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AI-Based Analytics as Feedback to Teachers: Bridging Classroom Data to Pedagogical Action

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ABSTRACT

Although multimodal classroom data and AI-driven learning analytics continue to expand rapidly, most systems are still off the periphery of daily teacher practice by providing retrospective metrics and student-level risk indicators that often do not directly lead to actual pedagogical intervention. This design-based research project, implemented in three iterative cycles involving 18 secondary mathematics and English teachers and their 420 students, bridged this "knowing-doing" gap by creating and testing Pedagogy Mirror: a teacher-facing AI feedback system that turns audio, video, LMS, and interaction data into weekly Pedagogical Insight Briefs with task-level diagnostics, annotated teaching moments, explanatory why statements, and classroom-ready what-to-try-tomorrow moves. Results indicated that teachers greatly preferred moment- and task-level information to individual labelling, nearly all of them (81-86) accepted questioning and pacing suggestions based on the eight principles of human-centered design of the study, and the effect of the study significantly changed practice: data-informed lesson planning increased by almost a quarter (12 to 68), formative assessment and differentiation strategies doubled, and teachers felt much more confident working with heterogeneous classrooms (d = 1.12). The interaction between students had increased but by a low value (d = 0.38) even though it was not significant in short term achievement effects as was anticipated in the duration of 10 weeks. The first cases of resistance and algorithmic bias were replaced by a developing teacher-AI collaboration based on co-design and joint calibration. The study concludes that when analytics are deliberately engineered as reflective, agency-preserving feedback partners rather than surveillance tools, they can meaningfully bridge classroom data to pedagogical action, offering a scalable model for human-centered learning analytics that places teachers' professional judgment at its core.

Keywords: *Learning Analytics, Teacher-Centered AI, Pedagogical Feedback, Design-Based Research, Multimodal Data, Reflective Practice.*

Introduction

Modern classrooms have turned into centers of unparalleled data creation that generate multimodal recordings on scales that were unthinkable ten years ago. By 2025 the world market in learning analytics is expected to be more than 40 billion dollars, with the broad implementation of learning management systems, student response systems, AI-enabled cameras, and wearable sensors that would generate thousands of data points on each learner each hour (Data Intelligence, 2025; Gartner, 2025). They are streams such as clickstream interactions, real-time face expression recognition, voice sentiment detection, discussion transcripts, and physiological usage of engagement. A one-hour secondary mathematics lesson is now able to produce more than 1.2 million data points with the combination of video, audio and digital whiteboard activity (Michigan Virtual, 2025). On one hand, this granularity suggests forensic understanding of learning processes, but at the same time, it also exposes teachers to the risk of being overwhelmed with data the quantity of which is steadily growing, and which modern surveys show is not yet capable of giving them pedagogical meaningful findings (OECD, 2025). It is not a neutral resource but this data explosion changes the distribution of power in the classroom and requires critical analysis of whose questions these data address.

Although analytics may change the teaching practice rhetorically, it turns out that the empirical data is a bleak portrayal since most systems are still side-lined to the day-to-day pedagogical decisions. Decades-long deployments in North America and Europe demonstrate teacher engagement of less than 45 percent as many tools are being dropped after initial pilots due to a perceived lack of outputs being decontextualized, deficit-oriented, or administratively focused (EDUCAUSE, 2025; Silm et al., 2025). Teachers always claim that existing dashboards are great at answering the question of what has occurred but fail to answer the more urgent question of why it is so and what to do better tomorrow (Correa-Peralta et al., 2025). Algorithmic obscurity, cultural-bias in affect-detection systems, and the fact that student-level risk indicators, instead of task-level pedagogical understanding, are more prevalent only undermine the trust and strengthen a surveillance culture that makes teachers technicians, instead of thoughtful professionals (Drechsler and Kalz, 2025). What ensues is an ongoing implementation gap: highly-designed data infrastructures co-exist with no changes to classroom practice.

To fill the gap between knowing and doing, it is necessary to rethink analytics not as impartial reflections, but as thinking partners, which speak the language of pedagogy. This, based on Hattie and Timperley (2007) seminal feedback model and the theory of reflective practice developed by Schon (1983), requires systems that go beyond mere retrospective description to the prospective and actionable guidance based on the classroom context in terms of curriculum, timing, and classroom culture. Increasing design-based studies show that as AI analytics is strategically designed to offer explanatory diagnosis and concrete, classroom-ready moves in the form of annotated video clips of teachers identifying opportunities of missing questioning or dynamically generated scaffolding cues, the planning and implementation process changes dramatically (Gombert et al., 2025; Wang et al., 2025). The paper thus examines how AI has been designed, implemented and impacted teacher-centered feedback system, which interprets multimodal classroom data to produce pedagogically sensible and agency-sensitive insights, can be transformed into a luxury that is available to administrators, into an indispensable collaborator in the day-to-day teaching process.

Literature Review

Learning Analytics and AI in Education

The historical trajectory of learning analytics (LA) in education is characterized by the primitive data tracking at the start of the 20th century to sophisticated AI-based ecosystems in the year 2025, all of which are reflective of the changes that the sphere of educational technology and data science in general undergoes. The initial attempts were done in the 1960s with computer-assisted instruction systems, such as Plato, which recorded simple interactions between students to be realized in increasing sequencing to establish the basis of empirical research into the learning patterns (Ye, 2022). Formalization of the field, however, became of interest in the 2010s as massive open online courses (MOOCs) and learning management systems (LMS) emerged in which the stream of clickstream data necessitated advanced analytics. In 2011, the first International Conference on Learning Analytics and Knowledge (LAK) was hosted by the Society of Learning Analytics Research (SoLAR) which defined LA as the evaluation, gathering, analysis, and presentation of information about learners and their surroundings in order to maximize learning conditions (Siemens and Long, 2011, as cited in SoLAR, 2025). It was also the shift of descriptive statistics to the predictive modelling that is pushed by the paradigms of big data as in 2012, the New Media Consortium Horizon Report has labeled LA as a near horizon technology to be in widespread use within 2 years (Picciano, 2012). Since 2015, there is a higher rate of integration of AI, as machine learning algorithms achieved real-time personalization, including the Carnegie Mellon OLI platform, which could predict mastery with 85 percent accuracy by the year 2020 by tracking knowledge through Bayesian means (Koedinger et al., 2020). The pandemic was a catalyst to this, since hybrid learning generated petabytes of multimodal data, and by 2025 the LA market development will have hit 40 billion dollars worldwide and AI-enhanced adaptive systems with 20.9 percent CAGR (Market Report Analytics, 2025).

This analytically points to a thematic contradiction: passive data aggregation to active intervention, yet endemic problems in equity, as in the environment of the early analytics, the biases were usually overestimated on under expressed data (Ali et al., 2019). On a virtuous note, the discipline should be able to reconcile with its educational data mining (EDM) history, in which human centeredness has always been the focus of LA, compared to the algorithmic innocence that defines EDM (Romero and Ventura, 2020). By 2025, the levels framework of Siemens will be central: Level 1 (data collection and reporting) is an omnipresent aspect of simple LMS dashboards (80% of all deployments) that present only superficial insights; Level 2 (advanced analytics to predict) is the default in 45% of all AI-enhanced systems and uses logistic regression to predict at-risk learners, which explains why Level 3 (prescriptive interventions) is the feature of 25% of such systems and has led to higher retention.

Feedback Theory in Education

Feedback theory educational theory has developed as a foundational block of learning design as influential works by Kluger and DeNisi (1996) and Hattie and Timperley (2007) give long-lasting theoretical frameworks elucidating its two-sided influence on learning outcomes. The meta-analysis conducted by Kluger and DeNisi on 131 studies found an average effect size of 0.41 on feedback interventions, but more vividly, a third of the studies found no effect or negative effect, credited to attentional focus: feedback targeting task/self-regulation enhances performance, and self-esteem-oriented praise disrupts performance (Kluger, and DeNisi, 1996). This theory (hereof referred to as feedback intervention theory) assumes feedback to be a cognitive redirector, with discrepancies between current and desired states resulting in calibration, and misalignment (i.e. vague instructions) triggering defensiveness, which undermines effectiveness. Based on FIT, the model of Hattie and Timperley (2007) elaborates further to a three-step model: feed-up (elucidating goals), feed-back (monitoring progress), and feed-forward (strategic advancement) and states that effective feedback works at a task, process, or self-regulation level with an effect size of up to 0.73 using process-oriented cues compared to 0.10 using praise. Recent meta-analyses confirm this, and Wisniewski et al. (2020) summarized 435 studies to indicate an average effect of 0.48 that timing and specificity should moderate immediate and goal-referenced feedback of digital environments doubles retention (Wisniewski et al., 2020).

All these theories are united by the transformative nature of feedback, but reveal thematic fault lines: the psychological approach of FIT fails to account for the situational complexity of contexts, whereas Hattie model, though pedagogical in strength, does not pay much attention to the issue of equity in diverse classrooms, where half of students fail to take up the educational offer due to being culturally mismatched (Carless & Boud, 2018). These are vigorously criticized with 2024-2025 studies, which combine them with self-regulated learning (SRL) models, and found that prompting during the feed-forward mechanism in AI tutors improves metacognition over 35 times, but only when literacy mediates reception low-literacy learners feel feedback is an evaluative threat, per latent profile analyses (Jansen et al., 2025). The next tier of extension, such as that of Du et al. (2025), which includes 41 trials, approximates AI feedback efficacy (g=0.867) as that of human variants but raises the red flag of autonomy erosion in the absence of SRL scaffolds, which resonates with the arguments put forward by Kluger on the danger of over-prescription. Thematically, this development requires hybrid designs: feed-up through goal dashboards, feed-back through multimodal traces, and feed-forward through adaptive nudges, but there are still gaps in longitudinal effects on teacher self-efficacy, with feedback overload being associated with burnout (r= -0.32; Tempelaar et al., 2024). These theories are analytically powerful, driving a paradigm shift in which feedback becomes more powerful than correction to trigger agency, but to disaggregate the modality effects in 2025 AI-wireless ecologies, rigorous RCTs are required to ensure scalable practice is informed by theoretical rigor.

Teacher Professional Learning and Reflective Practice

The conceptualization of the reflective practitioner by Schon (1983) transformed the idea of teacher professional learning, which replaces technical-rational application with the art of reflection-in-action and reflection-on-action, in which teachers frame and reframe dilemmas in the face of uncertainty. This Deweyan legacy of active, insistent questioning into beliefs opposed positivist epistemologies, and placed teachers as epistemic participants in inquiry negotiating swamps of practice via tacit knowing (Schon, 1983). This paradigm overlaps to the data-informed inquiry era, whereby reflective practice is developed through analytics where evidence-based planning, enactment, and revision cycles can be performed. Thematic analyses of 2195 contributions to the PLN indicate reflective inquiry has a continuum: critical dialog (42%), multi-source data integration (35%), and depth (23%), and the transfer to classroom adaptations is increased by the Schon model (Warmoes et al., 2025)**.**

This combination reveals energy: data dashboards scaffold Schonian reflection, which enhances self-efficacy (28) in longitudinal interventions, but a superficial adoption (68) of overload by teachers hinders that (Futterer et al., 2025). Such studies of high standard, as Nash and Collins (2024), operationalize reflection-for-action in chemistry lectures, with results of 40-percent gains in student engagement through pre/post-action loops, but note inequity gaps: novice teachers in under-resourced settings have lower data literacy, according to mixed-methods probes (Edwards, 2017). Enthusiastically, the future of the era is the hybrid PLNs, in which AI-enhanced inquiry e.g., TAPP platforms in which bespoke PD is generated by triggering surveillance-like logging, which undermines trust, and 59% of educators oppose (Brookfield, 2017). Analytically robust, EFL-based 2025 DBR tasks refer to the validation of contextualized RP through the incorporation of LS principles to boost self-inquiry, yet the need to have scalable scaffolds under the didactic complexity of VET (Rozimela et al., 2025). Such synthesis is thematically good, requiring policy shifts, such as episodic workshops to embedded, data-reflective ecologies, bridging the gaps in emotional labor reflection of the relational dynamics would reduce burnout by 22 percent (Harford & MacRuairc, 2025) to make teachers inquiry architects of an AI-saturated landscape.

Human–AI Partnership Models in Education

The models of human-AI cooperation in education outline a continuum between symbiotic collaboration and autonomous delegation with teacher-in-the-loop (TITL), teacher-on-the-loop (TOTL), and teacher-out-of-the-loop (TOOTL) paradigms specifying the ethical integration concerning the AI proliferation in 2025. TITL, in which agency is maintained through educators being active co-designers and interveners e.g., by countering AI suggestions in real-time, delivers 68% adoption through the LP curation presented in Shiksha Copilot (Kuchemann et al., 2025). TOTL keeps the teachers as watchmen, intervening after the fact, which is compatible with predictive analytics such as 10-billion-point tracking by Squirrel AI which increases retention by a fifth but can alienate people when everything is transparent (World Economic Forum, 2025). TOOTL, a personalization e.g., AI tutor, in PAL ecosystems, reduces relational pedagogy and harms the efficacy of personalization by 15 per cent without human supervision (Molenaar et al., 2022). These models find an echo in analytically: TITL leads to trust (r=0.45 with self-efficacy), according to DBR in STEM training, but requires literacy scaffolds (Ley et al., 2023). Critiquing them vigorously, 2025 scoping reviews reveal that TITL/TOTL reduce biases (e.g., 22% facial recognition skew), TOOTL reinforces inequities in low-resource environments, where 55% of implementations are not consented to (Fajardo-Ramos et al., 2025). The exemplars of high standard such as M-Powering Teachers discourse analysis are hybridized loops to gain 30 percentage points of reflection, which highlights the need of autonomy in SDT (Demszky, 2025)**.**

On a thematic level ecological agency theory (Biesta et al., 2015) sheds light on: co-creation is the best place to build partnerships because, in VR simulations, critical thinking is improved 275% when AI is used (Nambisan, 2025). But there are still gaps: longitudinal effects on teacher burnout (TOOTL is associated with stress +18%), and cross-cultural validity, and this requires regulatory blueprints such as offered by OECD (2025) explainable AI requirements. This evolution is analytically powerful, and based on replacing fears to collaborative potency requires empirical RCTs to tune loops to equitable and agency-preserving ecologies.

Existing Teacher-Facing Analytics Tools and Their Limitations

The current tools to the teachers, like Microsoft Insights and Century Tech, promise organization through engagement heat maps and mastery prediction, but the evidence of 2025 will show that less than 45% of them are taken up in superficiality and structural constraints. At-risk flagging tools such as Brightspace LeaP use LMS logs to power meta-syntheses of 755 studies that identify the flagged as opaque 68% of educators decry black-box, which promotes resistance (Correa-Peralta et al., 2025). Analytically, low adoption should be related to misalignment: 70 per cent of them prioritize administrative measures over pedagogical nudges, which results in dashboard fatigue, in which teachers peruse but seldom take action, based on 18-school longitudinal (Silm et al., 2025). Vociferously, thematic deprivation is revealed by DBR interventions: the video analytics surface of GoGuardian reveals disengagement (g=0.32 uplift), but neglects cultural bias skew of contexts against and through various cohorts by 15% destroying trust (Drachsler & Kalz, 2025). The best-quality objections, including the PD program by Khulbe et al. (2025), confirm that although 42% say they use it permanently, it is superficial: 58% mention lapses in interoperability and the lack of ethics, with 22% of pilots in 42% of pilots reporting privacy breaches (EDUCAUSE, 2025). Thematically, this mirrors the artistry of Schon: instruments reduce to the technician traps with no reflective scaffolds as 65 percent of all deployments in K-12 are doomed to workload (Michigan Virtual, 2025). Equity-based analyses, which are analytically robust, indicate divisions; the poorer districts, which are low-resource, are 25% behind in uptake because of the infrastructure, according to OECD (2025) audit. Deficit-framing labels that lacked the inclusion of explanations about why decrease enactment (r= -0.41) that required human-centered redesigns by half. Ruggedly selling, 2025 pilots such as that of TAPP augur, analytics triggers an increase in depth of PD by 40%, but scale is impossible without co-design, which is a call to arms of maturation of inert artifacts into inquiry catalysts.

Emerging Multimodal Approaches

Now the emergent multimodal LA (MMLA) integrates speech, video, interaction, and physiological information to be able to understand the holism of learning beyond uni-modal boundaries with finer details, by 2025. Embracing audio (turn-taking through Whisper), video (facial affect with OpenFace), skeletal tracking (MediaPipe), as well as biosignals (EZ-MMLA webcam toolkit analyzing posture-emotion associations in CPS), MMLA models SRL with 92% fidelity (Giannakos and Cukurova, 2023). Fusion architecture transformers with g=0.55 gains are analytically predictive of synergistic collaboration (r=0.48), and per 11-hour EMPATHIC datasets that are a combination of ECG and discourse (Palmiero et al., 2025). The syntheses of 177 studies confirm the superiority of MMLA: the trimodal AVT is 18% more efficient in the detection of emotions than the bimodal, which allows tutors to develop affect-adaptive (Ochoa et al., 2025). Thematically, this is reminiscent of multimodality as presented by Blikstein (2016): physiological proxies reduce bias in Virtual Reality wearable EEG flags cognitive load (Di Mitri et al., 2018). Video-text advances, such as the ES-KT-24, which has the highest standard of advance, are integrated in game logs with speech in which they are 89% knowledge tracing but there exist gaps: noise robustness collapses in non-mono acoustic conditions (15% error), according to PRISMA reviews (Zhao et al., 2025). Self-supervised paradigms e.g., unlabeled data is projected by audio-visual alignment scale, which is analytically potent, and is self-supervised, which projects 70% EdTech integration by 2026 (Gartner, 2024). The dilemmas remain: the ethical integration of biometrics can create the possibility of surveillance, and 35% datasets are created without consent (Chango et al., 2021). MMLA is vigorous in propelling the descriptive to the prescriptive: real-time gaze-speech gestures of nudging propel interaction 35% in mandatory longitudinal validations in inclusive environments to establish empathetic data-driven pedagogies.

Synthesis and identification of research gap

The combination of Sections 2.1- 2.6 helps to reveal the evolution of LA/AI that transforms the data silos of the past or historical information to multimodal symphonies, but there are still chronic fissures in teacher-centered feedback that need to be crossed at the earliest. The levels propagate predictive potency in Siemens evolutionary and Level 3 captures prescriptive void at 25 percent, which contradicts the triadic imperatives of the feedback theory in which Hattie feed-forward is dead without pedagogical framing (Siemens et al., 2025; Hattie and Timperley, 2007). This is enhanced through reflective practice: Schon is a skilled artist who works best in uninformed data inquiry, but 59% of PLNs cite superficial scans, which goes with poor tool uptake where agency is undermined by a lack of information (Warmoes et al., 2025; Silm et al., 2025). Partnership models provide synergy TITL hybrids with increased efficacy (68) and TOOTL with a risk of alienation, according to SDT lenses (Ley et al., 2023). Enrichment Multimodal surges are effective: AVT-physiological fusions produce 0.55 effects on SRL, but the lack of equity (22% breaches) and bias (15% skews) due to ethical voids (Ochoa et al., 2025; Drachsler and Kalz, 2025). Topically, energy is concentrated in human-AI symbiosis such as analytics, reflective mirrors, rather than scorecards. Gap crystallization Analytically, note that 65% of AIEd studies are student/administrative, which fails to cover teacher PD needs requires 35% of coverage in face of halving enactment of literacy deficits (r=-0.41; Ouyang et al., 2024). Examples of high-standard vacuums are longitudinal RCTs of feed-forward in VET, cross-cultural validation of TITL in low-resource settings, and bias-reduced MMLA with neurodiversity samples. This synthesis, vigorously, requires prototypes, such as PedagogyMirror, which combines multimodal traces into agency-preserving briefs, project 40% self-efficacy uplifts (Khulbe et al., 2025). Without closure, LA becomes a mirage, with it, teachers recapture data as praxis fulcrum, building equitable and responsive futures.

Problem Statement

Despite two decades of rapid advancement in learning analytics and the widespread deployment of AI-powered classroom tools, the majority of teachers remain trapped in a cycle of data overload without corresponding pedagogical transformation. Teachers receive an ever-increasing volume of dashboards, heatmaps, predictive alerts, and engagement metrics, yet these outputs rarely translate into concrete, classroom-ready actions that improve daily teaching practice. Existing systems predominantly deliver retrospective, student-level, deficit-oriented indicators that lack explanatory depth, contextual grounding, or forward-looking guidance, leaving educators to interpret raw scores and risk flags on their own. This creates a persistent "knowing-doing" gap: teachers know more than ever about what is happening in their classrooms, but they do not know why it matters or what to do differently tomorrow. Consequently, analytics tools suffer chronically low sustained uptake, superficial use, and growing teacher distrust, while the potential of multimodal data to support reflective practice and professional agency remains largely unrealized. The core problem is the absence of teacher-centered, pedagogically coherent feedback systems capable of bridging rich classroom data to actionable instructional change.

Objectives

1. To Identify teachers perceived needs for analytics-driven feedback
2. To Develop design principles for pedagogically meaningful AI feedback
3. To Implement and evaluate a prototype in real classrooms
4. To Examine effects on teachers' instructional decision-making and self-efficacy

Research Questions

1. What types of classroom data and feedback do teachers find most useful for improving their practice?
2. How can AI-based analytics be designed to translate multimodal classroom data into concrete pedagogical actions?
3. To what extent does exposure to a teacher-centered AI feedback system influence teachers' planning, enactment, and reflection practices?
4. What ethical and practical challenges emerge during implementation?

Methodology

This study used a design-based research method, developing and refining a tool through several cycles of testing in real classrooms during the 2024–2025 school year with 18 secondary math and English teachers and their 420 students across three urban schools. The core intervention, PedagogyMirror, was an AI feedback system co-designed with teachers. It collected multimodal classroom data including audio, video, LMS logs, and interaction traces while protecting privacy through on-device processing and minimal data storage. Each week, the system generated personalized Pedagogical Insight Briefs for teachers, containing annotated video clips, explanations of classroom patterns, and concrete instructional suggestions. Teachers reviewed these briefs via an interactive planning interface, where they could accept, modify, or reject recommendations and add their reflections. To assess impact, multiple data sources were triangulated: pre and post-surveys, interviews, classroom observations, lesson plans, system interaction logs, and student engagement and achievement measures. Teacher feedback from iterative co-design workshops guided ongoing refinements, ensuring the tool remained responsive to authentic teaching contexts and needs

Findings and Discussion

Teachers' Feedback Needs and Preferences

Across baseline interviews and weekly reflections, teachers overwhelmingly rejected student-level labeling in favor of task-level and moment-level insights. When asked to rank ten possible feedback types, 16 of 18 participants placed “specific teaching moments that went well or could be improved” and “patterns in whole-class discourse or task design” in their top three, whereas “individual student risk scores” ranked eighth or lower for all but two teachers. Participants described traditional at-risk flags as “stigmatizing,” “overwhelming,” and “rarely actionable without context.” They articulated a clear desire for explanatory depth paired with immediacy: 94% of stimulated-recall comments included phrases such as “tell me why the discussion died there” or “show me exactly what I could say next time.” Teachers particularly valued short video clips (8-20 seconds) with overlaid annotations that preserved classroom flow while highlighting missed opportunities for questioning, wait-time extension, or reiterating. These findings confirm that teachers seek analytics that align with the grain of pedagogical reasoning rather than administrative surveillance, prioritizing the “how” and “why” of instruction over the “who” of performance.

Effectiveness of Design Principles

The eight teacher-centered design principles proved robust across the three DBR cycles. Post-cycle evaluations showed that every principle received endorsement from at least 15 of 18 teachers as “essential” or “very important.” The most impactful were (1) task-level rather than student-level focus (100% endorsement), (2) explanatory plus suggestive format (94%), and (3) narrative-rich, multimodal presentation (89%). Usage logs revealed that questioning-move recommendations such as “After Maya’s partial explanation, try pressing with ‘Can someone add on or challenge that idea?’” were accepted or adapted in 86% of instances, followed closely by pacing adjustments (“This task took twice as long for the lower third; consider splitting into two phases next time”) at 81%. Teachers repeatedly cited the combination of a 15-second annotated clip plus a single concrete prompt as the “Goldilocks” level of support neither overwhelming nor vague. Iterative refinements, especially shortening briefs from eight to four pages and increasing override affordances, raised overall satisfaction from 61% in Cycle 1 to 92% in Cycle 3, providing strong empirical validation of the principles.

Impact on Teaching Practice

There was the most significant change in observed lesson plans: the percentage of ones with explicit statements about data-informed changes increased by half the baseline numbers (12 to 68 percent). Content analysis indicated a tripling of the planned formative assessment motions (e.g., planned hinge questions, exit-ticket variations), and a doubling of the explicit differentiation strategies. Incorrectly used wait time, intentionality in choosing the responses of students to be discussed in a group, and dynamic regrouping according to the real-time collaboration patterns were more frequently used, as reported by teachers and confirmed by observers. The heterogeneous-classroom management 10-item subscale self-efficacy scores increased (in a large effect of 1.12) between 3.1 and 4.4 (on a 5-point scale). The classroom engagement of students, as assessed by the use of the BROMP protocol in 126 lessons, improved in a small but significant way ($d = 0.38$), which was mostly due to an improvement in on-task behavior when working in small groups. In keeping with the research prediction that standardized achievement gains would be non-significant over ten weeks in an intervention centered on teacher practice, as opposed to direct student-facing intervention, end-of-unit mastery levels in mathematics intervention classes increased, although not significantly, (+6.2 percentage points, $p =. 09$)**.**

Difficulties and Professional Dilemmas

The first reaction was strongly negative: in Cycle 1 five teachers admitted that they felt a strong resistance and commented on it with the words like another tool to have us feel spied on and I already know my classroom. Fears of workload were widespread; two participants occasionally decreased the activity when briefs lasted longer than 12 minutes of reading time. Reliable and non-judgmental feedback coupled with the ability to maintain complete override control increased the level of trust during teachers. Three extreme events were used to show how algorithms are biased against female voices: in one instance, the speech-to-text system kept false alarms on some of the voices of the women, who would initially not be counted on the discourse maps; in another, facial-analysis identified several neuro-divergent students as being unengaged when they were actually fully concentrated. These problems were solved in a few sessions of rapid transparency and retraining of thresholds by teachers which, ironically, strengthened partnership. As of Cycle 3, the dominant storyline had changed to include it is not the AI judging me but it is me and teachers training, with educators to a larger extent proposing new prompt templates and offering to record extra lessons to make the system more efficient. The development of skepticism into a co-design partnership became one of the most crucial unexpected results of the study**.**

In all the four research questions, the conclusion is the same: In the event that AI analytics are re-engineered with the purpose of serving reflective practice by teachers as opposed to accountability by administrators, they can transform into more than a fringe curiosity to become true pedagogical allies. The strong focus on task- and moment-based insights, the tested principles of design, and the quantifiable change in the planning and execution along with the ultimate elimination of ethical obstacles all prove the idea that the knowing-doing gap is not an imperative state but a design failure that can be removed by the means of gradual, teacher-oriented trial**.**

Conclusion

This work shows that the historic separation between the richness of classroom information and its little impact on the day-to-day instruction are not only unavoidable but also not majorly technological in their origin. As AI-driven analytics are specifically reimagined as intelligent teachers-centric feedback companions providing task-based, explanatory, and future-oriented data and not merely collection of raw numbers or deficit-based labels, teachers quickly incorporate them into planning, implementation, and assessment. The fact that 12-percent of lesson plans have explicit data-informed adjustments to make turned to 68-percent, that the number of formative moves and differentiated moves doubled, and that the teachers showed a huge growth in their own self-efficacy to work with heterogeneous classes all prove that, in fact, multimodal data can be transformed into a mirror of professional development, but not a performance scorecard. More importantly, the development of a lack of trust to active co-design cooperation shows that the ethical conflicts regarding the elements of bias, privacy, and surveillance are not the obstacles to overcome but the challenges of design to be solved through transparent and repeated dialogue with teachers in the first instance**.**

Finally, the results lead to the general tendency of learning analytics to be inverted from an administrator-focused surveillance instrument to a teacher-focused reflection device. To realise this potential on scale, policy, and development practice will need to make pedagogical coherence a priority over predictive accuracy, agency over automation, and explanatory narrative over reductive dashboards. It is only when analytics learn the language of instruction that throws some light on why a conversation has stalled, what particular action might rejuvenate it tomorrow, and how current patterns are related to long-term curricular objectives that the promise of data-rich classrooms will be realized. The past of teachers drowning in data whilst teaching mostly the same thing can be over, but the field needs to invest in the approach of making reflective practitioners, as opposed to algorithm, the centre of design. This way AI can finally cease to be placed in the periphery of education to become a true partner in the very human process of teaching.

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