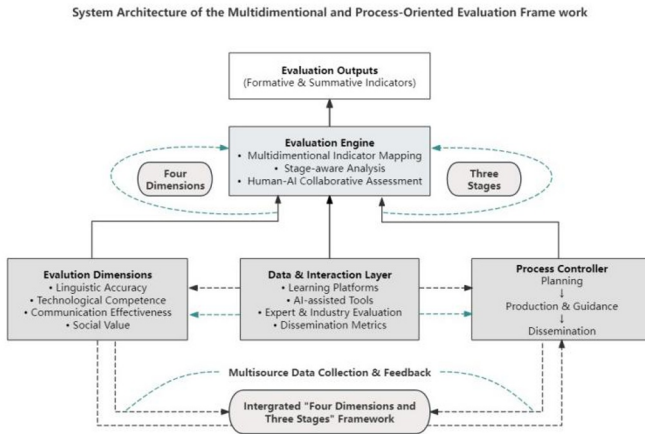
### 3.2 Process-Oriented Evaluation Stages

To improve temporal visibility of learning activities, the framework adopts a process-oriented evaluation structure. Practical learning is modeled as three sequential stages: planning, production and guidance, and dissemination, each supporting stage-aware data collection and feedback.

The planning stage is centered on task feasibility and consistency with learning objectives, enabling proactive intervention. The production and guidance stage stands for the core learning process, during which learners iteratively refine outputs under continuous multi-source feedback, generating rich process data for formative evaluation. The dissemination stage focuses on finalized outputs released to external audiences, providing summative evidence through communication reach and external response. By treating evaluation as an ongoing conversation throughout the project lifecycle, the framework goes beyond a single endpoint measure, valuing the process and progress as much as the final outcome.

### 3.3 Integrated “Four Dimensions and Three Stages” Framework

By integrating the multidimensional evaluation model with the process-oriented stages, a unified “Four Dimensions and Three Stages” framework is formed. Within this structure, each evaluation dimension is tracked across different stages, allowing for comparisons across dimensions at any given stage.



**Fig. 1.** Architecture of the Multidimensional and Process-Oriented Evaluation Framework for Practical Learning.

As illustrated in Figure 1, the integrated framework functions as a closed-loop evaluation information system in which stage-based data continuously inform instructional choices and learner adaptations. From an information system perspective, practical learn-

ing evaluation is organized as a structured flow of data acquisition, analysis, and feedback, thereby optimizing transparency, reliability, and scalability in intelligent education environments.

## 4 System Implementation and Data Sources

### 4.1 System Implementation Overview

Based on the proposed architecture, the framework is implemented as an information-driven evaluation system embedded in an intelligent education environment. Rather than operating as an isolated assessment tool, the system weaves together learning platforms, AI tools, and expert participation to sustain a dynamic flow of data collection, analysis, and feedback throughout the practical learning lifecycle.

As shown in Figure 1, the system adopts a layered design. Multisource data collected from digital platforms, intelligent tools, and external evaluators are transmitted to a centralized evaluation engine, where evaluation indicators are mapped and analyzed in a stage-aware manner. Dashed arrows indicate how evaluation dimensions are mapped onto multisource data, enabling structured interpretation of heterogeneous learning evidence across the learning lifecycle. The resulting analysis is transformed into formative and summative outputs that support instructional decision-making and learner self-regulation, while emphasizing process transparency, data traceability, and human–AI collaborative evaluation.

### 4.2 Data Sources and Collection Mechanisms

The system integrates heterogeneous data generated across different learning stages, which are organized into four categories.

Learning platform data are collected through a digital learning management system that supports task submission, version tracking, and instructor feedback. Time-stamped platform logs enable analysis of learner engagement and revision behaviors. AI-assisted evaluation data are generated primarily during the production and guidance stage through intelligent tools that provide auxiliary diagnostics, such as language accuracy checking and technical quality analysis. In line with ethical AI stewardship, AI-generated feedback is treated as supportive evaluation information rather than autonomous decision output [7].

Expert and industry evaluator data provide a validating perspective by combining qualitative judgments with quantitative scores, all of which are grounded in predefined dimensions. In addition, dissemination and impact metrics are collected after learning outputs are released to external platforms, reflecting audience engagement and expert response as evidence of communication effectiveness and social value.

### **4.3 Evaluation Engine and Analysis Logic**

The evaluation engine functions as the analytical core of the system. It performs three main tasks: mapping multisource data to the four evaluation dimensions through standardizing and interlinking the datasets; enabling stage-aware analysis by tagging data according to their originating learning stage; and supporting human–AI collaborative assessment by positioning AI-generated information as analytical support while retaining human authority over final evaluation decisions.

Through these mechanisms, raw learning data are transformed into actionable evaluation information.

### **4.4 Feedback Mechanism and Evaluation Outputs**

The system generates two types of outputs: formative feedback and summative indicators. Formative feedback is provided during the planning and production stages through platform-based comments, AI-supported suggestions, and expert guidance. Summative indicators are produced at the dissemination stage based on integrated multidimensional analysis.

These outputs are connected through a closed feedback loop so that summative results can be directly fed into the next phase of learning, supporting continuous improvement of evaluation processes.

### **4.5 Implementation Characteristics**

Overall, the system supports process-oriented evaluation across learning stages, enables data-driven assessment through multisource integration, and maintains evaluation reliability through human–AI collaboration. These characteristics make the proposed implementation applicable to a wide range of practical and project-based learning scenarios in intelligent education environments.

## **5 Case Study and Results**

### **5.1 Case Study Context**

In order to test the proposed framework's viability and validate its utility in real-world educational settings, a project-based learning activity implemented in an intelligent education environment was selected as a case study. The project involved real-world tasks spanning content planning, digital production, and public dissemination.

Participants were undergraduate students guided by instructors and external experts over a short-term intensive period. Learning activities followed the three predefined evaluation stages—planning, production and guidance, and dissemination—and were supported by digital learning platforms and AI-assisted technologies for data collection and feedback. Consistent with the framework's design, AI-assisted tools were used solely for auxiliary diagnostics and data processing. Final evaluation decisions were reserved for human experts, guaranteeing interpretability alongside solid pedagogical

foundation. The case was selected due to its complex learning processes, multisource evaluation data, and inclusion of external validation.

## 5.2 Evaluation Procedure

The evaluation procedure followed the framework and system architecture described in Sections III and IV. At the planning stage, learners submitted project proposals through the learning platform, which were reviewed by instructors and external experts considering on-the-ground constraints and contextual relevance. Data generated at this stage provided early indicators for instructional intervention.

During the production and guidance stage, learners iteratively developed project outputs. Platform logs captured submission frequency, revision history, and instructor feedback, while AI-assisted tools provided auxiliary diagnostics related to language accuracy and technical quality. External experts contributed qualitative evaluations in line with the predefined evaluation dimensions.

At the dissemination stage, finalized outputs were released to external platforms or evaluated in professional contexts. Dissemination metrics and expert reviews were collected as evidence of communication effectiveness and social value, and all evaluation data were integrated into the evaluation engine for cross-stage analysis.

## 5.3 Results and Observations

The case study results indicate that the proposed framework effectively facilitates process-oriented and multidimensional evaluation in practical learning. As an information system-level implementation, the framework is illustrative rather than domain-specific and can be adapted by reconfiguring evaluation indicators and data sources.

First, the framework improved process visibility by associating evaluation data with specific learning stages, enabling earlier identification of performance trends and learning difficulties. This stage-aware analysis reduced reliance on endpoint evaluation and supported timely instructional adjustment. Second, improvements were observed across those four evaluation dimensions. Linguistic accuracy and technological competence showed consistent enhancement during the production and guidance stage, reflected in fewer revision cycles and stonger intermediate evaluations. Communication effectiveness and social value were primarily confirmed at the dissemination stage through external feedback and expert judgement. Third, the integration of multisource evaluation data enhanced the credibility of the evaluation by mitigating bias associated with single-source assessment.

## 5.4 Results and Observations

External validation provided independent evidence of framework effectiveness. Learning outputs were reviewed by industry professionals and evaluated in open dissemination environments. Observable indicators, including expert feedback and audience interactions, served as proxies for communication effectiveness and social value, complementing internal instructional assessment.

## 5.5 Summary of Findings

Overall, the case study demonstrates the feasibility and analytical potential of the proposed evaluation framework in a realistic intelligent education setting. By facilitating continuous process monitoring, integrating diverse evaluation data, and supporting human–AI collaborative assessment, the framework achieves the improvement of both transparent evaluation and responsive instruction. These findings provide empirical support for the applicability and adaptability of the proposed system architecture in intelligent education environments.

## 6 Discussion

The case study results suggest that the proposed multidimensional and process-oriented evaluation framework effectively tackles the primary shortcomings of outcome-oriented evaluation in practical learning. From information science and intelligent education perspectives, the framework illustrates several important implications.

### 6.1 Enhancing Process Visibility Through Stage-Aware Evaluation

A key contribution of the framework is its capacity of enhancing process visibility. By explicitly associating evaluation indicators with specific learning stages, the system enables evaluators to distinguish formative evidence from summative outcomes. This stage-aware design reduces heavy reliance on final results and supports timely instructional intervention, which is particularly critical in complex project-based learning scenarios.

From an information systems perspective, modeling learning activities as stage-based evaluation processes transforms raw learning traces into analyzable process data, thereby making evaluation outcomes clearer and more trustworthy.

### 6.2 Multisource and Human–AI Collaborative Assessment

The framework further benefits from its multisource evaluation design. Platform logs, AI-assisted diagnostics, expert judgments, and dissemination metrics enrich the assessment of learning performance, mitigating bias associated with single-source assessment and strengthening evaluation robustness.

Consistent with recent research on human–AI collaboration in educational assessment [9], the proposed framework integrates AI-generated information as analytical support while reserving evaluation decisions for human evaluators. This design bridges the gap between streamlined efficiency and solid pedagogical foundation, and supports responsible use of intelligent technologies in evaluation processes.

### 6.3 Transferability and Applicability

Although the case study was conducted in a specific intelligent education setting, the framework is not domain-dependent. Its multidimensional indicators and process-oriented structure can be applied to a range of practical learning scenarios, from engineering design to media production and interdisciplinary projects. The system architecture is designed to support flexible inclusion of a range of data sources and evaluation participants, enabling scalability across data-driven and process-sensitive educational environments.

## 7 Conclusion and Future Work

This paper proposed a multidimensional and process-oriented evaluation framework for practical learning from an information science perspective and implemented it within an intelligent education environment. By orchestrating multidimensional evaluation attributes with stage-aware analysis and multisource data collection, the framework provides a new paradigm for practical learning evaluation as a transparent and evidence-based process.

A real-world case study demonstrated that the framework complements process visibility, supports timely instructional intervention, and optimizes assessment reliability through human–AI collaborative evaluation. The system architecture further blends formative and summative functions within a closed feedback loop, fostering continuous instructional refinement.

Future work will focus on three directions. First, advanced learning analytics techniques will be incorporated to support AI-assisted indicator extraction and longitudinal performance analysis. Second, adaptive feedback mechanisms will be integrated into the evaluation engine to tailor support that responds to learner characteristics. Third, the framework will be examined across multiple practical learning domains to further evaluate its ability to scale and capacity for generalization.

Overall, the proposed framework helps to create evaluations that can be reliably adapted and expanded across diverse intelligent educational contexts and contributes to the development of data-driven assessment methodologies for practical learning.

## References

1. G. Siemens and P. Long, “Penetrating the fog: Analytics in learning and education,” *Educational Review*, vol. 46, no. 5, pp. 30–40, 2011.
2. D. Gašević, S. Dawson, and G. Siemens, “Let’s not forget: Learning analytics are about learning,” *TechTrends*, vol. 59, no. 1, pp. 64–71, 2015, doi: 10.1007/s11528-014-0822-x.
3. M. Scheffel, H. Drachler, and M. Specht, “Developing an evaluation framework of quality indicators for learning analytics,” in *Proc. 5th Int. Conf. Learning Analytics and Knowledge (LAK)*, 2015, pp. 203–207, doi: 10.1145/2723576.2723629.
4. A. Muslim, M. A. Chatti, and M. Guesmi, “Open learning analytics: A systematic literature review and future perspectives,” *arXiv preprint arXiv:2303.12395*, Mar. 2023.

5. R. Bodily and K. Verbert, "Review of research on student-facing learning analytics dashboards and educational recommender systems," *IEEE Trans. Learning Technologies*, vol. 10, no. 4, pp. 405–418, Oct.–Dec. 2017, doi: 10.1109/TLT.2017.2740172.
6. R. Bodily, D. Nyland, and D. Wiley, "The RISE framework: Using learning analytics to automatically identify open educational resources for continuous improvement," *Int. Rev. Res. Open Distrib. Learn.*, vol. 18, no. 2, pp. 1–18, 2017, doi: 10.19173/irrodl.v18i2.2952.
7. M. Hernández-de-Menéndez, E. Barbera, and J. Morales-Menendez, "Learning analytics: State of the art," *Frontiers in Education*, vol. 7, art. no. 210, 2022, doi: 10.3389/feduc.2022.920622.
8. J. A. Behrens, R. J. Mislevy, M. DiCerbo, and J. Levy, "Introduction to evidence-centered design and lessons learned from its application in education," ETS Research Report RR-12-08, Educational Testing Service, Princeton, NJ, USA, 2012.
9. A. Morales Tirado, P. Mulholland, and M. Fernández, "Towards an operational responsible AI framework for learning analytics in higher education," arXiv preprint arXiv:2410.05827, Oct. 2024.
10. G. Fragiadakis, C. Diou, G. Kousiouris, and M. Nikolaidou, "Evaluating human–AI collaboration: A review and methodological framework," arXiv preprint arXiv:2407.19098, Jul. 2024.

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

