Enhancing Student Learning in Online and Face-to-Face Contexts Using Multimodal Learning Analytics and Artificial Intelligence

Alvaro Becerra[1,*], Ruth Cobos[1]

[1]GHIA Group, School of Engineering, Universidad Autónoma de Madrid, Spain

Abstract

Learning is inherently multimodal, and providing rich, personalized feedback requires capturing and interpreting diverse data about students' learning processes. In this context, Multimodal Learning Analytics (MMLA) shows strong potential for capturing complex aspects of learning by integrating biometric, contextual, and interaction data. However, current MMLA approaches face challenges related to scalability, data integration, and limited translation of analytics into feedback. This doctoral research explores the integration of Machine Learning (ML), MMLA, and Generative Artificial Intelligence (GenAI) to create adaptive and scalable feedback mechanisms for learners and teachers in online and face-to-face learning contexts. Two complementary case studies are conducted using multimodal sensor data. ML models are developed to identify learning-related indicators such as attention, engagement, and communication skills, which are integrated with GenAI tools to generate personalized feedback. The expected contributions include scalable multimodal data collection methods, predictive learning indicators, and GenAI-based feedback systems that translate complex analytics into pedagogically meaningful feedback

Keywords

Multimodal Learning Analytics, Generative Artificial Intelligence, Machine Learning, Feedback, Biosensors, Biometrics & Behavior, Online Learning, Oral Presentations

1. Problem Statement

Learning is inherently multimodal, involving cognitive, behavioral, and contextual processes that cannot be fully captured through traditional educational data alone. Providing timely, rich, and personalized feedback therefore requires collecting and interpreting diverse sources of data that reflect how students learn in real educational contexts.

In recent years, Learning Analytics (LA) [1] has emerged as a powerful field to improve teaching and learning through the analysis of educational data. Within this field, Multimodal Learning Analytics (MMLA) [2] has gained increasing attention for its potential to integrate diverse data sources, such as biometric, contextual, and interaction traces, in order to capture a more holistic representation of the learning process. This multimodal perspective has opened new opportunities for understanding complex aspects of learning, including student attention, motivation, and engagement, across different educational contexts. However, despite significant advances in the MMLA field, several critical challenges remain unresolved [3]:

- **Scalability and feasibility.** Many studies rely on costly or intrusive biosensors, making large-scale monitoring in real educational contexts difficult. Moreover, most experiments involve small samples.
- **Data integration and fusion.** Combining heterogeneous data streams (e.g., EEG, eye-tracking, webcams, smartwatches) into synchronized and meaningful learning indicators remains technically complex.
- **Standardization and reproducibility.** The lack of benchmark datasets and publicly available code limits comparability across studies and hinders reproducibility.

LASI Spain 26: Learning Analytics Summer Institute Spain 2026, Zamora, May 07–08, 2026
*Corresponding author.
alvaro.becerra@uam.es (A. Becerra); ruth.cobos@uam.es (R. Cobos)
0009-0003-7793-2682 (A. Becerra); 0000-0002-3411-3009 (R. Cobos)
© 2026 Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073
published 2026-08-03

CEUR-WS.org/Vol-4235/paper10.pdf

- **Generative AI integration.** Large Language Models (LLMs) show promise for automated educational feedback, yet their integration with multimodal data remains underexplored, raising open questions about trust, interpretability, bias, and the ethical use of sensitive biometric and contextual data.

This doctoral research addresses these challenges by proposing an integration of MMLA, ML, and GenAI in both online and face-to-face learning contexts. Two complementary case studies are designed to investigate how sensor-based multimodal data can extend traditional interaction logs to inform feedback processes in methodologically comparable settings. The research focuses on scalable and user-centered approaches for multimodal data collection, predictive modeling, and adaptive feedback that supports both students and teachers.

From a pedagogical perspective, this work is grounded in theories of self-regulated learning, formative feedback, and peer feedback, where timely, interpretable, and context-aware feedback plays a central role [4, 5]. In both case studies, multimodal indicators are used to enrich feedback and support learners' reflection, rather than to enable fully automated decision-making. In this context, Generative AI is positioned as an interpretative layer that translates multimodal analytics and human evaluations into actionable feedback aligned with the pedagogical goals of each learning context.

2. Related Works

The theoretical foundation of this research is based on Learning Analytics (LA) [1, 6] and its emerging subfield, Multimodal Learning Analytics (MMLA) [2]. While LA focuses primarily on the analysis of educational data such as interaction logs, clickstream data, and assessment results, to explain or predict academic performance and learner behaviors [7], MMLA expands this scope by integrating data from multiple sources, including biometric sensors, contextual information, and interaction data [3, 8]. This multimodal approach allows for a richer and more precise representation of teaching and learning processes and aims at understanding and improving the learning process through the integration of diverse sources of data [9, 10]. The term multimodal refers to the use of multiple modes of communication and interaction, such as textual, auditory, linguistic, spatial, and visual. In the context of MMLA, this involves analyzing different types of data, including eye-tracking, heart rate, digital traces, body language, facial expressions, and others. MMLA combines elements of computer-assisted learning analytics and educational data mining, employing advanced techniques of data processing and modeling such as machine learning and deep learning. By capturing and analyzing multiple dimensions of the learning experience, MMLA provides new insights into learning processes and ways to optimize educational environments. According to [11], this integration not only improves the accuracy of learning outcome predictions but also facilitates the interpretation of complex processes, such as behavioral trajectories and affective states. For instance, eye-tracking data can be used to measure attention patterns [12], while EEG signals can be employed to estimate cognitive load [13]. While the use of many sensors has shown that it improves the performance of predictive models, monitoring large numbers of students with multiple biosensors is very costly. For this reason, another major challenge of the field is the application of these models in real-world educational environments [3]. On the other hand, the use of Generative AI (GenAI) in education has become a highly novel topic since the emergence of Large Language Models (LLMs) such as ChatGPT, Gemini, or Llama2. For example, [14] used GenAI to provide feedback to programming students, and it has also been applied to feedback in writing, collaborative work, and self-regulated learning [15]. However, the use of GenAI also presents challenges that require further research, such as trust in generated responses, which can sometimes be inaccurate or difficult to interpret, and ethical concerns related to privacy and the use of educational data [16, 17].

In the specific context of oral presentation skills, previous work has explored multimodal systems that provide automated feedback on presentation performance. OpenOPAF, for instance, is an open-source multimodal system that analyzes body language, gaze direction, voice volume, articulation speed, filled pauses, and the use of text in visual aids to provide actionable feedback to presenters [18]. Similarly, projects such as Presentable and HyTea [19] investigate AI-supported or multimodal approaches for helping students practise presentation skills.

3. Research Objective

The primary goal of this research is to contribute to the field of MMLA by integrating multimodal data (biometric, contextual, and interaction) from both physical and online learning environments in order to develop new indicators, tools, and machine learning models that enhance teaching–learning processes. In addition, the research aims to leverage GenAI as an interpretative and feedback layer that translates multimodal learning indicators into personalized, context-aware, and actionable feedback for both students and teachers. To address this overarching goal, the research pursues the following specific objectives: 1) Review and synthesize the state of the art in LA and MMLA, with a focus on multimodal data integration; 2) Design and conduct two complementary case studies (online and face-to-face) to collect multimodal datasets; 3) Develop machine learning models to extract interpretable learning indicators related to attention, engagement, and performance 4) Design and evaluate GenAI-based tools that deliver personalized feedback to students and actionable insights to teachers.

The central research hypothesis is that the integration of multimodal data (biometric, contextual, and interaction) captured in both online and face-to-face learning environments will enable the development of new and meaningful indicators of learning. These indicators, combined with machine learning and Generative AI–based feedback systems, will improve teaching–learning processes. From this hypothesis, the research also addresses the following complementary research questions:

RQ1 Which types of multimodal data (biometric, contextual, interaction) are most effective in capturing relevant information about learning in online and face-to-face contexts?

RQ2 How can machine learning models integrate multimodal data streams to produce accurate and interpretable learning indicators?

RQ3 What is the effect of GenAI-based personalized feedback on students' engagement and performance, and on teachers' ability to guide learning?

4. Methodology

This doctoral research will follow the Design Science Research Methodology (DSRM) [20]. The design process in this thesis will also be enriched by a user-centered perspective, involving key stakeholders (students and teachers) in problem identification, definition of objectives, design of processes, and pilot studies. Participation will explicitly consider aspects such as diversity, inclusion, and gender equality. Following the DSRM framework, the research methodology is structured around the following pillars:

1. **State of the Art:** A comprehensive literature review in Learning Analytics (LA) and Multimodal Learning Analytics (MMLA) to identify open problems and gaps.
2. **Experimental Methodology:** Design of case studies in controlled and non-controlled learning environments, where biometric, interaction, and contextual data will be captured.
3. **Tool Development:** Implementation of specific tools for synchronizing multimodal signals and annotating relevant events during monitoring.
4. **Data Collection:** Execution of monitoring sessions to obtain multimodal datasets richer in both the number of users and data types than existing ones.
5. **Data Analysis and Modeling:** Application of machine learning techniques to analyze collected data, extract learning indicators, and evaluate predictive performance.
6. **Integration with GenAI:** Embedding predictive models into new tools powered by GenAI to provide personalized feedback for students.
7. **Validation:** Evaluation of the developed tools to assess their effectiveness in supporting students' learning processes and demonstrating their practical utility.

8. **Dissemination:** Publication of results in research articles and presentation at international conferences throughout the development of the thesis.

All research activities involving students will adhere to the ethical standards and will also undergo review and approval by the University's Ethics Committee. Informed consent will be obtained from all participants prior to data collection, ensuring that they are fully aware of the scope of the study, the types of data to be collected, and their rights to withdraw at any stage.

5. Contributions to date

To make explicit how the doctoral work addresses the identified research gaps, Table 1 maps each gap to the corresponding research questions, progress achieved so far, and remaining work.

Table 1
Mapping between research gaps, research questions, progress to date, and remaining work.

Research gap	RQ	Progress to date	Remaining work
Scalability and feasibility of multimodal data collection	RQ1	Creation of the IMPROVE dataset with 120 students in online learning and the SOPHIAS dataset with 65 students and 50 oral presentations in face-to-face settings.	Analyze which low-cost and less intrusive data sources provide sufficient pedagogical value compared with richer sensor configurations.
Integration and synchronization of heterogeneous data streams	RQ1, RQ2	Development of M2LADS, VAAD, Watch-DMLT, and multimodal synchronization workflows.	Further integrate audio, video, physiological, interaction, and assessment data into the MOSAIC-F pipeline.
Lack of interpretable learning indicators	RQ2	Development of machine learning models for detecting distraction events in online learning and initial behavioral indicators for oral presentations.	Improve the robustness, interpretability, and classroom validity of models for attention, engagement, and communication skills.
Limited translation of analytics into actionable feedback	RQ3	Development of GePeTo and AICoFe as GenAI-based feedback tools using pose indicators and human assessment data.	Incorporate additional multimodal indicators from audio and eye-tracking into the feedback generation process, and evaluate the pedagogical value, usability, and impact of GenAI-supported feedback.
Reproducibility and open science limitations in MMLA	RQ1, RQ2	Release multimodal datasets and associated technical prototypes, including IMPROVE, SOPHIAS, M2LADS, VAAD, and Watch-DMLT.	Explore the release of selected software components as open-source code.

5.1. Online Learning

A comprehensive systematic review of Multimodal Learning Analytics in online learning was conducted [3]. This review complements broader mappings of the MMLA field, such as Ouhaichi et al. [8], which examine research trends, methodologies, technologies, and themes across diverse learning contexts. In contrast, [3] focuses specifically on biosensor-supported MMLA in computer-based online learning, synthesizing 54 studies on how physiological signals, interaction data, preprocessing pipelines, and machine learning models are used to detect and predict student behavior, attention, engagement, and related learning states, while identifying limitations related to scalability, sensor intrusiveness, data fusion, and feedback generation.

Building on the insights and gaps identified in this review, a large-scale open-access multimodal dataset, IMPROVE , was created by monitoring 120 students during a 30-minute MOOC learning

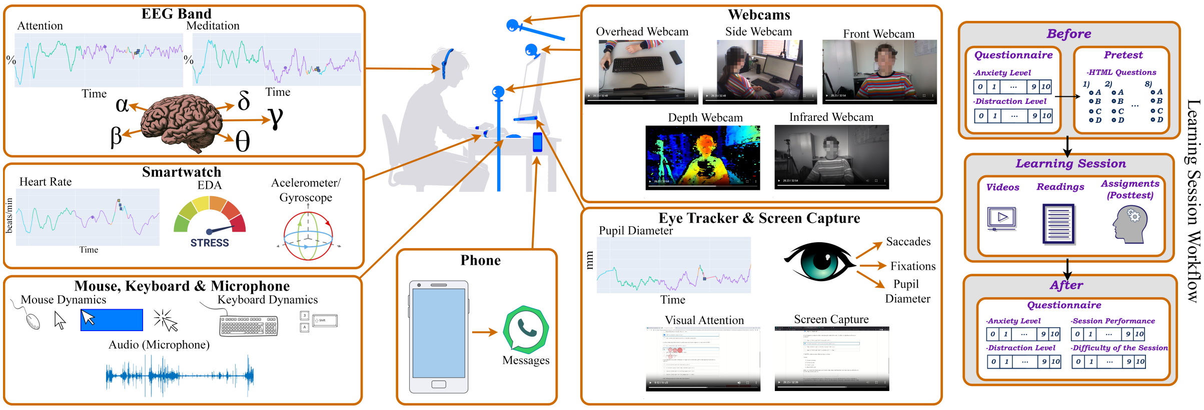

Figure 1: Overview of the IMPROVE multimodal data collection setup in online learning contexts and Learning Session workflow.

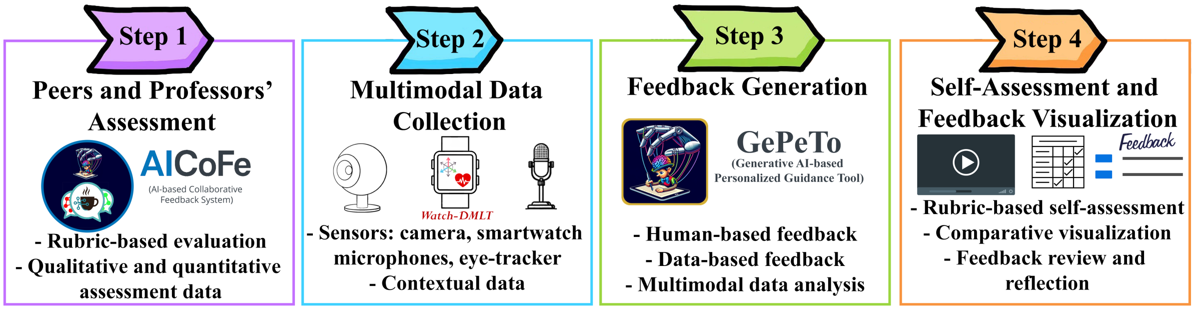

Figure 2: MOSAIC-F framework illustrating the integration of human-based assessments, multimodal sensor data, and ML-based analysis to generate personalized feedback in face-to-face learning environments.

session. During the session, students engaged in typical online learning activities, including watching instructional videos, reading learning materials, and completing short exercises, under controlled conditions regarding smartphone availability and use. The dataset integrates heterogeneous data sources, including EEG devices, smartwatches, and multiple cameras (RGB, depth, and infrared), enabling the study of attention, engagement, and distraction in online learning contexts [21] (Figure 1).

To operationalize this dataset and address the technical challenges of multimodal data synchronization and analysis highlighted in the literature, several systems and prototypes were designed and implemented. These include M2LADS, a system for synchronizing multimodal signals and generating dashboards for online sessions [22, 23] and VAAD, a system that integrates eye-tracking data to provide descriptive and predictive analytics of students' visual attention in online learning environments [24].

Building on this technological infrastructure, supervised machine learning models were trained to identify distraction events by combining physiological signals (EEG and heart rate) with interaction data, providing empirical evidence of the benefits of multimodal data integration for detecting attention-related states in online learning [25].

Finally, to address the gap identified in the literature regarding the limited translation of multimodal indicators into actionable feedback, GePeTo, a Generative AI–based personalized guidance tool, was developed. GePeTo leverages learning analytics indicators and model outputs to generate personalized, context-aware feedback messages for MOOC learners in natural language, supporting self-regulation and engagement [26].

5.2. Face-to-face Learning

In face-to-face learning contexts, this doctoral research has focused on improving the assessment and feedback of students' oral presentation skills through the integration of MMLA, collaborative assessment, and ML.

As an initial contribution, the MOSAIC-F framework [27] was proposed as a classroom-oriented, data-driven approach for generating personalized feedback on oral presentation skills. Unlike rehearsal-based systems, which mainly support individual practice before a presentation, MOSAIC-F is designed to support feedback generation after oral presentations delivered in authentic classroom assessment contexts. The framework integrates MMLA, sensor data, human observations, collaborative assessment, and AI within a four-step workflow (Figure 2): (1) peer and teacher assessment, (2) multimodal data collection, (3) AI-based feedback generation, and (4) self-assessment and feedback visualization.

By explicitly combining human-based evaluations with data-based multimodal indicators, MOSAIC-F addresses key challenges related to feedback quality, interpretability, and scalability in face-to-face learning environments. Its feedback scope is broader than that of rehearsal-oriented systems because it integrates peer and teacher assessments, self-assessment, video and audio recordings, gaze-related data, physiological signals, interaction logs, slide analysis, contextual annotations, and behavioral indicators. GenAI is then used as an interpretative layer to synthesize these heterogeneous sources into richer, personalized, and actionable feedback for students and teachers.

To operationalize and validate this framework in real classroom settings, AICoFe [28], an AI-based collaborative feedback system, was designed and implemented. AICoFe supports peer, self-, and teacher assessment through rubric-based dashboards, records interaction and evaluation data, and integrates GenAI through GePeTo to generate structured, personalized feedback. In the current GenAI-based feedback workflow, three LLMs are used to generate independent feedback drafts: GPT-4.1-mini, Gemini 2.5 Flash, and Llama 3.1. Each model is grounded through structured prompts that include human evaluations (both quantitative rubric scores and qualitative comments provided by peers and teachers), rubric descriptors (define the meaning of each performance level for each criterion), and selected multimodal indicators. Multimodal indicators provide additional evidence about the presentation, such as the time spent looking at the projected slides, the time spent with arms down, and other behavioral signals. Based on these inputs, each LLM generates formative feedback organized into strengths, areas for improvement, and concrete recommendations. The resulting drafts can then be reviewed and curated by the teacher before being delivered to the student.

Additionally, Watch-DMLT was developed to enable real-time collection, synchronization, and visualization of physiological and behavioral data from smartwatches [29].

Building on the deployment of MOSAIC-F, AICoFe and Watch-DMLT, the SOPHIAS multimodal dataset was subsequently collected [30]. SOPHIAS comprises approximately 12 hours of real classroom recordings from 50 oral presentations delivered by 65 undergraduate and master's students, integrating synchronized multimodal streams including video, audio, eye-tracking, smartwatch-based physiological signals, interaction logs, presentation slides, contextual annotations, and rubric-based evaluations from teachers, peers, and self-assessments (Figure 3).

At this stage, feedback generation in face-to-face learning contexts combines human-based evaluations with multimodal, data-driven support. More specifically, the current system relies on peer and teacher assessments [31] as the main pedagogically grounded input for feedback generation, while already incorporating head-pose and body-pose indicators to enrich the interpretation of students' oral presentation performance. The collection of SOPHIAS represents a key step toward the broader operationalization of the MOSAIC-F framework, as it enables the refinement of ML models for behavioral detection and the progressive incorporation of additional biometric and multimodal evidence into the feedback process. The remaining work in this doctoral research will focus on improving the robustness and precision of the current ML models, extending the framework with audio-based features [32] and feedback, and further integrating these multimodal indicators into the existing collaborative and GenAI-enhanced feedback workflows. Finally, the effectiveness of the fully developed MOSAIC-F framework will be evaluated through classroom-based studies, assessing its impact on students' oral presentation skills, engagement, and reflective learning, as well as its perceived usefulness and usability for teachers.

Some papers are currently cited as arXiv preprints because they correspond to manuscripts that are either under review or already accepted and pending publication.

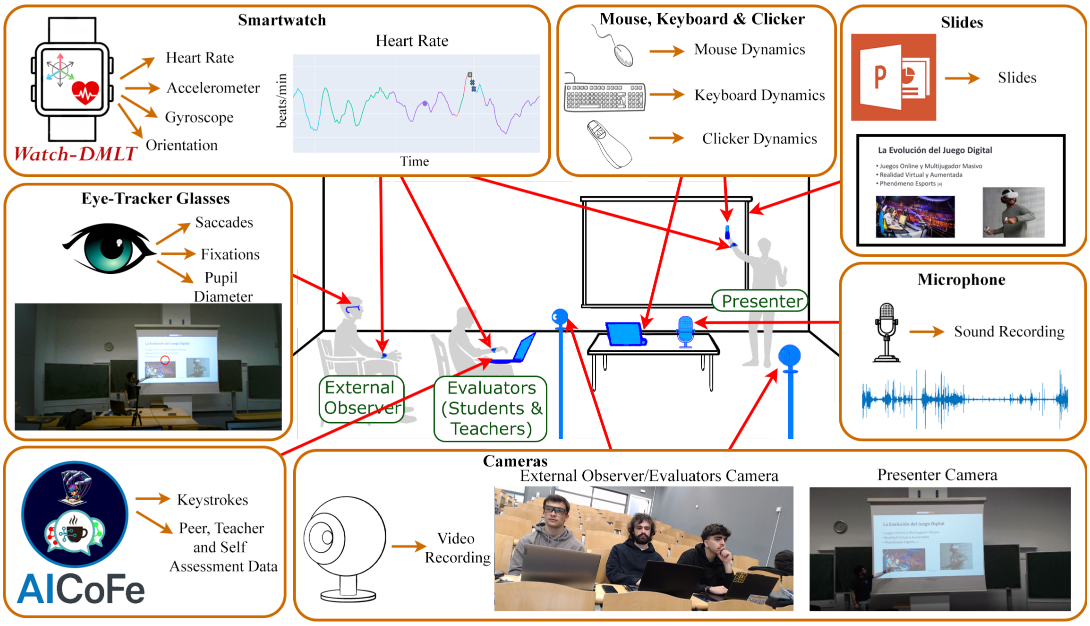

Figure 3: Overview of the SOPHIAS multimodal data collection setup in face-to-face learning contexts.

5.3. Current Limitations and Risks

Several limitations and risks remain for the next stages of the doctoral research. First, the current development of machine learning models still requires rich multimodal data collected with high-precision sensors, such as eye-tracking glasses or EEG devices. These sensors are useful at this stage because they provide detailed signals for training and validating learning indicators. However, they may not be scalable for everyday classroom use. Therefore, a future objective is to study whether some of these indicators can be estimated from lower-cost and less intrusive data sources. For example, gaze-related indicators obtained from eye-tracking could be approximated through screen-based gaze estimation or webcam-based visual attention estimation.

Second, the current classroom validation of MOSAIC-F is still mainly concentrated at Universidad Autónoma de Madrid. Although this provides ecological validity within a real institutional context, it limits the generalizability of the findings. To address this limitation, we are working toward extending the evaluation to Universidad Politécnica de Madrid and to different courses and learning scenarios.

Finally, the framework involves sensitive data, including biometric signals. All data collection procedures require informed consent, anonymization, and approval by the corresponding ethics committees. This is essential from an ethical and legal perspective, but it also creates practical risks for deployment: in some cases, not all students may agree to be recorded or monitored, which can prevent the full MOSAIC-F workflow from being applied to all participants. Current and future deployments therefore consider partial participation scenarios and alternative configurations that preserve the pedagogical value of the framework while respecting students' privacy and consent decisions.

6. Dissertation Status and Long-Term Goals

I am currently a second-year Ph.D. candidate in the field of Computer Science. My research is supervised by Dr. Ruth Cobos at the Universidad Autónoma de Madrid.

At this stage of my Ph.D., I have established the theoretical and empirical foundations of my research through a systematic review, the design and release of large-scale multimodal datasets, and the development of analytic systems and AI-based feedback tools for both online and face-to-face learning contexts. The remaining work in my dissertation focuses on fully integrating multimodal and biometric data into existing feedback frameworks, developing ML models to extract learning indicators, and evaluating the effectiveness of these approaches through classroom-based studies.

I plan to complete my doctoral studies within the next two years, with the goal of defending my dissertation by the end of 2027. Following graduation, my long-term career goal is to pursue an academic position where I can continue conducting interdisciplinary research at the intersection of Multimodal Learning Analytics, Biometrics and Behavior and Machine Learning.

Participation in the LASI'26 Doctoral Consortium represents a valuable opportunity to receive feedback on how to advance the face-to-face case study toward the full realization of the MOSAIC-F framework. In particular, I seek guidance on methodological and design decisions related to how to rigorously evaluate the effectiveness of the resulting hybrid feedback framework in real classroom settings, including the assessment of feedback quality and pedagogical value.

Acknowledgments

Support by: Cátedra ENIA UAM-VERIDAS en IA Responsable (NextGenerationEU PRTR TSI-100927-2023-2), M2RAI (PID2024-160053OB-I00, MICIU/FEDER) and SNOLA (RED2022-134284-T). Alvaro Becerra is funded by a predoctoral contract (FPI) from the Comunidad de Madrid (PIPF-2024/COM-34288).

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

References

[1] C. Lang, G. Siemens, A. Wise, D. Gasevic, Handbook of learning analytics, SOLAR, Society for Learning Analytics and Research New York, 2017.

[2] M. Giannakos, D. Spikol, D. Di Mitri, K. Sharma, X. Ochoa, R. Hammad, The multimodal learning analytics handbook, Springer, 2022.

[3] A. Becerra, R. Cobos, C. Lang, Enhancing online learning by integrating biosensors and multimodal learning analytics for detecting and predicting student behaviour: a review, Behaviour & Information Technology (2025) 1–26.

[4] J. Hattie, H. Timperley, The power of feedback, Review of educational research 77 (2007) 81–112.

[5] N. Falchikov, Peer feedback marking: Developing peer assessment, Innovations in Education and training International 32 (1995) 175–187.

[6] A. Martínez Monés, I. Dimitriadis Damoulis, E. Acquila Natale, A. Álvarez, M. Caeiro Rodríguez, R. Cobos Pérez, M. Á. Conde González, F. J. García Peñalvo, D. Hernández Leo, I. Menchaca Sierra, et al., Achievements and challenges in learning analytics in spain: The view of snola, RIED. Revista Iberoamericana de Educación a Distancia 23 (2020) 187.

[7] Á. Hernández-García, C. Cuenca-Enrique, L. Del-Río-Carazo, S. Iglesias-Pradas, Exploring the relationship between lms interactions and academic performance: a learning cycle approach, Computers in Human Behavior 155 (2024) 108183.

[8] H. Ouhaichi, D. Spikol, B. Vogel, Research trends in multimodal learning analytics: A systematic mapping study, Computers and Education: Artificial Intelligence 4 (2023) 100136.

[9] M. Worsley, P. Blikstein, A multimodal analysis of making, International Journal of Artificial Intelligence in Education 28 (2018) 385–419.

[10] X. Ochoa, C. Lang, G. Siemens, A. Wise, D. Gasevic, A. Merceron, Multimodal learning analytics-rationale, process, examples, and direction, The handbook of learning analytics 2 (2022) 54–65.

[11] K. Sharma, M. Giannakos, Multimodal data capabilities for learning: What can multimodal data tell us about learning?, British Journal of Educational Technology 51 (2020) 1450–1484.

[12] K. Sharma, M. Giannakos, P. Dillenbourg, Eye-tracking and artificial intelligence to enhance motivation and learning, Smart Learning Environments 7 (2020) 13.
[13] P. Antonenko, F. Paas, R. Grabner, T. Van Gog, Using electroencephalography to measure cognitive load, Educational psychology review 22 (2010) 425–438.
[14] Z. Zhang, Z. Dong, Y. Shi, T. Price, N. Matsuda, D. Xu, Students' perceptions and preferences of generative artificial intelligence feedback for programming, in: Proceedings of the AAAI Conference on Artificial Intelligence, volume 38, 2024, pp. 23250–23258.
[15] S. S. Lee, R. L. Moore, Harnessing generative ai (genai) for automated feedback in higher education: A systematic review., Online Learning 28 (2024) 82–106.
[16] M. Giannakos, R. Azevedo, P. Brusilovsky, M. Cukurova, Y. Dimitriadis, D. Hernandez-Leo, S. Järvelä, M. Mavrikis, B. Rienties, The promise and challenges of generative ai in education, Behaviour & Information Technology 44 (2025) 2518–2544.
[17] M. Á. Conde, R. García-Pascual, F. J. Rodríguez-Sedano, J.-Á. Román-Gallego, Expanding the lens: multi-institutional evidence on student use of chatgpt in higher education, Universal Access in the Information Society 25 (2026) 48.
[18] X. Ochoa, H. Zhao, Openopaf: An open-source multimodal system for automated feedback for oral presentations., Journal of Learning Analytics 11 (2024) 224–248.
[19] DIPF | Leibniz Institute for Research and Information in Education, HyTea – Model for Hybrid Teaching, https://www.dipf.de/en/research/projects/model-for-hybrid-teaching, 2025.
[20] K. Peffers, T. Tuunanen, M. A. Rothenberger, S. Chatterjee, A design science research methodology for information systems research, Journal of management information systems 24 (2007) 45–77.
[21] R. Daza, A. Becerra, R. Cobos, J. Fierrez, A. Morales, A multimodal dataset for understanding the impact of mobile phones on remote online virtual education, Scientific Data 12 (2025) 1332.
[22] A. Becerra, R. Daza, R. Cobos, A. Morales, M. Cukurova, J. Fierrez, M2lads: A system for generating multimodal learning analytics dashboards, in: 2023 IEEE 47th Annual Computers, Software, and Applications Conference (COMPSAC), IEEE, 2023, pp. 1564–1569.
[23] A. Becerra, R. Daza, R. Cobos, A. Morales, J. Fierrez, M2lads demo: A system for generating multimodal learning analytics dashboards, arXiv preprint arXiv:2502.15363 (2025).
[24] A. Becerra, R. Cobos, Integrating eye-tracking and artificial intelligence for human-centered visual attention analytics in online learning, IE Comunicaciones: Revista Iberoamericana de Informática Educativa (2025) 22–33.
[25] A. Becerra, R. Daza, R. Cobos, A. Morales, M. Cukurova, J. Fierrez, Ai-based multimodal biometrics for detecting smartphone distractions: Application to online learning, in: European Conference on Technology Enhanced Learning, Springer, 2025, pp. 31–46.
[26] A. Becerra, Z. Mohseni, J. Sanz, R. Cobos, A generative ai-based personalized guidance tool for enhancing the feedback to mooc learners, in: 2024 IEEE Global Engineering Education Conference (EDUCON), IEEE, 2024, pp. 1–8.
[27] A. Becerra, D. Andres, P. Villegas, R. Daza, R. Cobos, MOSAIC-F: A framework for enhancing students' oral presentation skills through personalized feedback, in: Proc. Learning Analytics Summer Institute Spain, CEUR WS, volume 4148, 2025.
[28] A. Becerra, R. Cobos, Enhancing the professional development of engineering students through an ai-based collaborative feedback system, in: 2025 IEEE Global Engineering Education Conference (EDUCON), IEEE, 2025, pp. 1–9.
[29] A. Becerra, P. Villegas, R. Cobos, Real-time multimodal data collection using smartwatches and its visualization in education, arXiv preprint arXiv:2512.02651 (2025).
[30] A. Becerra, R. Cobos, R. Daza, A multimodal dataset of student oral presentations with sensors and evaluation data, arXiv preprint arXiv:2601.07576 (2026).
[31] A. Becerra, R. Cobos, Leveraging peer, self, and teacher assessments for generative ai-enhanced feedback, in: 2026 IEEE Global Engineering Education Conference (EDUCON), IEEE, 2026, pp. 1–9.
[32] F. Pardo, Ó. Cánovas, F. J. G. Clemente, Audio features in education: A systematic review of computational applications and research gaps, Applied Sciences 15 (2025) 6911.