Creation Of Additional Multimodal Data Reports Within Dashboards For Teachers Based On Piloting Results (WP5)

“Improving the quality and sustainability of learning using early intervention methods based on learning analytics”

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Abstract	We developed multimodal data reports within dashboards for teachers based on piloting results – based on the collected data, additional learning analytics methodologies will be applied on the data, in order to identify student profiles. These additional reporting will be added to the dashboard, and will be more suitable to be used by wider group of teachers, other than the ones who were participating in the piloting
Keywords	Learning Analytics, Interventions, Student Learning, Teacher Support, Dashboards

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1. Multimodal Data and Learning Analytics in Educational Contexts

Learning processes are complex, dynamic, and inherently multidimensional, involving cognitive, behavioral, emotional, and social components that unfold over time and across learning contexts. Despite this complexity, much of the early work in learning analytics and educational data mining relied predominantly on digital interaction traces such as clickstreams, log files, and submission records (Long & Siemens, 2011; Pardo et al., 2017). While these data sources have enabled scalable analyses of learner behavior, they offer only a partial view of learning processes and risk privileging what is easily measurable over what is pedagogically meaningful.

This limitation has been discussed in the literature as the streetlight effect in learning analytics, referring to the tendency to infer learning constructs from readily available traces rather than from theoretically grounded indicators of learning (Ochoa et al., 2022; Ochoa & Worsley, 2016). Scholars argue that constructs such as engagement, self-regulated learning, collaboration, or affect cannot be robustly estimated from single data streams alone, but require the triangulation of multiple sources of evidence that capture different manifestations of learning activity (Blikstein et al., 2014).

In response to these challenges, research in learning technologies has increasingly emphasized the role of multimodal data for understanding learning more holistically. Multimodal data refers to the integration of heterogeneous data sources that capture complementary aspects of learners’ activity and experience, including self-reports, interaction traces, verbal and non-verbal communication, physiological signals, and collaborative behaviors (Giannakos et al., 2019; Sharma & Giannakos, 2020). Rather than increasing data volume for its own sake, multimodal approaches aim to enhance interpretive validity by combining evidence across modalities that are theoretically linked to underlying learning constructs.

A growing body of empirical work demonstrates that multimodal data can reveal learning phenomena that remain largely invisible when relying solely on behavioral logs. Studies combining behavioral traces with physiological, visual, or self-reported data have shown improved interpretations of learner engagement, affective states, cognitive load, and collaborative processes (Calvo & Mello, 2010; Grawemeyer et al., 2017; Hutt et al., 2019). These studies highlight that learning constructs are not directly observable but emerge through patterns across modalities, reinforcing the need for theoretically informed integration rather than isolated signal detection (Mangaroska & Giannakos, 2019).

Building on these developments, the field of Multimodal Learning Analytics (MmLA) has emerged as a focused research area within learning analytics. MmLA builds on earlier traditions of multimodal interaction analysis (Norris, 2020) and was formally introduced to the learning analytics community by Blikstein (2013). It is commonly defined as a set of techniques for collecting, synchronizing, and analyzing multiple high-frequency data sources in order to study learning processes in ecologically valid, real-world learning environments (Blikstein & Worsley, 2016; Ochoa & Dominguez, 2020). Central to MmLA is the mapping of theoretical learning constructs to observable multimodal traces, followed by the fusion and interpretation of these traces to support both research insights and pedagogical decision-making (Ochoa et al., 2022).

At the same time, the literature cautions against equating multimodality with technological sophistication. While some MmLA studies rely on advanced sensing infrastructures and automated analysis pipelines, others demonstrate that meaningful multimodal insights can be obtained from more accessible and scalable data sources, provided that these are grounded in learning theory and aligned with pedagogical goals (Cukurova et al., 2020; Sharma et al., 2019). Surveys, communication tools, and game-based learning environments can all serve as valuable components of multimodal data ecosystems when their contributions are clearly articulated and pedagogically interpreted.

Within this broader research landscape, the ISILA project adopts a pragmatic and teacher-centered approach to multimodal data. Rather than aiming for exhaustive sensing or fully automated interpretation, ISILA focuses on combining multiple data sources that are feasible within authentic course settings and meaningful for instructors' reflective practice. By integrating self-reported data, interaction traces from digital communication tools, and game-based learning data, the project aligns with calls in the literature to democratize multimodal learning analytics and support human decision-making rather than replace it (Cukurova et al., 2019; Giannakos et al., 2019).

The following sections describe how multimodal data were operationalized within the ISILA pilots, how they informed intervention planning, and how additional learning analytics methods were applied to support the identification of learner profiles and the development of teacher-oriented reporting that can be reused across diverse higher education contexts.

2. Mutimodal Data in the ISILA Project

The ISILA project adopts a flexible and extensible data collection architecture designed to support the integration of heterogeneous learning data sources into a unified learning analytics ecosystem. This architecture enables the collection of multimodal data across different learning environments and tools, while maintaining interoperability and reusability through the use of the Experience API (xAPI) standard and a centralized Learning Record Store (LRS) (ADL, 2015; Kevan & Ryan, 2016; Rustici-Software-LLC).

Within ISILA, three main models of data collection were implemented to support the aggregation of learning traces from diverse sources and modalities. Together, these models allow the project to move beyond a sole reliance on Learning Management System (LMS) interaction data and to incorporate additional sources that capture complementary aspects of learners’ activity and experience.

First, data generated through Learning Management Systems (LMSs) are collected and delivered to a centralized Learning Record Store (LRS) using the xAPI standard. This model covers the typical interaction data produced during students’ engagement with learning platforms, such as access to resources, participation in activities, and submission of assignments. LMS-generated data constitutes the backbone of the ISILA data ecosystem and provides a baseline representation of learners’ behavioral engagement within formal learning environments.

Second, ISILA supports the integration of data from external tools and platforms that are not natively part of the LMS, such as communication tools, video platforms, or interactions with large language models. In these cases, ad-hoc interfaces were developed to capture relevant learning events and translate them into xAPI statements that can be sent to the learning repository. This approach enables the inclusion of learning-relevant interactions that occur outside traditional LMS boundaries, while preserving a common data representation and analysis workflow.

Third, the architecture allows for the submission of data to the LRS generated by any additional tool through the use of the csv2xAPI conversion mechanism. This model supports the integration of tabular data sources—such as survey responses, observational data, or logs exported from external applications—by transforming them into xAPI-compatible records. As a result, data that was not originally produced in an event-based or xAPI-compliant format can still be incorporated into the ISILA analytics infrastructure in a standardized and interoperable way.

A detailed description of this data collection architecture, including the core tools and data collection mechanisms, is provided in Report 2.2 ("An online ecosystem for the collection and analysis of learner data"). Figure 1 summarizes the overall architecture and illustrates how learning data from multiple sources are aggregated into a shared LRS to support subsequent analysis and reporting.

This multimodal data collection approach provides the technical foundation for the analyses and reporting presented in the following sections. In particular, it enables the integration of self-reported data, interaction traces from communication and collaboration tools, and gameplay data from educational games, which are discussed in more detail through concrete examples in the subsequent subsections.

The following subsections describe three tools employed in the ISILA pilots that generated multimodal learning data outside traditional LMS environments, highlighting how these sources extended the analytical scope of the ISILA data ecosystem.

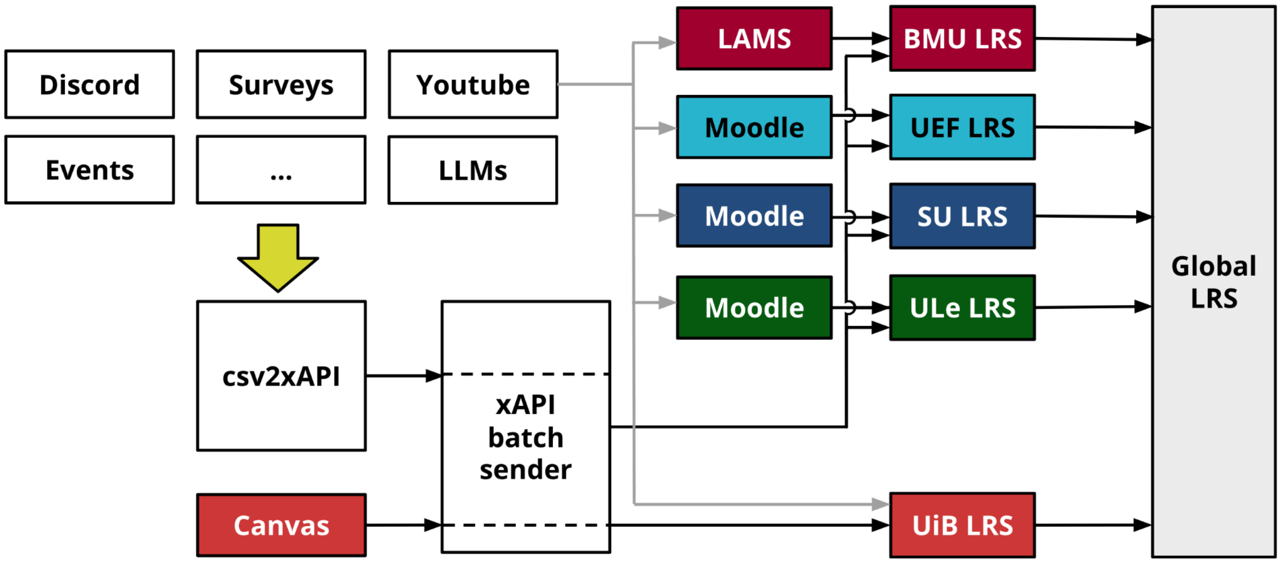

Figure 1. ISILA infrastructure

2.1. Surveys

During the ISILA project, several types of surveys were implemented as part of the multimodal data collection strategy. Among these, the Self-Regulated Learning (SRL) survey (Saqr et al., 2024; Saqr & López-Pernas, 2024) was particularly relevant, as it captured students' self-reported perceptions related to motivation, emotional states, and learning strategies—dimensions that are not directly observable through platform interaction data alone. In this sense, survey-based data provided a complementary modality that enriched the interpretation of behavioral learning traces.

From a technical perspective, the implementation of the SRL survey followed a common interoperability principle across partners, while accommodating differences in local learning platforms. For most partner institutions, the survey was implemented directly within Moodle, and responses were automatically transmitted to the Learning Record Store (LRS) using the xAPI plugin integrated into the platform. This enabled the integration of survey data with other LMS-generated learning traces within a unified analytics infrastructure.

However, this integration approach was not uniformly available across all partners. In particular, BMU used LAMS as its learning platform, for which no native xAPI plugin was available. To address this limitation, a dedicated development originally carried out within the ILEDA project (Conde et al., 2023) was adapted and reused during ISILA. This solution allowed survey responses collected in LAMS to be converted into xAPI statements and delivered to the same LRS used by other partners, ensuring interoperability across heterogeneous learning environments.

Once survey data was available in the LRS, it could be processed and visualized using the same reporting mechanisms applied to other data sources, regardless of the originating platform. From a dashboard perspective, this made it possible to present SRL indicators alongside behavioral metrics such as activity frequency, temporal engagement patterns, or assignment submissions, supporting a more nuanced analytical view of student engagement. Samples of these visualizations can be seen in Figure 2.

Across the ISILA pilots, SRL survey data contributed to the identification of recurring patterns in students’ learning-related perceptions and behaviors. In combination with interaction data, these patterns informed the characterization of learner profiles, which are discussed in later sections of this report. Importantly, at this stage, surveys functioned primarily as an additional analytical lens rather than as a direct trigger for intervention.

Overall, the use of surveys within ISILA illustrates how self-reported data can be integrated as a scalable and interoperable component of multimodal learning analytics. By capturing dimensions of learning that are not accessible through interaction logs alone, surveys expand the analytical scope of dashboards and provide a richer basis for interpretation, while leaving pedagogical decision-making and intervention strategies to be addressed in subsequent sections.

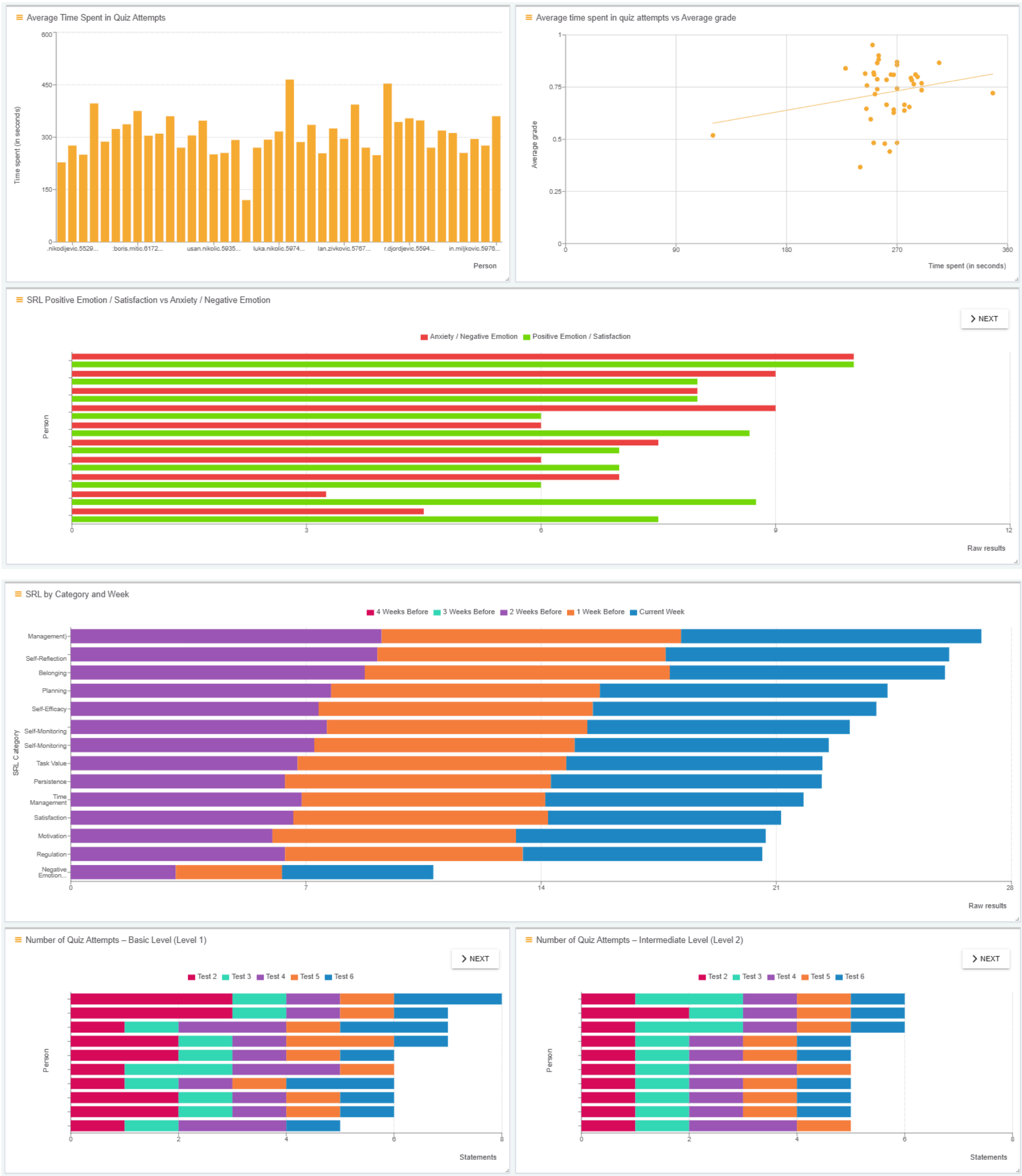

Figure 2. Dashboard overview for a specific course in a week.

2.2. Discord

Another relevant source of multimodal data explored in the ISILA project is the use of Discord as a collaborative workspace for teamwork activities. Originally developed to support communication within online gaming communities, Discord is a freeware application based on Voice over Internet Protocol (VoIP) that facilitates text, image, audio, and video-based interactions among users. Over time, the platform has evolved into a widely adopted communication environment and is now commonly used across different operating systems and web browsers to support sustained online interaction (Fonseca Cacho, 2020). Its flexibility and low entry barrier have contributed to its increasing adoption beyond gaming contexts, including informal and educational collaborative settings (Kumar, 2026).

Within ISILA, Discord was employed as the main communication environment for group-based work, enabling students to engage in both synchronous and asynchronous discussions while coordinating tasks and decisions related to teamwork activities. As with other external collaboration tools, Discord does not natively provide learning analytics data aligned with educational interoperability standards.

To enable the collection of learning-relevant interaction data, a custom Discord bot was developed and deployed during the pilots. The bot automatically captured messages exchanged by students within dedicated group channels and transformed these interactions into structured xAPI statements, which were subsequently sent to a centralized Learning Record Store (Learning Locker). This approach allowed collaborative activity occurring outside the Learning Management System to be integrated into the same analytics infrastructure used for other ISILA data sources.

This implementation was carried out in the course Computer Animation, involving 69 students organised into 18 groups, with an average of four students per group. Group work in this course followed the CTMTC (Comprehensive Training Model of the Teamwork Competence) (Fidalgo-Blanco et al., 2015; Lerís et al., 2014) methodology, which emphasizes structured collaboration and continuous monitoring of group processes. Within this framework, several group-level indicators (such as participation balance, frequency of interaction, and temporal patterns of contribution) are considered relevant for understanding the dynamics and effectiveness of teamwork.

The Discord-based data collection was therefore explicitly aligned with the CTMTC methodology, as it enabled the capture of interaction traces that could be aggregated and analysed at the group level. Rather than focusing on individual message content, the collected data supported the computation of statistical indicators reflecting how groups communicated, coordinated, and sustained collaboration over time. This provided an additional multimodal perspective on teamwork processes that complemented individual-level data collected from other sources.

Figure 3 illustrates the architecture of the Discord-based data collection approach, showing how student interactions within group channels are captured by the bot, transformed into xAPI statements, and stored in Learning Locker as part of the ISILA analytics ecosystem.

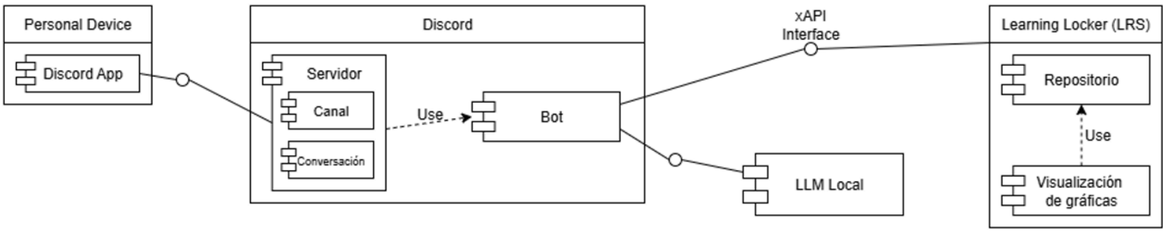

Figure 3. Dashboard overview for a specific course in a week.

Once stored in the Learning Record Store, Discord-derived data could be accessed using the same reporting mechanisms applied to other ISILA data sources. From a dashboard perspective, this enabled the visualization of group-level collaboration indicators alongside other learning analytics data, supporting a unified view of student activity across tools and contexts.

Figure 4 and 5 presents examples of dashboard views based on Discord interaction data, illustrating how collaborative activity is represented within Learning Locker.

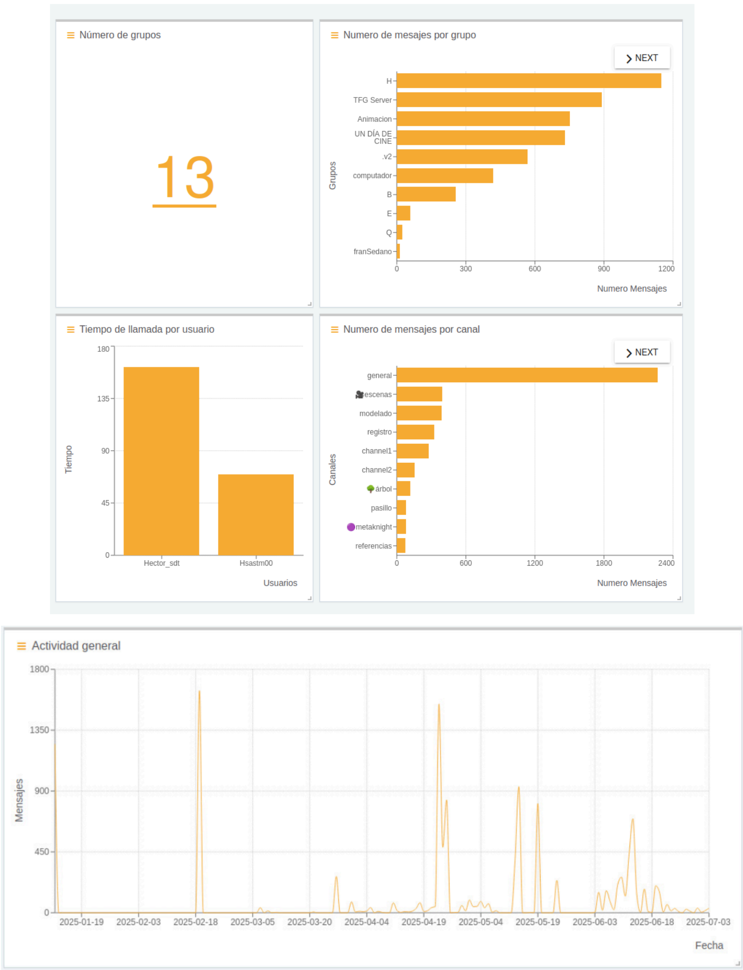

Figure 4. Dashboard visualizations with information about groups interactions

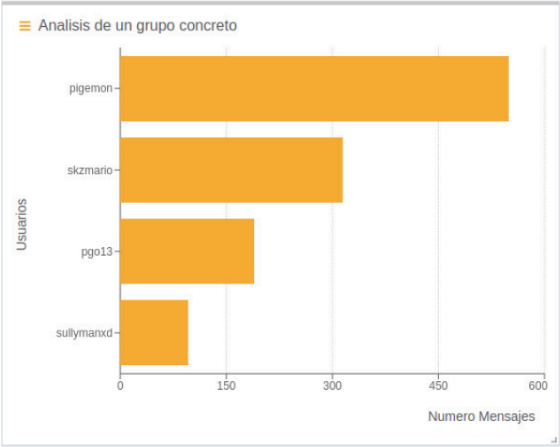

Figure 4. Dashboard visualizations with specific information about the interaction in a group

Overall, the integration of Discord data within ISILA demonstrates how informal communication platforms can be transformed into meaningful sources of multimodal learning data when combined with a clear pedagogical framework and an interoperable analytics infrastructure. In the following sections, these collaborative data sources are further connected to multimodal learning analytics methods and intervention strategies.

2.3. Educational escape Rooms

Educational escape rooms have emerged as a form of game-based and active learning that combines problem-solving, collaboration, and narrative-driven challenges. They are typically designed as team-based activities in which learners must solve a sequence of interconnected puzzles under time constraints in order to achieve a predefined goal (Nicholson, 2015). When adapted to educational contexts, escape rooms embed disciplinary content into the challenges, requiring students to actively apply knowledge rather than passively consume information (Fotaris & Mastoras, 2019).

From a pedagogical perspective, educational escape rooms are aligned with constructivist and social constructivist approaches, as learning emerges through active engagement with tasks and peer interaction (Kolb, 2014; Vygotsky, 1978). Empirical studies across different disciplines suggest that escape rooms can foster high levels of engagement and support the development of transversal skills such as collaboration, communication, and critical thinking (McFadden & Porter, 2018; Pan et al., 2017; Warmelink et al., 2017; Williams, 2018; Willis et al., 2024; Wu et al., 2018).

In recent years, virtual educational escape rooms have gained prominence as digital adaptations of physical escape room experiences. Virtual formats enable remote participation and integration with online learning environments, while preserving key characteristics such as challenge progression and time pressure (Fotaris & Mastoras, 2019). From a learning analytics perspective, these environments are particularly relevant because they generate rich gameplay data, including interaction sequences, task completion patterns, and temporal indicators of engagement (López-Pernas et al., 2019).

Within the ISILA project, virtual educational escape rooms are considered a promising source of multimodal learning data that captures task-oriented and problem-solving behaviors in highly engaging scenarios. The technical approach for integrating escape room activities into the ISILA consists of downloading the event log data from the Escapp platform (developed in the IGLUE Erasmus+ project: https://iglue.dit.upm.es), which is a step that the admin of the platform or the teacher that created the escape room need to perform. Subsequently, the log is uploaded to the web application csv2xAPI, developed during the ISILA project precisely to incorporate data from other sources. The event log downloaded from Escapp contains the escape room team, user id, actions and objects (solve puzzle, request hint), and timestamp. These fields need to be mapped to the corresponding xAPI elements in the csv2xAPI interface and sent to the LRS.

The data from the educational escape room gameplay can be used to inform the improvement of the escape room design (see Fig. 5). For instance, we can see in which game tasks students were struggling to complete to identify misconceptions. We can also analyze which hints they have requested to ascertain in which moments of the game they required extra support. These can shed light on problems in the game design, such as a lack of cognitive engagement with the game, but also on conceptual gaps in students’ knowledge or skills required to complete the game.

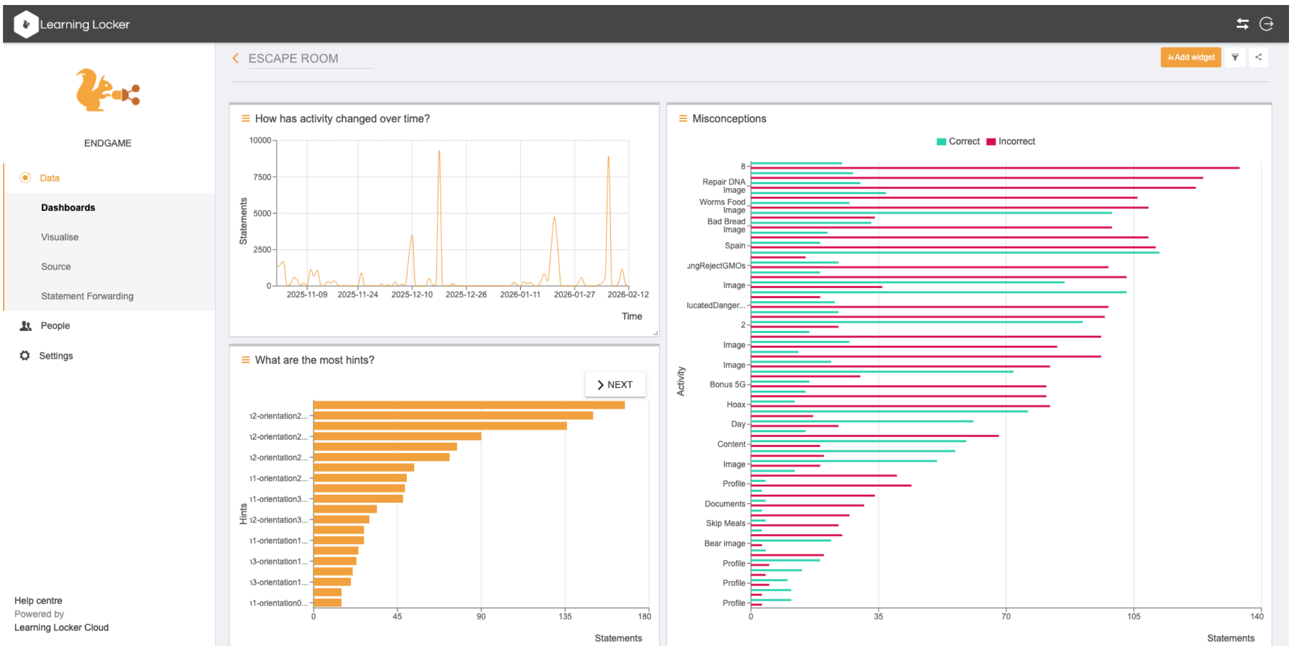

Figure 5. Dashboard visualizations with information about the escape room gameplay

3. Interventions based on Multimodal Data

The multimodal data sources described in the previous section provided the basis for a range of analytics-informed interventions implemented during the ISILA pilots. Rather than relying on single data streams, these interventions were informed by the combined interpretation of self-reported data, interaction traces from collaborative tools, and gameplay data. The following subsections describe how multimodal data supported different types of pedagogical interventions, focusing on survey-informed interventions, interventions supporting teamwork and collaboration, and the potential extension of this approach to other game-based learning environments.

3.1 Interventions informed by survey-based data

Within the ISILA project, survey-based data (particularly data derived from the SRL surveys) played a key role in informing pedagogical interventions grounded in a multimodal interpretation of student engagement. By complementing behavioral traces with self-reported indicators related to motivation, emotional state, and learning strategies, surveys enabled instructors to move beyond surface-level interpretations of activity data and to adopt more context-sensitive intervention approaches.

Survey-informed interventions were primarily designed to support interpretation and decision-making, rather than to trigger automated actions. Instructors used survey results to better understand the reasons behind observed engagement patterns, such as delayed participation, irregular activity, or inconsistent performance. For example, similar behavioral signals (such as low platform activity) were interpreted differently depending on whether survey responses indicated high self-regulation, elevated anxiety, or low perceived control over learning tasks.

Based on this multimodal interpretation, several types of interventions were enabled. These included targeted communication aimed at emotional reassurance, clarification of expectations for students reporting high anxiety, and academic scaffolding for students who demonstrated strong effort and self-regulation but struggled with task performance. In other cases, survey data helped instructors identify students who were disengaged due to external or contextual factors, supporting decisions related to flexibility in deadlines or learning pathways.

Importantly, survey-based interventions were not limited to early detection scenarios. The availability of SRL indicators at multiple points during the semester allowed instructors to revisit earlier interpretations and to adapt interventions as learning conditions evolved. This iterative use of survey data supported a more dynamic intervention strategy aligned with reflective teaching practices, rather than one-off responses to static indicators.

From a dashboard perspective, the integration of survey data with behavioral metrics enabled instructors to access interpretable visual representations that supported these intervention decisions. Rather than presenting survey results in isolation, dashboards combined SRL indicators with activity and performance data, providing a unified analytical view that could be readily reused by instructors across different courses and institutional contexts. An example of such a dashboard view, combining survey-based indicators with behavioral data, is shown in Figure 6.

Overall, interventions informed by survey-based data within ISILA illustrate how self-reported information can function as a central component of multimodal learning analytics. By enriching the interpretation of behavioral data, surveys supported differentiated, proportionate, and pedagogically grounded interventions, while remaining scalable and transferable to a wider group of teachers beyond the original piloting settings.

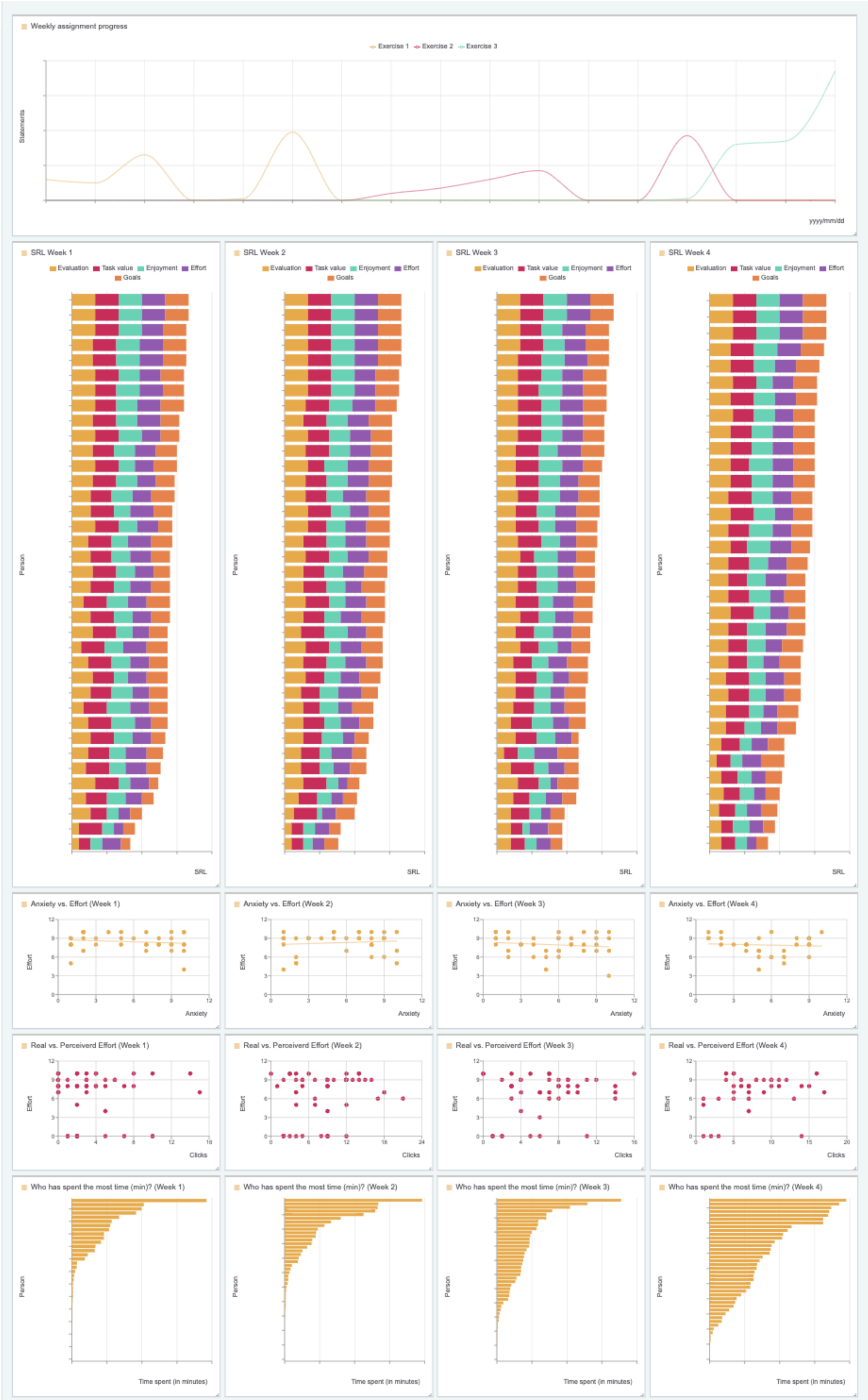

Figure 6. *Example of a dashboard view integrating survey-based indicators (SRL) with behavioral activity data to support analytics-informed pedagogical interventions.*

3.2 Interventions supporting teamwork and collaboration

Within the ISILA project, the CTMTC-informed approach to teamwork monitoring was applied in the course *Computer Animation*, building on the integration of Discord-based interaction data into the learning analytics infrastructure. As described in the previous section, students carried out teamwork discussions through Discord channels structured by task, and their interactions were captured through a dedicated bot and stored in the Learning Record Store using xAPI.

Interventions supporting teamwork were informed by a two-level analytical perspective: a global view of group activity across the course, and a more detailed examination of interaction patterns within individual groups. At the global level, instructors analysed participation indicators aggregated at group level in order to identify teams whose level of interaction deviated significantly from the course average. Groups whose participation was approximately 20% below the mean were flagged for further attention.

Based on this global analysis, instructors contacted the identified groups and organised follow-up meetings to better understand the underlying causes of reduced interaction. In many cases, low participation was associated with external workload saturation, a tendency to postpone collaborative work until the final stages of the assignment, or organisational difficulties rather than interpersonal conflict within the team. In total, six groups required this type of group-level feedback and support.

At a more fine-grained level, instructors examined individual interaction patterns within each group to identify students whose level of participation deviated substantially from their peers. When such cases were detected, instructors engaged in targeted communication with the group and, when appropriate, with the individual student concerned. These conversations focused on clarifying the importance of making collaborative work visible through the designated communication channels, both for effective coordination and for formative assessment purposes. Overall, eight groups required this type of more specific, individual-focused feedback.

Analysis of these cases indicated that limited individual participation was primarily associated with students who had effectively disengaged from the course or with students who demonstrated low interactive proactivity despite remaining enrolled. Importantly, the combination of group-level and individual-level views enabled instructors to distinguish between structural collaboration issues and isolated cases of disengagement, supporting proportionate and context-sensitive interventions.

These interventions illustrate how multimodal data derived from collaborative platforms can support reflective teaching practices in teamwork-intensive courses. Rather than relying on automated alerts, instructors used dashboard-based summaries of interaction data to guide dialogue with students and groups, reinforcing coordination practices and supporting more effective collaboration. The experience gained in ISILA demonstrates how this approach can be transferred to other courses that rely on external communication tools for group work.

3.3 Extending multimodal interventions to game-based learning environments

The multimodal intervention approaches described in the previous subsections illustrate how different data sources can inform pedagogical decision-making when interpreted in a contextualized and reflective manner. While surveys and collaborative communication tools played a central role during the ISILA pilots, the underlying intervention logic is not limited to these specific data sources.

Game-based learning environments, such as **virtual educational escape rooms**, represent a particularly promising context for extending multimodal interventions (López-Pernas et al., 2024a). These environments are designed around problem-solving, collaboration, and progressive challenge completion, generating rich game-based data that can complement self-reported and interaction-based indicators. Visualizing students' trace log data while participating in a virtual escape room makes it possible for teachers to interpret learning as a process unfolding over time rather than as a final outcome. When students' actions are represented chronologically—showing how long they spend on each puzzle, when they request support, and how often they attempt solutions—teachers gain insight into patterns of engagement that would remain invisible in aggregate statistics.

For example, dashboards can help identify teams or individuals who are progressing more slowly than others. When timelines reveal that a group has spent substantially more time on a specific challenge, instructors can intervene early with targeted guidance. This allows support to be timely rather than reactive, reducing frustration and preventing disengagement.

Dashboards can also highlight trial-and-error behavior. If repeated failed attempts cluster within a short time frame, this may indicate guessing rather than reflective problem solving. Instructors can then prompt students to pause, reconsider their strategy, or engage in structured discussion. Such information helps differentiate between productive struggle and inefficient effort.

Dashboards can further support monitoring of help-seeking patterns. Visualizing when and how often hints are requested enables educators to detect both underuse and overreliance on support mechanisms. This can inform adaptive scaffolding, such as limiting excessive hint requests, encouraging peer discussion before external help, or refining the design of hints that appear ineffective.

Periods of inactivity are another meaningful indicator. When no actions are logged for extended intervals, teachers can assess whether learners are disengaged, experiencing confusion, or collaborating offline. Prompt check-ins during these moments can re-establish focus and clarify expectations.

Beyond real-time interventions, dashboards support reflective teaching. After the activity, instructors can analyze which tasks consistently required more time, generated more failed attempts, or triggered frequent hint requests. Such insights can inform redesign decisions, adjustments to difficulty levels, or improvements in instructions and materials. Unusually rapid task completion may also prompt a review of task design or integrity safeguards.

Overall, dashboards in game learning environments enable educators to connect behavioral traces with pedagogical action. When interpreted thoughtfully and combined with contextual knowledge of learners, these visualizations support more responsive, personalized, and evidence-informed teaching decisions.

Importantly, the intervention principles applied to surveys and collaborative tools can be transferred to escape room–based learning scenarios. At an aggregate level, activity data can support the identification of learners or groups whose engagement deviates from expected patterns. At a more detailed level, fine-grained interaction and progression data can inform targeted support related to task understanding, coordination, or pacing.

By focusing on transferable indicators and dashboard-based summaries rather than tool-specific implementations, instructors can apply similar multimodal intervention strategies across diverse learning environments. This flexibility supports the adoption of analytics-informed interventions by a wider group of teachers beyond the original piloting settings.

4. Application of other Learning Analytics Methods to the data

Beyond the descriptive and dashboard-based analyses presented in the previous sections, the multimodal data collected within ISILA also enables the application of additional learning analytics methods. These methods can support deeper pattern identification, learner profiling, and exploratory analysis, while remaining aligned with the project’s emphasis on pedagogically grounded interpretation rather than automated decision-making. This section outlines examples of learning analytics approaches that can be applied to different ISILA data sources.

4.1 Learning analytics methods applied to survey-based data

Survey-based data, particularly data derived from SRL instruments, is well-suited for the application of a range of learning analytics methods aimed at identifying patterns across learners and over time. Given the structured and standardized nature of survey responses, these data can be analysed using relatively lightweight analytical techniques that remain interpretable for instructors.

One common approach involves the use of descriptive and comparative analyses to examine distributions of SRL indicators across cohorts, course editions, or time points. Such analyses can help instructors identify shifts in motivation, anxiety, or perceived workload during the semester, supporting reflective interpretation of engagement trends when combined with behavioral data.

In addition, clustering techniques can be applied to survey responses to identify recurring learner profiles based on combinations of SRL indicators. For example, unsupervised clustering methods can group students according to patterns of self-regulation, emotional state, and effort, providing an empirical basis for the learner profiles discussed in earlier sections. Importantly, these profiles should be interpreted as dynamic and contextual, rather than as fixed student categories.

Longitudinal analysis of repeated survey measures also enables the exploration of temporal trajectories in students’ self-reported learning experiences. Changes in SRL indicators over time can be examined in relation to key course events, assessment points, or observed changes in behavioral engagement, supporting a richer understanding of how learning conditions evolve during the semester.

Overall, the application of learning analytics methods to survey data within ISILA illustrates how structured self-reported information can be leveraged beyond static reporting, while preserving transparency and interpretability for instructors.

4.2 Learning analytics methods applied to collaborative interaction data

Collaborative interaction data collected through communication platforms such as Discord enables the application of a wide range of learning analytics methods that go beyond basic activity counts. When student discussions are captured as structured interaction traces, these data can support deeper analyses of affective, social, and behavioral dimensions of teamwork.

One potential line of analysis involves sentiment analysis applied to the textual content of students' messages. By examining linguistic features and emotional valence in written communication, sentiment analysis can provide insights into students' emotional states during collaborative work, such as frustration, confidence, or disengagement. From an intervention perspective, persistent negative sentiment at group level may prompt instructors to initiate supportive communication, clarify task requirements, or adjust workload expectations. At an individual level, changes in sentiment over time can inform timely check-ins with students who may be experiencing stress or disengagement.

In addition to affective analysis, discourse analysis techniques can be applied to examine how students communicate during teamwork activities. Interaction patterns and linguistic features can be analyzed to identify behaviors associated with effective teamwork, such as coordination, negotiation, explanation, or shared problem-solving. These analyses can support formative interventions aimed at reinforcing desired collaborative practices, for example by providing targeted feedback to groups that show limited task-oriented discussion or by modelling effective communication strategies when collaboration remains superficial.

Collaborative interaction data also supports the analysis of non-verbal and paralinguistic cues, such as the use of emoticons and reactions. Patterns in emoticon usage can provide complementary signals related to affective expression, agreement, encouragement, or social presence. From an instructional standpoint, low levels of affective expression or feedback within a group may indicate weak social cohesion, suggesting the need for interventions that promote peer acknowledgement, group reflection, or explicit coordination activities.

Furthermore, social network analysis (SNA) techniques can be applied to interaction data to model the structure of collaboration within and across groups. By representing students as nodes and interactions as edges, SNA can help identify participation imbalances, isolated students, or overly centralized interaction patterns. These insights can inform interventions such as reassigning coordination roles, encouraging more equitable participation, or supporting students who remain peripheral to group communication.

At a more fine-grained level, interaction logs can be analysed to detect proactivity and leadership-related behaviors**.** Indicators such as the frequency of conversation initiation, responsiveness to peers, or sustained facilitation of discussion threads can signal emerging leadership roles. When such behaviors are absent or concentrated in a single group member, instructors may intervene by explicitly rotating roles, prompting shared responsibility, or providing guidance on effective coordination practices.

Together, these learning analytics methods illustrate how collaborative interaction data can be leveraged not only to describe teamwork processes, but also to support actionable, pedagogy-driven interventions. Within the ISILA framework, these techniques are intended to augment instructors’ situational awareness and professional judgment, enabling reflective monitoring and proportionate support rather than automated or prescriptive decision-making.

4.3 Extending learning analytics methods to game learning environments

Previous works have made use of learning analytics methods to gain insights from students’ gameplay data. For example, the work by Alonso-Fernández et al. (2019) showcased how game learning analytics data can be effectively used for different purposes at different stages of the serious games’ lifecycle, and specifically to validate the game design, to validate and simplify deployment of a game, and to simplify assessment of learners with games.

Research on educational escape rooms has increasingly adopted a learning analytics perspective to move beyond simple outcome measures and examine how learners interact with puzzles, collaborate, request help, and progress over time. López-Pernas et al. (2022) conceptualized educational escape rooms as complex learning environments where every interaction—such as solving a puzzle, requesting a hint, or navigating between challenges—can be captured and analyzed. They argued that learning analytics can support multiple purposes: understanding students’ behavioral trajectories, identifying bottlenecks in puzzle design, and examining how collaboration unfolds under time pressure. Rather than focusing solely on final success (escape or not), their approach highlights process data as the main source of insight, aligning escape rooms with broader trends in process-oriented learning analytics.

Further developments extended this perspective to the dynamics of student profiles. For instance, López-Pernas et al. (2024b) used Gaussian mixture models to cluster students' according to the time spent on each puzzle and found four distinct playing profiles derived from students' behavioral traces. Efficient players progressed smoothly through the puzzles with minimal reliance on hints. Supported players also advanced successfully, but did so with systematic use of hints. Relentless players devoted substantial time to requesting hints rather than engaging directly with puzzle-solving, while laggers showed limited progress and insufficient help-seeking, ultimately struggling to complete the activity.

Subsequent work has examined other temporal methods. For example, Santamaría-Urbieta and López-Pernas (2024) applied process mining to investigate hint strategies in escape rooms. Process mining makes it possible to reconstruct common pathways leading to hint usage, revealing whether students request help early as a strategic move or late as a sign of impasse. This type of analysis supports evidence-based refinement of hint systems, allowing designers to balance autonomy and scaffolding while maintaining the motivational aspects of gameplay.

Temporal pathway analysis has also been central in the work by Vartiainen and colleagues (2023), who mapped students' trajectories in a computational thinking escape room. Their study reconstructed ordered sequences of actions to identify common and divergent pathways, offering insight into how learners navigate interconnected puzzles. The authors analyzed transitions between tasks and were able to detect typical routes, detours, and moments of stagnation. This approach provides a nuanced understanding of how computational thinking unfolds in a game-based setting and how different temporal strategies relate to success.

5. CONCLUSIONS

This report has presented the creation of additional multimodal data reports within dashboards for teachers, building on the results of the ISILA piloting activities. By integrating heterogeneous data sources (including self-reported survey data, collaborative interaction data from external platforms, and game-based learning environments) ISILA demonstrates how learning analytics dashboards can support a richer and more contextualized understanding of student learning processes.

A key contribution of this work is the emphasis on multimodal interpretation rather than isolated indicators. Surveys provided insight into motivational and emotional dimensions of learning, collaborative platforms such as Discord enabled the analysis of teamwork processes, and game learning environments offered detailed traces of problem-solving and engagement. When combined within a unified analytics infrastructure based on interoperable standards such as xAPI, these data sources support dashboards that are meaningful, scalable, and adaptable to different educational contexts.

The report has also highlighted how multimodal data can inform pedagogically grounded interventions without relying on automated decision-making. Across different data sources, dashboards were used to support reflective teaching practices, enabling instructors to identify atypical patterns, contextualize student behavior, and engage in proportionate dialogue with learners and groups. This approach reinforces the role of learning analytics as a support for professional judgment rather than as a prescriptive mechanism.

Finally, the ISILA experience illustrates the transferability of multimodal learning analytics beyond the original piloting settings. By focusing on generic indicators, interpretable visualizations, and flexible data integration, the proposed dashboards and analytical approaches can be adopted by a wider group of teachers and applied to diverse courses and learning designs. This positions multimodal learning analytics as a practical and sustainable approach for supporting teaching and learning in complex, digitally mediated educational environments.

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