Contents lists available at International Journal Press

Journal of Interdisciplinary Learning and Knowledge Sciences

journal homepage: https://ijpress.com/jilks

Volume 1 · Issue 1 · 2026 pp.34-45

Designing Formative Assessment Through Multimodal Learning Analytics: Integrating Knowledge Tracing, Dashboards, and Epistemic Feedback in Higher Education

Dr. Deepika Rani[1], Prem Lata[2 *]

[1] *Mahatma Jyotiba Phule Rohilkhand University, Bareilly, U.P.*

[2] *Researcher in Human Rights Law and Technology Law, Advocate at Supreme Court of India, New Delhi, India*

* Corresponding author: nimmogautam5@gmail.com

ARTICLE INFO

Article history:
Received: 1-8-26
Received in revised form: 3-8-26
Accepted: 4-8-26
Available online: 5-8-26

Keywords:
Epistemic Feedback
Formative Assessment
Higher Education
Knowledge Tracing
Learning Analytics Dashboards
Multimodal Learning Analytics

ABSTRACT

Formative assessment remains central to higher education quality, yet many digital implementations still privilege summative grades over actionable knowledge representations that support teaching and learning. This narrative review synthesises research on multimodal learning analytics, knowledge tracing, learning analytics dashboards, and epistemic feedback as design resources for formative assessment in blended and online higher education. Drawing on learning sciences, educational data science, and assessment theory, the review maps how latent knowledge models, multimodal behavioural traces, and dialogic feedback processes can be aligned with Black and Wiliam's formative strategies. Evidence indicates that knowledge tracing and related learner models can externalise evolving mastery, that multimodal analytics can capture process evidence beyond clickstreams, and that dashboards and feedback analytics tools are most effective when they prompt reflection rather than merely display metrics. Persistent risks include opaque algorithms, equity harms, over-reliance on prediction, and weak pedagogical integration. The review proposes an integrative design framework linking evidence collection, knowledge representation, interpretive mediation, and instructional action, and identifies research priorities for transparent models, teacher and student feedback literacy, and culturally situated evaluation, especially in under-represented higher education systems.

1. INTRODUCTION

Higher education institutions have invested heavily in digital learning platforms, learning management systems, and data infrastructures, yet assessment practice often remains dominated by end-of-module grades that arrive too late to reshape teaching or learning [1]. Formative assessment, understood as assessment used to adapt teaching and learning while learning is still underway, has a long empirical pedigree as a lever for achievement and self-regulation . Related scholarship develops this point further [2]. Converging evidence is reported in additional work [3]. Parallel findings support the same conclusion [4]. At the same time, learning analytics has matured into a field concerned with measuring, collecting, analysing, and reporting data about learners and their contexts in order to understand and optimise learning and the environments in which it occurs [5]. Subsequent studies reach a similar position [6]. Further research reinforces this interpretation [7]. Related scholarship develops this point further [8]. The intersection of these agendas is strategically important for the knowledge sciences: if learning analytics can represent what learners know and how they are learning, those representations should, in principle, strengthen formative assessment design rather than merely automate ranking [9]. Converging evidence is reported in additional work [10]. Parallel findings support the same conclusion [11].

In practice, the promise has been uneven. Dashboards frequently display engagement metrics that are weakly connected to disciplinary knowledge; predictive models can flag risk without explaining which concepts remain fragile; and automated feedback systems can scale comments without building the epistemic dialogue that makes feedback formative [12]. Subsequent studies reach a similar position [13]. Further research reinforces this interpretation [14]. Related scholarship develops this point further [15]. Multimodal learning analytics extends the data repertoire by combining logs, video, audio, physiological signals, spatial traces, and artefacts, recognising that learning is a multimodal phenomenon rather than a sequence of clicks alone [16]. Converging evidence is reported in additional work [17]. Parallel findings support the same conclusion [18]. Knowledge tracing and related student modelling techniques provide a complementary strand: they treat mastery as a latent, dynamically updated knowledge state rather than as a static score [19]. When these strands are joined to contemporary work on feedback literacy and dialogic feedback analytics, a coherent design space emerges for assessment that is both data-informed and pedagogically purposeful [13]. Subsequent studies reach a similar position [20]. Further research reinforces this interpretation [21]. Related scholarship develops this point further [22].

This narrative review addresses four questions. First, how do knowledge tracing and related learner models function as knowledge representations for formative assessment? Second, what does multimodal learning analytics contribute to the collection and interpretation of assessment evidence in higher education? Third, under what design conditions do learning analytics dashboards and epistemic feedback tools support, rather than dilute, formative purposes? Fourth, what ethical, equity, and governance constraints must shape the deployment of such systems? The contribution is an integrative design framework that links evidence collection, knowledge representation, interpretive mediation, and instructional action, together with a research agenda oriented to transparency, teacher and student agency, and context-sensitive evaluation.

The argument is deliberately positioned for the *Journal of Interdisciplinary Learning and Knowledge Sciences*: it treats assessment design, educational data science, and knowledge representation as mutually constituting problems rather than as separate technical or pedagogical specialisms. Algorithmic systems used in educational assessment also raise questions of accountability and justice that extend beyond the classroom, including the need to govern algorithmic agents that shape opportunities, feedback, and judgements about competence [23]. Developmental assessment alternatives in digitally mediated education further underscore that assessment redesign is not only a measurement problem but also an organisational and pedagogical one [24].

2. Theoretical and Conceptual Framework

2.1 Formative Assessment as Adaptive Practice

Black and Wiliam define formative assessment as encompassing activities by teachers and students that provide information used as feedback to modify teaching and learning [1]. Their later theoretical elaboration emphasises five strategies: clarifying learning intentions and success criteria; engineering discussions and tasks that elicit evidence of learning; providing feedback that moves learning forward; activating learners as instructional resources for one another; and activating learners as owners of their own learning [2]. These strategies provide a pedagogical yardstick against which analytics-mediated assessment designs can be judged. Analytics that only predict end-of-term failure without altering tasks, feedback, or peer processes may be administratively useful yet formatively weak.

A crucial distinction is between evidence of learning and evidence for learning. Summative artefacts can be reused formatively when they are interpreted in time to change subsequent activity; conversely, continuous digital traces can remain non-formative if they are never translated into instructional action [12]. The review therefore treats formative quality as a property of the assessment *cycle* (evidence, interpretation, action) rather than of any single data source or algorithm.

2.2 Learning Analytics and Knowledge Representation

Siemens and Gašević's early framing of learning and knowledge analytics highlighted the dual aims of understanding learning processes and optimising educational environments [5]. Converging evidence is reported in additional work [8]. Subsequent scholarship has repeatedly warned that the field must not forget learning itself: analytics that optimise retention or course completion without modelling knowledge construction risk becoming managerial instruments rather than educational ones [6]. Parallel findings support the same conclusion [9]. Subsequent studies reach a similar position [25]. Knowledge representation in this context includes both formal learner models (for example, skill mastery probabilities) and human-interpretable externalisations such as open learner models, concept maps, and dashboard visualisations that make knowledge states discussable [10]. Further research reinforces this interpretation [11]. Related scholarship develops this point further [26]. Converging evidence is reported in additional work [27]. Educational data mining and learning analytics provide complementary methods for deriving those representations from interaction data [28].

Knowledge tracing, classically formulated as Bayesian knowledge tracing, models the probability that a learner has mastered a skill as a hidden state updated from observed correct and incorrect responses [19]. Later variants and deep knowledge tracing approaches expand the representational capacity of such models, yet the educational stake remains the same: to maintain a dynamic representation of what has been learned so that instruction, practice, and feedback can be adapted [29]. For formative assessment, the decisive question is not only predictive accuracy but whether the model supports human interpretation, contestability, and pedagogically meaningful intervention.

2.3 Multimodality, Feedback, and Shared Regulation

Multimodal learning analytics (MMLA) starts from the premise that learning is embodied, social, and distributed across media [16]. Parallel findings support the same conclusion [18]. In assessment terms, multimodality expands the evidentiary base beyond discrete item responses to include process indicators such as collaborative discourse, gaze patterns, handwriting trajectories, laboratory actions, or design iterations. This expansion is valuable only if the additional signals are mapped to learning constructs rather than treated as surveillance by default [17]. Subsequent studies reach a similar position [30].

Feedback research has likewise shifted from transmission models toward dialogic and literacy-oriented models. Students need not only comments but the capacity to interpret, prioritise, and act on feedback; educators need tools that support such processes at scale without collapsing dialogue into automated monologue [13]. Further research reinforces this interpretation [14]. Related scholarship develops this point further [15]. Converging evidence is reported in additional work [20]. Parallel findings support the same conclusion [22]. Learning analytics can scaffold feedback literacy when designs make feedback processes visible, comparable, and discussable, rather than when they simply accelerate comment generation [13]. Subsequent studies reach a similar position [21]. The framework adopted here therefore positions analytics as potential co-regulators of assessment activity among teachers, peers, and individual learners, consistent with socially distributed accounts of regulation in technology-mediated environments [16]. Further research reinforces this interpretation [31]. Related scholarship develops this point further [32]. Converging evidence is reported in additional work [33].

3. Review Approach

This article is a narrative review with a design-oriented synthesis aim rather than a PRISMA systematic review. Literature was identified through iterative searches of major scholarly databases and publisher platforms using combinations of terms including “formative assessment,” “learning analytics,” “multimodal learning analytics,” “knowledge tracing,” “open learner model,” “learning analytics dashboard,” “feedback literacy,” and “higher education.” Priority was given to peer-reviewed journal articles, major conference proceedings in learning analytics and artificial intelligence in education, and high-quality reviews and theoretical papers from approximately 1995 to 2026, with heavier weighting on work published since 2015.

Sources were retained when they contributed theoretically or empirically to at least one of the four review questions. Selection favoured conceptual clarity, methodological transparency, and relevance to higher education or transferable adult learning settings. Because the goal is integrative design synthesis, the review includes foundational works (for example, formative assessment theory and classical knowledge tracing) alongside contemporary empirical studies of dashboards, multimodal analytics, and feedback tools. Approximately fifty sources are cited. Limitations of the narrative approach include possible selection bias and the absence of a formal risk-of-bias protocol; these are mitigated by cross-checking claims against multiple independent reviews where available and by flagging contested findings explicitly.

4. Knowledge Tracing as Dynamic Knowledge Representation for Formative Assessment

4.1 From Static Scores to Latent Mastery Trajectories

Classical assessment practice often collapses learning into a total score. Knowledge tracing reframes the problem as sequential inference over skills: each opportunity provides evidence that updates a latent mastery estimate [19]. In intelligent tutoring systems, such estimates have long been used to select the next problem, decide when a skill has been learned, and allocate practice efficiently [19]. Parallel findings support the same conclusion [29]. For formative assessment design in broader higher education courses, the transferable idea is that assessment evidence should update a structured representation of knowledge components rather than only a cumulative gradebook.

This representational shift matters pedagogically. A mid-term mark of 58 percent does not tell a student which concepts are unstable; a skill-level mastery profile can, at least in principle, support targeted feedback, differentiated tasks, and peer grouping by complementary strengths. Open learner models extend this logic by making the system's representation inspectable or negotiable, turning the model into a boundary object for discussion between learner and teacher rather than a hidden scoring engine [26]. Subsequent studies reach a similar position [27]. When learners can contest or refine the model's claims about their knowledge, assessment becomes more dialogic and potentially more accurate.

4.2 Affordances and Limits For Higher Education Practice

Empirical programmes around cognitive tutors and subsequent adaptive platforms show that well-specified knowledge components and timely practice can improve learning efficiency in procedural and conceptual domains [19]. Further research reinforces this interpretation [29]. However, higher education curricula are often less finely skill-tagged than intelligent tutoring curricula. Without careful domain modelling, knowledge tracing degrades into opaque prediction: the system may forecast success while remaining silent about the knowledge that success would require. Deep learning-based tracers can improve fit to data yet may further reduce interpretability, creating a tension between representational richness and pedagogical transparency [29].

A second limit is construct coverage. Knowledge tracing historically privileges skills that generate frequent, machine-scorable responses. Complex higher education outcomes such as critical argumentation, design judgement, clinical reasoning, or interdisciplinary synthesis generate sparser and more ambiguous evidence. In those domains, knowledge representations may need to combine coarse-grained competency models, rubrics, and qualitative artefacts with finer-grained tracers where appropriate, rather than forcing all learning into binary correctness sequences. Developmental assessment alternatives in business and professional education similarly argue for broader assessment repertoires that capture growth, not only discrete test events [24].

4.3 Implications for Formative Strategy Alignment

Mapped to Black and Wiliam's strategies, knowledge tracing primarily strengthens the elicitation and interpretation of evidence and can support feedback that moves learning forward when mastery estimates are translated into actionable next steps [1]. Related scholarship develops this point further [2]. It supports learner ownership when open learner models make progress visible and discussable [26]. It supports peer resources when grouping and peer review are informed by complementary knowledge profiles rather than by overall rank alone. The design risk is over-automation: if the system always selects the next task, learners may outsource planning and monitoring, weakening the very self-regulatory capacities formative assessment seeks to build [31]. Effective designs therefore treat knowledge models as scaffolds that can fade, not as permanent substitutes for learner judgement.

5. Multimodal Learning Analytics as Expanded Assessment Evidence

5.1 Why Multimodality Matters for Assessment Design

Learning analytics that rely only on login counts, page views, or assignment timestamps risk confusing behavioural compliance with intellectual engagement [6]. Multimodal learning analytics responds by integrating heterogeneous sensors and data streams that better reflect collaborative, embodied, and studiobased learning [16]. For formative assessment, the opportunity is to capture process evidence while learning is happening: how a team negotiates a problem, how a student revises a draft, how attention is distributed during a simulation, or how laboratory procedures unfold over time.

Gašević and colleagues have argued that multimodal approaches recognise both the multimodality of learning and the need for theory-informed fusion of signals, rather than naive concatenation of every available sensor [16]. In assessment terms, this means each modality should be justified by a learning construct. Speech features might index collaborative reasoning; code edit histories might index iterative problem solving; eye-tracking might index attention to relevant representations; handwriting or sketch streams might index conceptual externalisation. Without construct mapping, multimodality inflates data volume without improving educational interpretation.

5.2 Evidentiary Gains and Interpretive Burdens

Studies of multimodal analytics in collaborative and face-to-face learning contexts show that combinations of audio, video, and digital traces can reveal participation imbalances, phases of joint problem solving, and moments of confusion that gradebooks miss [16]. Converging evidence is reported in additional work [34]. Such insights can support formative moves: a tutor can intervene when collaboration stalls, redesign a task that systematically excludes quieter students, or prompt reflection on strategy use after a failed experiment. The same data, however, create interpretive burdens. Teachers rarely have time to inspect raw multimodal streams; students may not understand how a risk score was derived; and institutions may struggle to store sensitive audio-visual data ethically.

Consequently, MMLA for formative assessment depends on intermediate representations: episode segmentations, discourse codes, collaboration quality indicators, or process dashboards that compress multimodality into pedagogically legible forms [16]. Parallel findings support the same conclusion [34]. The quality of those compressions is itself an assessment design decision. Over-simplified indicators can reintroduce the reductionism multimodal methods were meant to overcome; over-complex visualisations can overwhelm users and produce dashboard fatigue [12]. Subsequent studies reach a similar position [27].

5.3 Blended and Online Higher Education Contexts

In blended higher education, multimodal evidence is often partial: some activity occurs in rooms without sensors, some online, and some offline with phones and laptops. Practical designs therefore combine sparse high-value multimodal snapshots (for example, recorded studio critiques or lab sessions) with continuous digital traces from platforms and documents. Learning analytics research on online assessment emphasises that frequency and stakes of digital quizzes alone do not guarantee learning gains; what matters is how evidence is interpreted and acted upon within the pedagogical design [12]. Further research reinforces this interpretation [35]. Multimodality should be treated as a selective amplifier of formative evidence, not as a mandate for continuous biometric monitoring.

6. Dashboards and Epistemic Feedback: Mediating Analytics for Action

6.1 Learning Analytics Dashboards Beyond Metric Display

Learning analytics dashboards visualise learner data for students, teachers, or advisors with the aim of informing awareness and action [27]. Related scholarship develops this point further [36]. Converging evidence is reported in additional work [37]. Parallel findings support the same conclusion [38]. Early institutional deployments demonstrated that timely signals can support retention interventions, yet subsequent reviews caution that visualisation alone rarely produces metacognitive or formative gains [12]. Subsequent studies reach a similar position [27]. Further research reinforces this interpretation [39]. Effective dashboards tend to embed learning-science principles: they relate indicators to goals and success criteria, support comparison against meaningful referents, prompt reflection, and connect insight to concrete next actions [27]. Related scholarship develops this point further [36]. Converging evidence is reported in additional work [40]. Student-facing designs require particular care so that analytics support self-regulation rather than surveillance anxiety [37]. Parallel findings support the same conclusion [40].

From a formative assessment perspective, dashboards are mediational tools. They sit between raw evidence and instructional action. A teacher-facing dashboard that highlights which knowledge components remain fragile across a cohort can guide reteaching; a student-facing dashboard that shows progress against success criteria can support self-monitoring; a peer dashboard that reveals complementary expertise can structure collaborative learning. Designs that emphasise social comparison without developmental guidance may increase anxiety or strategic grade-chasing rather than deep learning [27].

6.2 Epistemic Feedback and Feedback Analytics

Feedback is formative only when it is used to improve learning. Contemporary research therefore focuses on feedback processes and feedback literacy rather than on comment volume alone [13]. Subsequent studies reach a similar position [20]. Analytics-supported feedback tools can help students track which feedback they received, which actions they took, and which quality criteria remain unmet. Generative artificial intelligence has intensified this agenda by making large-scale feedback generation technically easy while raising new questions about accuracy, authorship, and critical evaluation of machine comments [13]. Further research reinforces this interpretation [20].

Jin and colleagues' work on generative AI-powered feedback analytics tools illustrates both the opportunity and the conditionality of benefit: integration should be examined through a feedback literacy lens, ensuring that tools scaffold students' capacity to interpret and use feedback rather than merely replace teacher comments [13]. Wongvorachan and colleagues similarly map artificial intelligence, educational data mining, and learning analytics as complementary contributors to future feedback practices, while warning that technical capability must be aligned with pedagogical purpose [20]. In this review, the term *epistemic feedback* denotes feedback that targets the quality of knowledge claims, justifications, and knowledge-building moves, not only surface correctness or stylistic polish. Analytics that surface argument structure, evidence use, or misconception patterns are more tightly coupled to knowledge sciences than analytics that only score sentiment or length.

6.3 Closing the Loop: From Insight to Instructional Redesign

Banihashem and colleagues synthesise how learning analytics can optimise formative assessment by connecting teachers, students as peers, and students as self-regulated learners within a shared formative model [12]. Their analysis underscores a persistent disconnect: analytics outputs often stop at reporting, while formative assessment requires modification of subsequent teaching and learning activities. Closing the loop may involve adaptive task selection, timely teacher intervention, peer review reorganisation, or curriculum redesign when cohort-level misconception patterns recur [41]. Related scholarship develops this point further [42]. Without institutional time and assessment literacy for such action, sophisticated analytics remain ornamental. European higher education studies similarly report that organisational barriers, not only technical limits, constrain learning analytics adoption [43].

7. An Integrative Design Framework

Synthesising the preceding strands, this review proposes a four-layer design framework for formative assessment supported by multimodal learning analytics and knowledge representation. Figure 1 summarises the layers and their relations; Table 1 details design questions and failure modes for each layer.

Table 1. *Four-Layer Design Framework for Analytics-Supported Formative Assessment*

Layer	Primary function	Core design questions	Typical failure mode
Evidence collection	Capture multimodal and unimodal traces aligned to learning constructs	Which constructs matter? Which modalities are necessary and proportionate?	Collecting high-volume data with weak construct validity
Knowledge representation	Maintain dynamic, inspectable models of mastery and process quality	Can teachers and students interpret and contest the model?	Opaque prediction without pedagogically meaningful structure
Interpretive mediation	Translate models into dashboards, prompts, and epistemic feedback	Does the interface support reflection, dialogue, and next-step planning?	Metric display without guidance or feedback literacy support
Instructional action	Adapt teaching, tasks, peer processes, and learner strategies	What changes in time to affect learning? Who acts, and with what agency?	Insights that never alter teaching or learning activity

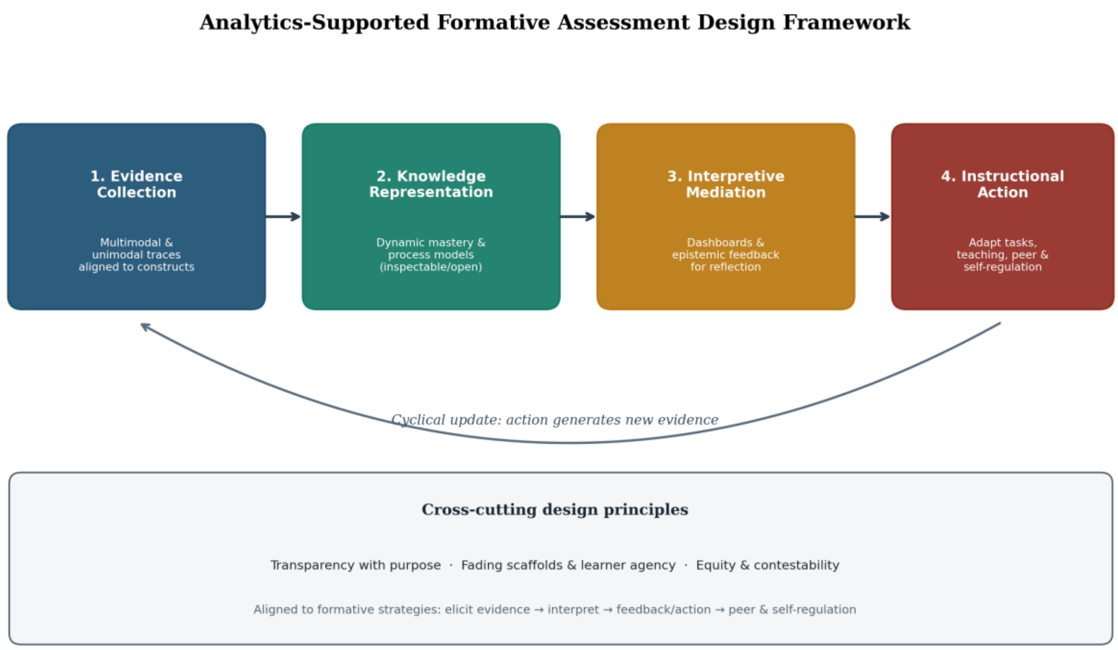

Figure 1. Integrative design framework linking multimodal evidence, knowledge representation, interpretive mediation, and instructional action for formative assessment

Figure 1. Integrative design framework for formative assessment supported by multimodal learning analytics and knowledge representation.

The framework is intentionally cyclical. Instructional action generates new evidence; updated knowledge representations recalibrate mediation; mediation shapes which actions appear feasible. Alignment with Black and Wiliam's strategies can be checked at each layer: evidence collection should elicit valid learning evidence; representation and mediation should clarify criteria and support feedback that moves learning forward; action should activate peer and self-regulatory resources [1]. Converging evidence is reported in additional work [2]. Knowledge tracing and related models primarily populate the representation layer; MMLA primarily enriches the evidence layer; dashboards and feedback analytics primarily occupy the mediation layer; teachers, peers, and learners jointly own the action layer [12]. Parallel findings support the same conclusion [16]. Subsequent studies reach a similar position [19]. Further research reinforces this interpretation [27].

Two design principles cut across layers. First, *transparency with purpose*: every automated inference that influences assessment-related opportunities should be explainable at a level appropriate to the stakeholder, consistent with broader calls to govern algorithmic agents that affect justice-relevant outcomes [23]. Second, *fading and agency*: automated scaffolds should be designed to build, not permanently replace, human assessment and self-regulatory capacities [31]. These principles distinguish educational analytics from industrial optimisation.

8. Equity, Ethics, and Algorithmic Governance

Data-intensive assessment systems redistribute visibility and risk. Students who learn in sensor-rich environments may receive richer formative support than those in resource-constrained settings, widening opportunity gaps even when tools are framed as personalisation. Multimodal data can encode disability, language background, affect, and socio-economic circumstance in ways that are difficult to anticipate and easy to misuse [16]. Related scholarship develops this point further [30]. Converging evidence is reported in additional work [34]. Predictive flags can become self-fulfilling if staff lower expectations for labelled "at-risk" students without offering constructive support [6]. Parallel findings support the same conclusion [12]. Subsequent studies reach a similar position [44]. Critical reviews of the learning analytics landscape emphasise that ethical dilemmas are structural rather than incidental [30]. Further research reinforces this interpretation [45]. Related scholarship develops this point further [46].

Governance questions therefore belong inside assessment design rather than after deployment. Who owns learner data? What is the legitimate purpose limitation? How can learners contest model outputs that affect feedback, progression advice, or access to support? How are false positives and false negatives distributed across demographic groups? Pandey and Kumar's analysis of algorithmic agents and challenges to justice provides a useful cross-domain reminder that overt and covert harms can arise when automated systems shape life chances without adequate accountability structures [23]. In educational settings, analogous harms include opaque grading assistance, biased risk prediction, and feedback systems that systematically misread the work of second-language writers or non-dominant knowledge practices. Broader analyses of artificial intelligence in education likewise stress that promise claims must be tempered by implications for teaching labour, learner agency, and institutional power [47]. Converging evidence is reported in additional work [48]. Parallel findings support the same conclusion [49].

Ethical formative analytics should therefore prefer minimal sufficient data, purpose-bound multimodal capture, human oversight for high-stakes interpretations, and explicit pathways for appeal and discussion [44]. Subsequent studies reach a similar position [45]. Open learner models and dialogic feedback designs are not only pedagogical preferences; they are accountability mechanisms that keep knowledge claims about learners contestable [13]. Further research reinforces this interpretation [26]. Institutions also need assessment governance that distinguishes low-stakes formative experimentation from high-stakes automated decision-making, with stricter scrutiny for the latter. Work on twenty-first-century competencies further suggests that analytics should surface complex capabilities such as collaboration and epistemic quality, not only easily measured compliance behaviours [50].

9. Research Gaps and Agenda

Despite rapid growth in learning analytics and AI-in-education research, several gaps limit confidence in large-scale claims about formative benefit.

First, many studies evaluate predictive performance or engagement metrics rather than changes in teaching practice and learning outcomes that are specifically attributable to formative use of analytics [12]. Related scholarship develops this point further [35]. Converging evidence is reported in additional work [46]. Future work should measure whether instructors and students actually modify activities and whether those modifications improve knowledge quality, not only grades or retention [41]. Parallel findings support the same conclusion [42].

Second, interpretability research remains under-integrated with classroom assessment practice. Comparative studies are needed of transparent knowledge component models versus high-performing black-box tracers when the outcome of interest is usable formative action rather than residual error alone [9]. Subsequent studies reach a similar position [25]. Further research reinforces this interpretation [29].

Third, multimodal studies are still unevenly distributed across disciplines and regions. Studio, laboratory, clinical, and field-based higher education programmes remain under-served relative to fully online courses with abundant clickstream data [16]. Related scholarship develops this point further [17]. Converging evidence is reported in additional work [34]. South Asian and other Global South higher education contexts, where infrastructure, class size, and multilingual realities differ from the settings that dominate the literature, require situated design research rather than uncritical tool transfer [43]. Parallel findings support the same conclusion [49].

Fourth, feedback analytics and generative AI tools need longitudinal evidence on feedback literacy development and on risks of shallow revision or uncritical acceptance of machine comments [13]. Subsequent studies reach a similar position [20]. Further research reinforces this interpretation [21]. Related scholarship develops this point further [48]. Fifth, equity audits should become standard in analytics-supported assessment research, including disaggregated error analysis and participatory design with students who are most exposed to surveillance harms [23]. Converging evidence is reported in additional work [30]. Parallel findings support the same conclusion [44]. Subsequent studies reach a similar position [45]. Sixth, organisational studies should examine the assessment alternatives and staff development conditions under which institutions can move from grade-centric cultures toward developmental, analytics-informed formative cultures [24]. Further research reinforces this interpretation [50].

10. Discussion

Taken together, the literature supports a qualified claim: multimodal learning analytics and knowledge tracing can strengthen formative assessment in higher education when they are designed as pedagogically governed knowledge infrastructures rather than as scoring engines. The strongest contributions arise when (a) evidence is construct-aligned, (b) knowledge representations are dynamic and inspectable, (c) dashboards and feedback tools mediate interpretation in ways that build literacy and dialogue, and (d) instructional action is resourced and expected [1]. Related scholarship develops this point further [10]. Converging evidence is reported in additional work [11]. Parallel findings support the same conclusion [12]. Subsequent studies reach a similar position [13]. Further research reinforces this interpretation [16]. Related scholarship develops this point further [19]. Converging evidence is reported in additional work [27]. Where any of these conditions fails, analytics may increase institutional visibility while leaving classroom formative practice unchanged or even eroded [6]. Parallel findings support the same conclusion [30].

This conclusion differs from both technological optimism and blanket scepticism. The review does not argue that every course should deploy sensors and deep tracers. It argues that when institutions do invest in learning analytics for assessment, the design centre of gravity should shift from prediction and display toward knowledge representation and formative action [9]. Subsequent studies reach a similar position [25]. In that sense, the knowledge sciences contribution is precise: assessment improvement depends on how knowledge is modelled, made public, discussed, and revised over time [10]. Further research reinforces this interpretation [26]. Systematic reviews of AI applications in higher education reinforce a related caution: educators' pedagogical roles are often under-theorised relative to technical system descriptions [49].

The framework also clarifies boundary conditions. Highly standardised procedural domains may benefit quickly from knowledge tracing; discursive and creative domains may need hybrid representations that combine analytics with human judgement [24]. Related scholarship develops this point further [50]. Multimodal capture is most defensible when it answers a clear formative question that cheaper data cannot answer [16]. Converging evidence is reported in additional work [18]. Dashboards are most valuable when coupled to workflows that teachers and students already inhabit [36]. Parallel findings support the same conclusion [40]. Governance is not an annex; it is part of validity, because an assessment process that systematically misrepresents some learners is educationally invalid even if it is computationally elegant [23]. Subsequent studies reach a similar position [44]. Further research reinforces this interpretation [45].

11. Conclusion

This narrative review examined how multimodal learning analytics, knowledge tracing, dashboards, and epistemic feedback can be integrated into formative assessment design for higher education. Foundational assessment theory continues to supply the pedagogical criteria of success: evidence must be elicited, interpreted, and used to adapt teaching and learning while learning is still in motion. Learning analytics and student modelling supply representational and mediational means for meeting those criteria at scale, provided that designs remain transparent, contestable, and action-oriented.

The proposed four-layer framework connects evidence collection, knowledge representation, interpretive mediation, and instructional action, and identifies characteristic failure modes at each layer. Realising the framework in practice requires not only technical capacity but also assessment literacy, institutional time for instructional response, and governance arrangements that protect equity and learner agency. Future research should prioritise classroom-level formative outcomes, interpretable models, multimodal designs justified by learning constructs, and context-sensitive studies beyond the current geographic and disciplinary concentration of the evidence base. Under those conditions, analytics-supported assessment can become a genuine instrument of interdisciplinary learning and knowledge development rather than a refined apparatus for ranking.

REFERENCES

[1] Black, P., & Wiliam, D. (1998). Assessment and classroom learning. *Assessment in Education: Principles, Policy & Practice, 5*(1), 7–74. https://doi.org/10.1080/0969595980050102

[2] Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability, 21*(1), 5–31. https://doi.org/10.1007/s11092-008-9068-5

[3] Bennett, R. E. (2011). Formative assessment: A critical review. *Assessment in Education: Principles, Policy & Practice, 18*(1), 5–25. https://doi.org/10.1080/0969594X.2010.513678

[4] Wiliam, D. (2011). What is assessment for learning? *Studies in Educational Evaluation, 37*(1), 3–14. https://doi.org/10.1016/j.stueduc.2011.03.001

[5] Siemens, G., & Gašević, D. (2012). Guest editorial: Learning and knowledge analytics. *Journal of Educational Technology & Society, 15*(3), 1–2.

[6] Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

[7] Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning, 4*(5–6), 304–317. https://doi.org/10.1504/IJTEL.2012.051816

[8] Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 31–40.

[9] Wise, A. F., & Shaffer, D. W. (2015). Why theory matters more than ever in the age of big data. *Journal of Learning Analytics, 2*(2), 5–13. https://doi.org/10.18608/jla.2015.22.2

[10] Pellegrino, J. W., Chudowsky, N., & Glaser, R. (Eds.). (2001). *Knowing what students know: The science and design of educational assessment*. National Academy Press.

[11] Mislevy, R. J., Almond, R. G., & Lukas, J. F. (2003). *A brief introduction to evidence-centered design* (Research Report RR-03-16). Educational Testing Service.

[12] Banihashem, S. K., Gašević, D., & Noroozi, O. (2025). Optimizing formative assessment with learning analytics. *Review of Educational Research*. Advance online publication. https://doi.org/10.3102/00346543251370753

[13] Jin, F. J. Y., Maheshi, B., Martinez-Maldonado, R., Gašević, D., & Tsai, Y.-S. (2025). Students' perceptions of generative AI-powered learning analytics in the feedback process: A feedback literacy perspective. *Journal of Learning Analytics*. https://doi.org/10.18608/jla.2025.8609

[14] Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189. https://doi.org/10.3102/0034654307313795

[15] Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education, 31*(2), 199–218. https://doi.org/10.1080/03075070600572090

[16] Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

[17] Azevedo, R., & Gašević, D. (2019). Analyzing multimodal multichannel data about self-regulated learning with advanced learning technologies: Issues and challenges. *Computers in Human Behavior, 96*, 207–210. https://doi.org/10.1016/j.chb.2019.03.025

[18] Ochoa, X., & Worsley, M. (2016). Augmenting learning analytics with multimodal sensory data. *Journal of Learning Analytics, 3*(2), 213–219. https://doi.org/10.18608/jla.2016.32.10

[19] Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction, 4*(4), 253–278. https://doi.org/10.1007/BF01099821

[20] Wongvorachan, T., Lai, K. W., Bulut, O., Tsai, Y.-S., & Chen, G. (2022). Artificial intelligence: Transforming the future of feedback in education. *Journal of Applied Testing Technology, 23*, 95–116.

[21] Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

[22] Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112. https://doi.org/10.3102/003465430298487

[23] Pandey, J. K., & Kumar, R. (2025). Governing the algorithmic agent: Confronting overt and covert challenges to justice and the future of work. *International Journal of Law Management & Humanities, 8*(4), 1974–1984. https://doij.org/10.10000/IJLMH.1110648

[24] Maurya, S. K., & Pandey, J. K. (2026). Developmental assessment alternatives in business education. In K. Mili (Ed.), *Reimagining business education in the age of artificial intelligence* (pp. 271–316).

[25] Knight, S., & Buckingham Shum, S. (2017). Theory and learning analytics. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 17–22). Society for Learning Analytics Research. https://doi.org/10.18608/hla17.001

[26] Bull, S., & Kay, J. (2010). Open learner models. In R. Nkambou, J. Bourdeau, & R. Mizoguchi (Eds.), *Advances in intelligent tutoring systems* (pp. 301–322). Springer. https://doi.org/10.1007/978-3-642-14363-2_15

[27] Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 31–40). ACM. https://doi.org/10.1145/3170358.3170421

[28] Baker, R. S. J. d., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White (Eds.), *Learning analytics: From research to practice* (pp. 61–75). Springer. https://doi.org/10.1007/978-1-4614-3305-7_4

[29] Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L., & Sohl-Dickstein, J. (2015). Deep knowledge tracing. In *Advances in Neural Information Processing Systems* (pp. 505–513).

[30] Selwyn, N. (2019). What's the problem with learning analytics? *Journal of Learning Analytics, 6*(3), 11–19. https://doi.org/10.18608/jla.2019.63.3

[31] Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates.

[32] Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology, 8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

[33] Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice, 41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

[34] Ouhaichi, H., Spikol, D., & Vogel, B. (2023). Research trends in multimodal learning analytics: A systematic mapping study. *Computers and Education: Artificial Intelligence, 4*, 100136. https://doi.org/10.1016/j.caeai.2023.100136

[35] Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

[36] Matcha, W., Uzir, N. A., Gašević, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies, 13*(2), 226–245. https://doi.org/10.1109/TLT.2019.2916802

[37] Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies, 10*(4), 405–418. https://doi.org/10.1109/TLT.2017.2740172

[38] Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies, 10*(1), 30–41. https://doi.org/10.1109/TLT.2016.2599522

[39] Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267–270). ACM. https://doi.org/10.1145/2330601.2330666

[40] Kitto, K., Lupton, M., Davis, K., & Waters, Z. (2017). Designing for student-facing learning analytics. *Australasian Journal of Educational Technology, 33*(5), 152–168. https://doi.org/10.14742/ajet.3607

[41] Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior, 47*, 157–167. https://doi.org/10.1016/j.chb.2014.05.038

[42] Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior, 60*, 333–341. https://doi.org/10.1016/j.chb.2016.02.074

[43] Tsai, Y.-S., Rates, D., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Jivet, I., Scheffel, M., Drachsler, H., Delgado Kloos, C., & Gašević, D. (2020). Learning analytics in European higher education: Trends and barriers. *Computers & Education, 155*, 103933. https://doi.org/10.1016/j.compedu.2020.103933

[44] Prinsloo, P., & Slade, S. (2017). An elephant in the learning analytics room: The obligation to act. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 46–55). ACM. https://doi.org/10.1145/3027385.3027406

[45] Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529. https://doi.org/10.1177/0002764213479366

[46] Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

[47] Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

[48] Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promise and implications for teaching and learning*. Center for Curriculum Redesign.

[49] Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*, 39. https://doi.org/10.1186/s41239-019-0171-0

[50] Buckingham Shum, S., & Crick, R. D. (2016). Learning analytics for 21st century competencies. *Journal of Learning Analytics, 3*(2), 6–21. https://doi.org/10.18608/jla.2016.32.2