

Associated conference: Beyond Technology: Human-AI Collaboration for Learning and Teaching

Conference location: University of Porto, Porto, Portugal

Conference date: 14–16 June 2026

How to cite: Chowdhury, S., De Santis, A., & Minerva, T. 2026. An Umbrella Review on Learning Analytics Dashboards: A Focus on Teachers' Practices, *Ubiquity Proceedings*, 7(1): 25. DOI: https://doi.org/10.5334/uproc.247

Published on: 30 September 2026

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An Umbrella Review on Learning Analytics Dashboards: A Focus on Teachers' Practices

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Abstract:
Learning Analytics Dashboards (LADs) are increasingly used to support data-informed teaching and to improve student outcomes. Although research in this area has grown significantly, questions remain on how these dashboards are designed, implemented, and used in practice. This study delivers an umbrella review of 17 systematic reviews published between 2015 and 2025, bringing together existing evidence on learning analytics dashboards. The analysis looks at three main aspects: the elements included in dashboards, the technologies and tools used to develop them, and their impact on teaching practices.

Focusing on teachers' practices, the data show that dashboard research is gradually moving from a purely technical emphasis to more pedagogically informed approaches aimed at supporting teachers' decision-making and helping them better comprehend student learning processes. However, multiple challenges still remain. While dashboards are effective in raising awareness, they frequently fall short in supporting concrete actions. Teachers are often involved in initial design stages but less so in later development and evaluation, and many studies rely on short-term or self-reported measures. This may explain why most dashboards remain at the prototype stage. In addition, while artificial intelligence is often used for prediction, limited attention is given to transparency or instructional use. Issues such as privacy and bias also receive relatively little consideration.

Keywords: Learning Analytics Dashboards, Teacher-facing Tools, AI in Education, Data Visualization, Umbrella Review

1. Introduction

The increasing digitization of education has transformed learning environments into data-rich ecosystems, where large volumes of learner interaction data are continuously generated through Learning Management Systems (LMS) and other digital platforms. This shift has accelerated the development of Learning Analytics (LA), a field that seeks to enhance teaching and learning processes through the collection, analysis, and visualization of educational data (Schwendimann et al., 2017; Vieira et al., 2018). By making student activity visible, analytics offers new opportunities to better understand learning behaviours and support more informed educational decisions.

In this scenario, the role of teachers is evolving: rather than focusing solely on teaching and content delivery, teachers are now expected to interpret complex data, monitor student engagement, and design timely and targeted pedagogical interventions (Ndukwe & Daniel, 2020; Ley et al., 2023). This transition reflects a broader move toward data-informed teaching and aligns closely with the EDEN 2026 theme of "visual and conceptual frameworks for educational change". In this context, teachers are not just users of data but active decision-makers who must translate analytics into meaningful instructional actions.

Learning Analytics Dashboards (LADs) play a key role in this transformation by visualizing student performance, engagement, and learning behaviour. While they make complex data more accessible and can support decision-making, their effectiveness in improving teaching practice remains uneven (Kaliisa et al., 2023).

A significant challenge lies in the fragmented nature of existing research: numerous works have explored LADs focusing on student-focused tools, with comparatively less attention given to teacher-centric applications

(Valle et al., 2021). Furthermore, prior studies have consistently highlighted several limitations, including weak connections to learning theory, limited support for actionable decision-making, and a lack of robust evaluation in real-world teaching contexts (Matcha et al., 2020; Ramaswami et al., 2023). These issues raise important questions about whether current dashboards truly meet educators' needs.

To address these gaps, this study conducts an umbrella review of reviews published between 2015 and 2025, with the aim of synthesizing current knowledge on teacher-centric LADs. Essentially, the study is guided by three research questions:

- (RQ1-DATA) What elements should be included in the dashboards?
- (RQ2-VISUALIZATION) What tools and technologies are used to design the dashboards?
- (RQ3-PEDAGOGY) What effects do dashboards have on teaching practices?

By bringing together findings across multiple reviews, this work seeks to provide a more coherent understanding of the field and to identify directions for future research and practice.

2. Methodology

This study employs an umbrella review methodology to synthesize findings from existing systematic reviews on learning analytics dashboards (LADs). An umbrella review, also known as a "review of reviews", provides a comprehensive overview of research trends, key findings, and gaps across multiple studies (Grant & Booth, 2009). This method is particularly appropriate for fields such as Learning Analytics, where the literature is both extensive and fragmented (Schwendimann et al., 2017; Masiello et al., 2024).

2.1 Search Strategy

A structured literature search was performed in the Scopus and Web of Science journal databases to identify relevant review studies on LADs. The search strategy incorporated keywords associated with dashboards, learning analytics, and review methodologies such as systematic review, scoping review, and meta-analysis. Boolean operators refined the search to ensure comprehensive coverage of pertinent publications.

To ensure consistency and relevance, the search was restricted to the following criteria:

- Peer-reviewed journal articles
- Publications written in English
- Studies published between 2015 and 2025.

The complete search queries and the number of results retrieved from each database are provided in Table 1.

Table 1: Search queries for the Umbrella review

Database	Query	Results
Scopus	(TITLE-ABS-KEY (("learning analytics dashboard*" OR "educational dashboard*" OR "teacher dashboard*" OR "instructor dashboard*" OR "data dashboard*" OR "analytics visuali?ation" OR "learning dashboard")) AND TITLE-ABS-KEY (("learning analytics" OR "academic analytics" OR "educational data mining")) AND TITLE-ABS-KEY (("systematic review" OR "scoping review" OR "literature review" OR "meta-analysis" OR "umbrella review"))) AND (LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English"))	8
Web of Science	("learning analytics dashboard*" OR "educational dashboard*" OR "teacher dashboard*" OR "instructor dashboard*" OR "data dashboard*" OR "analytics visualization" OR "learning dashboard")) AND (("learning analytics" OR "academic analytics" OR "educational data mining")) AND (("systematic review" OR "scoping review" OR "literature review" OR "meta-analysis" OR "umbrella review")) and Review Article (Document Types) and English (Languages)	24

2.2 Inclusion and Exclusion Criteria

Studies were included if they focused on educational dashboards and were peer-reviewed. Non-educational dashboards and primary studies were excluded (9 reviews). After screening and duplicate removal (6 reviews), 17 studies were included from a total of 32 results.

2.3 Data Extraction and Analysis

Data were extracted on design elements, technologies, and teaching effects. A thematic synthesis approach was used to identify recurring patterns and research dimensions aligned with the research questions.

A three-layer conceptual model (data, visualization, pedagogy) was developed to interpret findings and position dashboards as pedagogical systems.

3. Results

3.1 Overview of Included Studies: design elements

This figure presents an overview of research focus areas and key design elements in learning analytics dashboards. The left chart shows that most studies focus on **teacher-facing dashboards**, highlighting a strong emphasis on supporting educators, while fewer studies address AI-based analytics or visual analytics interventions.

The right chart shows how often key dashboard design elements appear in the reviewed studies. The percentages indicate the share of studies identifying each element, reflecting their prominence in the literature rather than exact statistics. Elements like **real-time feedback, data visualization, and predictive indicators** appear most often, showing a strong focus on data representation and monitoring. In contrast, **teacher data literacy and privacy** are less commonly addressed.

Overall, the figure indicates that while dashboards are effective in presenting and analyzing data, there is still a need to strengthen features that support actionable insights and pedagogical use.

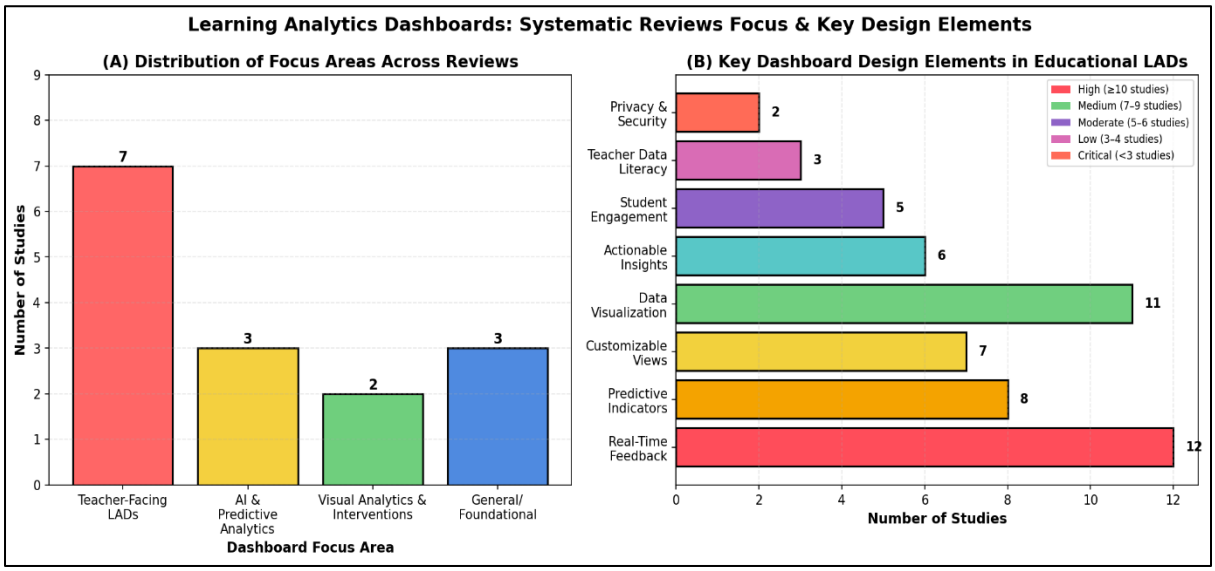


Figure 1. Distribution of focus areas and key design elements across 17 literature reviews.

Table 2 shows that LADs are strong in technical features but often lack a connection to teaching practices. Although there is some progress in including learning sciences, most studies do not use educational theory as a foundation. Because of this, many dashboards focus on standard visuals instead of offering useful insights or ways to customize, so teachers get data but little guidance on how to act on it.

The data also shows a sharp drop in teacher involvement. Teachers help define problems at the start, but are mostly left out of the final evaluation. This gap may explain why most tools do not move past the research or

pilot stage, and few are used long-term. To improve, the process should focus more on making results clear, measuring outcomes carefully, and addressing issues like data privacy.

Table 2: 10 research dimensions with findings, supporting reviews, and implications
*See the correspondences of reference numbers in Table 4.

Research Dimension	Key Finding	Main Supporting Reviews*	Implications
Dashboard Evolution	Shift from analytics-driven to pedagogy-informed approaches	[1,7,11,17]	Field maturing toward learning sciences integration
Theoretical Grounding	~3 explicitly theory-grounded; ~7 weak/no theoretical foundation	[3,11,12]	Critical gap limiting design guidance and effectiveness
Design Elements	Visual design most emphasized; customization/theory underemphasized	[1,2,4,7]	Need for theory-to-design mapping and co-design frameworks
Teacher Involvement	~14-15 in problem definition; drops to ~3-4 in evaluation	[6,7,12]	Teacher co-design must extend beyond problem definition
Actionability	~4 provide actionable insights; ~6-7 awareness-only	[5,7,9,10]	Gap between dashboards intended and actual implementation
Visualization	~13 use traditional charts; ≤1 use advanced techniques	[2,14,17]	Disciplinary divide between visualization and pedagogy experts
AI/ML Implementation	Prediction dominant; explainability underdeveloped	[8,15,16]	Risk of deployment without human understanding
Evaluation Methods	~15 use self-reports; ≤3 use rigorous outcome assessment	[4,7,13,16]	Limited evidence of sustained behavior change
Deployment Status	~9 prototypes; ~5 pilots; 0-1 sustained deployment	[7,16]	Research-to-practice pipeline underdeveloped
Ethical Considerations	~1 explicitly address privacy	[5,7,16]	Significant risks regarding privacy and equity

3.2 Tools and Technologies

Learning analytics systems follow a multi-layer architecture that integrates data sources, processing tools, visualisation platforms, and AI techniques. Replying to RQ2, we listed the main tools used to develop LADs in **Table 3**.

Table 3: Architecture of Learning Analytics Systems and Supporting Technologies

Architecture Layer	Key Technologies & Platforms	Primary Function & Role
Learning Analytics Platforms	Moodle, Blackboard, Canvas, OpenLAP	Data collection source and native dashboard integration
Data Processing Tools	Python, R, KNIME	Backend analytics, ETL (Extract, Transform, Load), and predictive modeling
Visualization Tools	Tableau, Power BI, Grafana, D3.js	Transforming processed data into interactive, teacher-facing representations

Data Infrastructure	xAPI, LRS (Learning Record Store), APIs	Ensuring data interoperability and seamless integration between systems
AI Technologies	Machine Learning (Decision Trees, Ensemble Methods)	Advanced predictive analytics (e.g., identifying students at risk)

Despite these advances, most systems remain at the prototype stage with limited integration into teaching practice.

Artificial intelligence is increasingly used for predictive purposes, particularly to identify at-risk students and forecast performance trends; however, explainability remains limited. Frequently, the underlying models operate as "black boxes", which complicates teachers' understanding of how predictions are generated and how they should be interpreted in educational practice. This lack of transparency can diminish trust and constrain the practical utility of AI-driven insights within teaching contexts. Additionally, implementation challenges, including limited integration with existing LMS platforms, scalability concerns, and inadequate teacher training, continue to impede widespread adoption. These patterns and broader research trends are depicted in **Figure 2** that summarizes AI techniques, applications, visualization methods, and key research gaps in LADs.

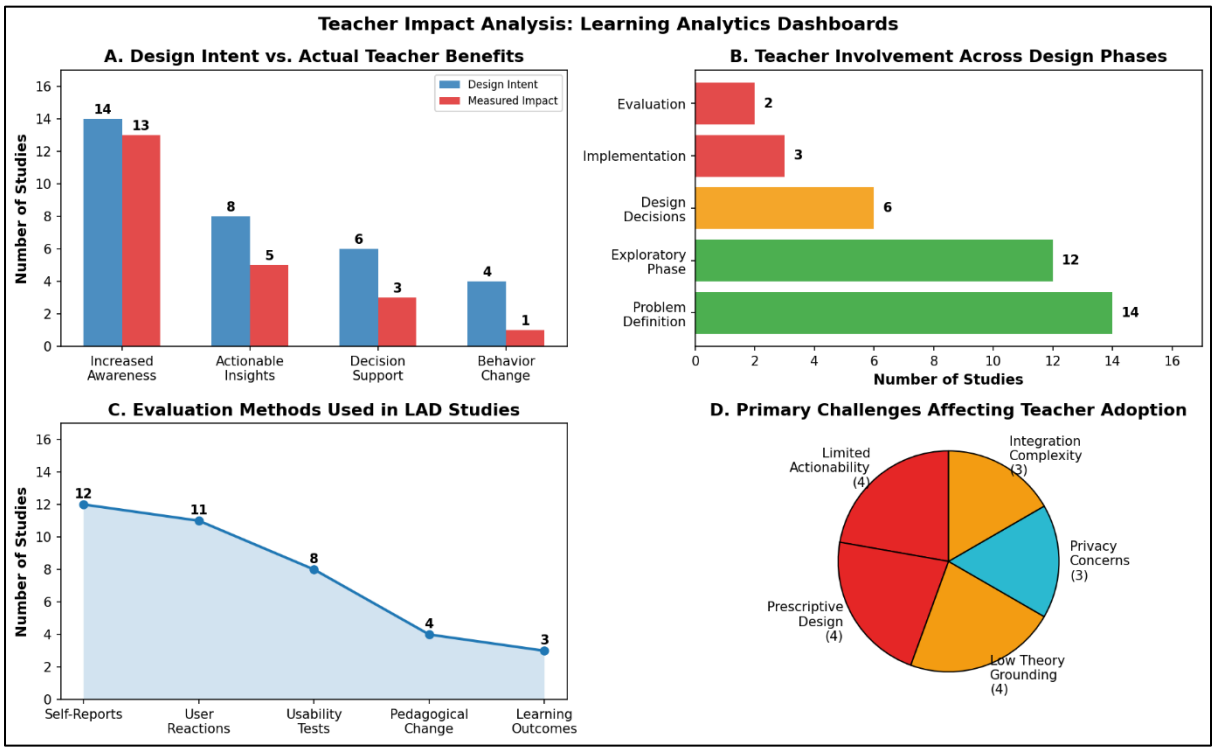


Figure 2. Teacher-centric implementation analysis of learning analytics dashboards, highlighting impact, teacher involvement, evaluation methods, and adoption challenges.

3.3 Effects on teaching

Figure 3 shows how learning analytics dashboards (LADs) impact teachers and how they are implemented. Dashboards are mainly designed to increase awareness (14 studies) and achieve similar results (13 studies), but their effectiveness is much lower for actionable insights (5 studies), decision support (3 studies), and behaviour change (1 study). Teacher involvement is highest in early stages such as problem definition (14 studies) and exploration (12 studies), but drops during implementation (3 studies) and evaluation (2 studies). Most studies rely on self-reports (12 studies), while fewer assess real pedagogical change (4 studies) or learning outcomes (3 studies). Key challenges include limited actionability (4 studies), prescriptive design (4 studies), and weak theoretical grounding (4 studies).

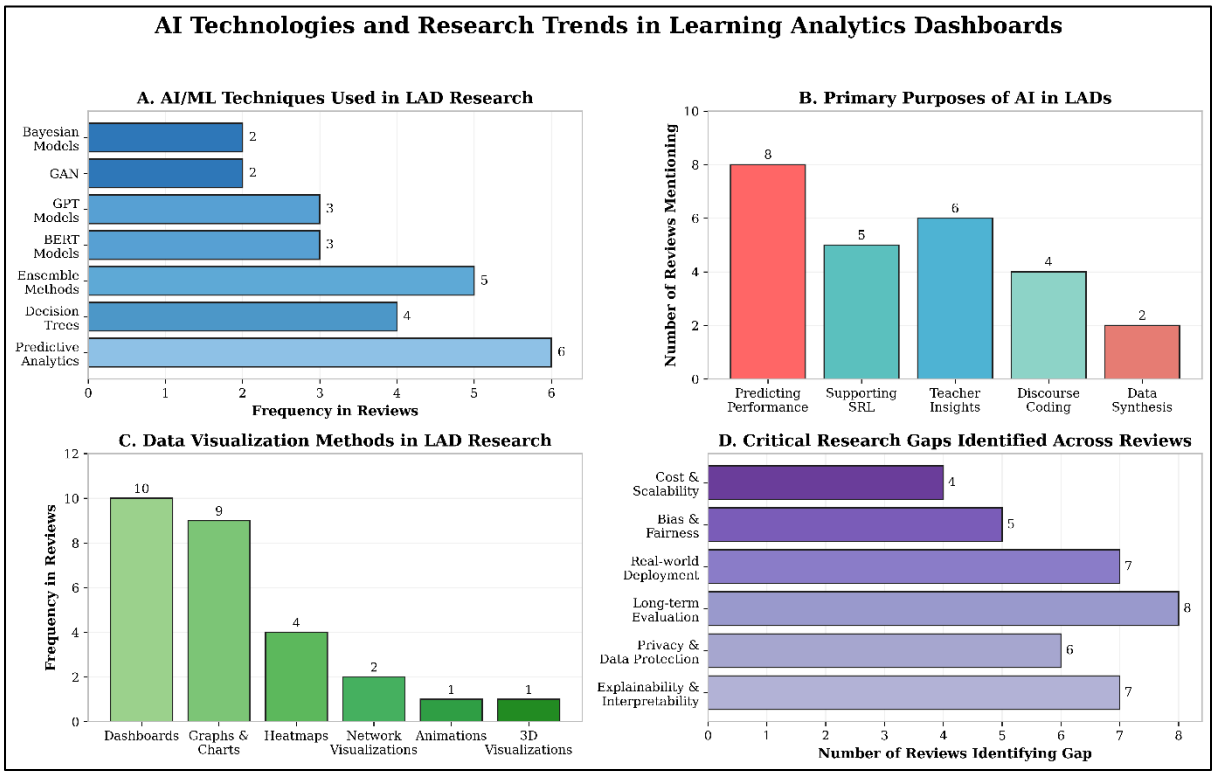


Figure 3. Teacher-centric implementation analysis of learning analytics dashboards, showing impact, teacher involvement, evaluation practices, and adoption challenges.

3.4 Review Inventory

A detailed overview of the included studies, including focus areas and key findings, is provided in Table 4.

Table 4: 17 literature reviews inventory with focus areas and key findings

No.	Review	Year	Studies Reviewed	Primary Focus	Target Stakeholder	Key Finding
1	Schwendimann et al.	2017	55	Learning Dashboard Design	Multi-stakeholder	Most exploratory; limited real-world deployment
2	Vieira et al.	2018	40	Visual Learning Analytics	Students/ Teachers	Basic visualizations dominant; theory underengaged
3	Matcha et al.	2020	32	Self-Regulated Learning	Students	LAD rarely ground in learning theory
4	Valle et al.	2021	28	Learner-Facing LAD	Students	Misalignment: cognitive outcomes vs affective evaluation
5	Gauthier et al.	2022	2	Teacher Bias & Equity	Teachers	Minimal evidence of bias mitigation in practice
6	Ndukwe & Daniel	2020	30	Teaching Analytics	Teachers	Teacher data literacy critical but underdeveloped
7	Kaliisa et al.	2023	50	Teacher-Facing LAD	Teachers	Limited actionable insights; teacher involvement drops post-design

8	Ramaswami et al.	2023	15	Predictive Analytics	Teachers/ Students	Prediction-action gap; weak intervention linkage
9	Alam et al.	2023	1	Gamified Dashboard Impact	Students	Gamified design yields ~13% grade improvement
10	Masiello et al.	2024	12	LAD Overview	Multi-stakeholder	Growing integration of learning science with analytics
11	Paulsen & Lindsay	2024	25	Pedagogy-Informed LAD	Students	Emerging trajectory toward pedagogy-informed designs
12	Ley et al.	2023	42	Model-Based Analytics	Teachers	Theory-driven insights improve teacher decision support
13	Tretow-Fish & Khalid	2023	32	Adaptive Platform LAD	Multi-stakeholder	Surface-level pedagogy evaluation predominates
14	Mohseni et al.	2024	18	Visual LA Interventions	Teachers/ Students	Moderate-to-clear learning gains with VLA
15	Misiejuk et al.	2025	41	GenAI in Learning Analytics	Developers/ Teachers	GenAI mostly for discourse coding; validation often lacking
16	Cabral et al.	2025	21	AI-Powered LAD	Teachers/ Students	Small-scale evaluations; limited classroom deployment; AI focus on prediction
17	Yuan et al.	2026	604	LA Research Visualization	Researchers	LA research concentrating in prediction, AI, precision education

4. Discussion and Conclusion

This umbrella review synthesizes findings from existing literature reviews to address the three research questions guiding this study, offering a comprehensive perspective on teacher-centric learning analytics dashboards.

For **RQ1 (dashboard elements)**, the findings identify six core components consistently present in the literature: performance indicators, engagement data, predictive indicators, comparative views, actionable insights, and visualization features. While these elements provide a foundation for dashboard design, their implementation is often fragmented. Actionable insights and advanced visualization remain underdeveloped, limiting dashboards' ability to support meaningful pedagogical decisions.

For **RQ2 (tools and technologies)**, results show that dashboards use a multi-layer architecture that integrates learning platforms, data processing tools, visualization systems, and artificial intelligence (AI) techniques. Although these technologies enable advanced data analysis and visualization, most deployments remain at the prototype stage. Key challenges include limited integration with educational systems, inadequate scalability, and insufficient teacher training, which hinder broader adoption. The increasing use of AI focuses mainly on prediction, with limited attention to explainability and instructional relevance.

For **RQ3 (effects on teaching practices)**, the review finds that dashboards can increase teachers' awareness of student learning patterns and encourage more proactive monitoring. However, their impact on teaching practices remains limited. This highlights the ongoing awareness; action gap, where dashboards inform teachers but do not sufficiently support instructional decisions. Most studies rely on short-term or self-reported evaluations, providing limited evidence of sustained changes in teaching practices or student outcomes.

Overall, these findings suggest that while LADs have significant potential, their current design and implementation do not fully support data-informed teaching. Future research should focus on integrating key

dashboard elements into cohesive, teacher-centered designs that combine data, visualization, and actionable guidance. This approach should be grounded in learning theory, involve teachers throughout the design process, improve the interpretability of AI-driven insights, and include real-world, longitudinal evaluations.

In line with the EDEN 2026 theme of educational change, dashboards should be viewed not only as technical tools but as systems that shape how teachers engage with data in daily practice. Enhancing their pedagogical relevance is essential to realizing their potential to support reflective and adaptive teaching.

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