Refined Guidelines Based on Learner Profiles (WP5)

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

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Abstract	This guidelines refined the ones described in WP3 in order to include the students profiles find out during the pilots. Guidelines have recommendations of intervention methods to other types of courses, other than the ones included in the pilot.
Keywords	Learning Analytics, Interventions, Student Learning, Teacher Support, Dashboards

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1 Introduction

Learning analytics (LA) is a field concerned with collecting and analyzing learning-related data to understand and advance teaching and learning. Through analysis of data from a variety of sources, insights can be derived that can inform teachers about patterns in student behavior that may go unnoticed, especially in large classrooms or in online educational settings. Being able to identify, from digital learning traces, how students interact with course materials and engage in learning activities is particularly relevant in various modalities of distance learning as well as in emergency teaching cases, such as the COVID pandemic, where teachers are not able to interact with their students in person.

While there is no widely accepted definition of LA intervention, it is often defined as “the surrounding frame of activity through which analytic tools, data, and reports are taken up and used” (Wise, 2014). Ideally, insights from learning-related data should compel instructors to act. The ISILA project is focused on LA interventions in higher education settings. More precisely, the focus is on supporting university teachers to derive context-specific and meaningful pedagogical interventions, starting from the visual representation of digital learning traces collected in their courses, and to apply those interventions to (positively) affect learning processes, the learning environments and ultimately, learning outcomes of their students.

Ten courses from five institutions located in different countries were selected for the ISILA project. The courses have different modalities (face-to-face, online, blended) and cover topics from *Computer Architecture* and *Data Management Systems* to *Basic Statistics.* Each course has developed a unique LA dashboard using available learning trace data. Based on the visualizations integrated into the LA dashboards, instructors are able to identify struggling students and challenging aspects of their courses. These insights can compel them to intervene either on an individual or a group level.

The guidelines contained in this report are aimed at assisting teachers in going from defining the motivation/purpose for a data-informed inquiry to visual exploration of learning-related data to selection of appropriate interventions to examining the intervention’s effects. The report is structured as follows: First, we provide an overview of LA interventions for instructors, which includes an overview of distinct kinds of interventions and distinct targets interventions may have, as well as a selection of examples and recommendations from the recent literature on LA interventions. Next, we describe the overall inquiry process to serve as an overall conceptual framework and guideline for interventions, starting with the rationale for designing and applying an intervention to the selection and deployment of intervention. This is followed by an illustrative example of applying the presented framework in practice. The document concludes by integrating reflections and recommendations derived from the ISILA pilot studies into the proposed intervention framework.

Building on this foundation, the present version of the ISILA guidelines has been further refined based on evidence gathered during the project’s piloting phase. The pilots were conducted across multiple institutions, courses, and learning modalities, allowing the guidelines to be validated, contextualized, and extended beyond their initial theoretical formulation. In particular, insights from the pilots informed the refinement of intervention strategies, the integration of learner profiles, and the articulation of tiered and iterative intervention approaches that can be adapted to a wide range of higher education contexts.

2 Learning analytics interventions

2.1 Distinct kinds of learning analytics interventions

LA interventions may take a variety of forms depending on their modality, goals, timing, etc. LA interventions for instructors can be divided into two main groups: LA dashboards and LA-informed interventions (Zhen et al., 2023).

2.1.1 Learning analytics dashboards

LA dashboards refer to visual representations of either raw learning-related data or insights derived (through distinct kinds of analytics methods) from such data. Typically, a dashboard includes plots showing different learning indicators such as indicators of student engagement, performance, or procrastination. As dashboards directly convey insights derived from learning-related data, they are considered a flagship LA intervention (Kaliisa et al., 2024).

Dashboards can be directed at different stakeholders, though most often they are designed and developed for students or teachers as the target users. Teacher dashboards can include information about the overall cohort of students, selected student groups, and/or individual students. Analytics displayed in a teacher dashboard can be descriptive (i.e., presenting information about the current learning state of students), predictive (i.e., showing predictions about student progress), or prescriptive (i.e., suggesting actions based on the predictions). Descriptive teacher dashboards can monitor student progress, behavior, or emotional states. This information can be used to support teachers in identifying struggling students or to aid teachers in improving their learning design and/or learning materials. Dashboards can also be used to support teachers in providing feedback to students. Some teacher dashboards are not focused on student data but rather help teachers with self-reflection (Kaliisa et al., 2023).

Depending on the design of a teacher dashboard, it can be used as an intervention itself, as it provides additional insights into student learning; however, it is also often a starting point for conducting dashboard-based interventions (Karademir et al., 2021). This role of dashboards as a starting point for pedagogical action was also reflected in the ISILA pilots, where teacher dashboards primarily supported sense-making and informed subsequent instructional and support decisions rather than acting as stand-alone interventions.

2.1.2 Learning analytics-informed interventions

LA-based interventions other than LA dashboards are “interventions that are based on the results of learning analytics” (Zhen et al., 2023). Depending on the modality, they can be divided into: face-to-face interventions, internet-based interventions, and mixed interventions. Interventions in each of these three categories can be either manual (i.e., a teacher acts upon the analytics) or automated (i.e., results of analytics trigger an automated intervention).

Face-to-face interventions. As instructors get insights from, for example, a LA dashboard, they can incorporate this information into their teaching practice. On an individual level, an instructor could, for example, approach a student who struggles with a specific course topic. If an instructor notices that several students struggle with the same course topic or assignment, they can devote more time to that topic or assignment, diving deeper into it and providing additional resources for students. Furthermore, the instructor may arrange additional learning activities, during the class, to address the challenging topic / assignment.

Internet-based interventions. This group of interventions includes email reminders, prompts, and recommendations, which can be triggered either manually (e.g., by a teacher) or automatically (e.g., using a system of triggers to activate intervention based on the LA results). For example, a student who is estimated as having low engagement in course activities, may automatically receive a motivational email or resources for additional support. Another option may include an instructor sending email to individual students based on the analytics-based insights, to offer support. Student analytics could also be used to create immediate feedback in the form of prompts or recommendations. This may include, for example, writing suggestions in writing applications or a list of recommendations for further learning trajectories based on student activities in digital learning environments.

Often, face-to-face and internet-based interventions are combined. For example, a teacher could use an automated system to generate feedback for their students and then discuss the feedback with a student in a one-to-one session. Across the ISILA pilots, this combined approach proved particularly relevant, as instructors frequently relied on dashboards to identify emerging issues and then implemented a mix of general and individualized interventions adapted to their specific course contexts.

A recent meta-analysis by Zhen et al. (2023) found that LA interventions were particularly effective in collaborative learning settings. In addition, LA interventions has, so far, achieved the strongest positive impact in the domains of engineering and technological sciences.

There are a few key aspects to consider while developing LA interventions:

1) *Pedagogical goal.* An intervention can target various student skills (e.g., domain-specific skills or self-regulated learning skills) or aid an instructor in a variety of activities, such as lesson planning, student monitoring, or classroom orchestration. Pedagogical goals will determine the extent of an intervention. For example, depending on the educational level of students, different levels of task scaffolding can be expected: Master-level students may receive support guiding them towards additional learning resources on a challenging topic, while an already developed set of additional exercises with explanations may be more appropriate for high school students. This consideration was especially evident in the ISILA pilots, where interventions targeting emotional support and self-regulated learning complemented those addressing domain-specific performance.
2) *Timing*. There are several timing options for interventions. By applying diagnostic tools at the beginning of a course, historical data from previous semesters can be used to predict the current student performance and intervene from the beginning of the course. The other option is to schedule interventions during the course when several data points from a particular student have already been collected and analyzed, but there is still enough time to intervene and for a student to improve. These decisions influence not only the timing of interventions but also the temporal dimension of student analytics. For example, one needs to decide on the time interval to be used for determining a struggling student (a whole semester, last week, or a specific learning activity). Insights from the ISILA piloting activities further highlighted that effective timing of interventions depends not only on early detection but also on course structure, student context, and institutional conditions.
3) *Cost.* It is not always feasible to develop a complex automated system, especially if it is to deliver personalized interventions based on analytics. The cost of development and maintenance of interventions plays a big role. The cost includes not only the financial cost but also the cost of time required for developing, first, the analytics and then an intervention system. Some solutions may be easier to implement than others. As such, to be broadly adopted, LA interventions have to be easy enough to implement in courses, without excessive cost. This consideration was reflected in the ISILA pilots, where instructors favored interventions that could be implemented with minimal additional workload while still allowing for meaningful personalization.

2.2 Distinct targets of learning analytics interventions

The main objective of LA is to improve learning processes and environments in which learning takes place, both of which should ultimately result in improved learning outcomes. Accordingly, LA interventions may target learning environments, learning processes, and learning outcomes (Knobbout & Van Der Stappen, 2020). All three aspects are mutually related and change in one propagates to the others. The ISILA pilots demonstrated that these targets are closely interrelated in practice, as interventions aimed at improving learning processes and emotional engagement often resulted in indirect effects on performance and retention.

The learning environment may be affected by LA interventions in several ways, such as:

- Increasing teacher awareness of students and problems they may be facing
- Increasing teacher productivity and effectiveness in teaching
- Improving the quality and selection of learning materials (e.g., through recommendations)

Furthermore, learning processes may be affected by LA interventions in five major ways, which include:

- Learner awareness - e.g., by enabling increased awareness about peers and their activities or progress based on the data presented in a LA dashboard
- Learner productivity - e.g., increased productivity and/or effectiveness resulting from the change in the teaching approach or student reflection on their learning (informed and/or motivated by the intervention).
- Self-regulated learning (SRL) - e.g., improved self-reflection or metacognitive monitoring or metacognitive judgement, or some other aspect of SRL, resulting from SRL-focused interventions (often in the form of metacognitive prompts).
- Online activity / behaviour - e.g., more frequent participation in group discussions or more frequent access to learning materials in the online learning platform, as a result of an intervention that included, e.g., changes in the course instructional design.
- Engagement - change in academic, behavioral, cognitive, or affective engagement, as a consequence on an intervention.

Finally, LA interventions are often directly targeting distinct categories of learning outcomes, including:

- Knowledge and skills - measured based on assessment scores and grades
- Learning gain - often measured as the difference between pre- and post-test results
- Retention and dropout - measured, e.g., through withdrawal and absence rates, computed at the cohort level.

2.3 Examples and recommendations from the literature

Wong and Li (2018) presented a comprehensive review of LA interventions in higher education (HE) through systematic selection and analysis of relevant case studies. The review includes 23 case studies, selected on criteria that are fully relevant for the ISILA project: i) all studies are set in the HE context, in courses that were delivered either fully online or in a blended mode; ii) each paper includes the rationale for the adopted LA intervention, a description of how the intervention was applied, and the outcomes; and iii) each paper illustrates how the intervention was informed by data and analytics. As such, this review offers a great source of examples not only of the intervention strategies themselves, but also regarding why and how the interventions were introduced and how their effects were measured, thus serving as valuable informal guidelines for instructors who lack experience with data and analytics informed interventions.

The main categories of LA interventions, as identified by Wong and Li (2018) are described below. Interested readers are advised to examine Tables 1-4 in Wong and Li's (2018) review, since these offer concise and informative summaries of LA interventions in the reviewed case studies.

Direct messages. Interventions in this group include directly contacting students who were identified as being at-risk (of having low performance or dropping a course or a study program), usually via emails or phone calls. The messages are typically aimed at encouraging students' engagement, offering assistance and advice, or reminding them of deadlines.

Personalised feedback. This group includes provision of personalized information and recommendations (e.g., via email) based on the insights derived through analytics. It also includes providing students with personalised dashboards allowing them to explore visual representation of their learning-related data and analytics and reflect on their engagement, progress and / or performance.

Course redesign. These interventions pertain to adjusting the course structure and content, to better suit the students' needs and consequently enhance their learning experiences and outcomes. A valuable source of further information on how LA has been and could be deployed to adapt the curriculum to better meet the students' needs, is the systematic review by Ifenthaler and Yau (2022). Among other findings, this review highlights that, via analytics, HE teachers could rapidly visualize common course pathways and identify, in real-time, difficulties that students were experiencing, both of which offered valuable input for curriculum adaptation.

Another relevant source of information and recommendations regarding deployment of LA interventions in HE settings is the work by Herodotou and colleagues (2019). They present the perspectives of 20 educational managers involved in the implementation of a large-scale implementation of predictive LA at a distance-learning HE institution and offer recommendations for scalable adoption of interventions based on predictive LA (i.e., LA focused on early detection of at-risk students).

Since several courses planned for the ISILA pilots are based on the blended study mode, guidelines offered by Ameloot et al. (2023) for LA interventions in such learning settings may prove valuable. In particular, Ameloot and colleagues conducted a two month long quasi-experimental study during which, in the experimental group, the teachers provided students with LA-informed feedback and adjusted face-to-face instruction accordingly. Based on the study findings, the researchers offered advice on how to use insights derived from the data collected (directly from students and indirectly through learning logs) in the online part of the course to adapt the face-to-face part, in a manner that would meet both competence and interest needs of the students.

Considering that in the ISILA project, the project partners aim to leverage LA interventions not only for advancing learning of subject matter topics covered by courses included in the project’s pilots, but also to advance students’ self-regulated learning (SRL), LA interventions presented and evaluated by Ustun et al. (2023) may serve as useful examples. In particular, aiming to advance students’ learning achievements and their SRL skills, Ustun and colleagues deployed personalized interventions, comprising visual feedback and written recommendations, in each week of a ten week long course. A comparison of the academic achievement and SRL skills between students exposed to the interventions and the students in the control group confirmed the effectiveness of the applied interventions. Further examples of LA interventions aimed at affecting both students’ learning outcomes and their SRL skills are offered by recent studies that explored the effects of distinct support mechanisms, such as scaffolding prompts (Li et al., 2023), teaching strategies focused on fostering students’ SRL (Russell et al., 2023), LA dashboards that combine feedback provision with peer comparison (Fleur et al., 2023), and formative feedback offered by peers (Bellhäuser et al., 2022) or AI-based chatbots (Guan et al., 2024).

The studies reviewed in this section provided an important conceptual foundation for the design of the ISILA intervention framework, which was subsequently tested and refined through its application in real higher education courses.

3 Guidelines for LA interventions

3.1 The guiding model for going from data to interventions

When going from data to interventions, especially when facing this task for the first time, it is recommended to ground the inquiry process in a theoretical framework that provides guidance and scaffolding along the way. The *Analytics Model for Teacher Inquiry*, proposed by Saar and colleagues (2022) is the latest model of that type and builds on top of the lessons learned from previous similar frameworks (e.g., Hansen & Wasson, 2016). It offers guidelines in every step of the inquiry process, including explanations and examples, and thus reduces the efforts needed for going from data to actions. The model anticipates five phases in the teacher inquiry process.

Phase 1. As with any inquiry, this one starts with the **Why** question, that is, by defining what one wants to learn about the teaching and learning process and what insights are expected from data analyses. Saar and colleagues (2022) present several examples of motivation / purpose for the teacher analytics inquiry, thus offering solid grounds for getting started and reflecting on one’s own teaching situation and clarifying motivation and purpose of the inquiry.

Insights from the ISILA pilots suggest that, in addition to pedagogical intentions, the formulation of the “Why” should explicitly take into account contextual constraints that may influence student engagement and responsiveness to interventions. Such constraints may include course modality, assessment structure, institutional policies, external disruptions, or overlapping academic demands. Making these factors explicit at the outset of the inquiry helps instructors set realistic intervention goals and interpret analytics findings more accurately.

The piloting activities showed that similar learning analytics signals may require different pedagogical responses depending on the broader learning context. Explicitly acknowledging contextual conditions in the purpose-setting phase supports more adaptive and context-sensitive intervention planning.

Phase 2 is about answering the **What** question. This includes defining more precisely what one is interested to explore and learn about, that is, what specific questions they would like to answer through analytics. Examples of inquiry questions include: which activities do students find engaging? Is regular engagement associated with better learning results? How much do students engage in class preparation activities? The questions one defines determine the kind of data they would need to collect. However, a reality check needs to be present as the data collection is constrained by several factors (e.g., tools used for teaching and learning, data privacy, and administrative issues).

Findings from the ISILA pilots indicate that, in addition to behavioral and performance-related data, indicators of self-regulated learning (SRL) play a critical role in shaping meaningful inquiry questions. SRL-related data provided valuable insights into students’ motivational, emotional, and self-management states, which often explained engagement patterns that could not be inferred from behavioral data alone.

The pilots further showed that making SRL data an explicit part of the “What” phase supports more precise interpretation of learning analytics and more targeted intervention planning. When instructors explicitly consider whether and how SRL data can be collected, they are better positioned to distinguish between students facing external constraints, those experiencing emotional or motivational challenges, and those requiring academic scaffolding.

Phase 3 is about answering the **How** question, specifically, how the required data is to be collected and from which sources. Potential sources include learning logs from distinct learning systems and tools, sensory data, survey data, etc. Furthermore, if data is collected from multiple distinct sources, as is done in the ISILA project, it is also important to think about the technology to be used to aggregate the data. In ISILA, this is done by mapping the gathered data from its source format to the Experience Application Programming Interface (xAPI)[1], which is a widely adopted, open learning specification for representing data about learning experiences.

The ISILA pilots further highlighted that data availability and aggregation are not only technical considerations, but are also shaped by pedagogical design choices, institutional policies, and student participation, which should be taken into account when planning analytics-informed inquiries.

Phase 4 focuses on the **So What** question and includes the steps of *Sense making* and *Interpreting* data and analytics. This phase assumes that either the aggregated raw data or some indicators derived from such data have been made available for exploratory analyses, typically as a collection of distinct data visualisations forming a LA dashboard. In the ISILA project, data aggregation, visualisation, and dashboard creation are facilitated through the use of Learning Locker[2]. Learning Locker is an open source learning record store, based on xAPI, which allows for seamless creation of data visualisations and their composition into custom LA dashboards. It also allows for easy configuration of a LA dashboard and its customisation to the individual needs and preferences of any instructor, thus greatly facilitating the steps of *Sense making* and *Interpreting*.

The *Sense making* step is about identifying patterns in the data and understanding what the data and analytics suggest. To properly understand data visualisation and identify patterns, instructors need well developed data literacy skills. Such skills are required to understand what a particular visualization communicates, that is, how it should be interpreted, and also what its limitations are, so as to avoid misinterpretation. The *Sense making* step is immediately followed by the *Interpreting* step, which is about the interpretation of the identified patterns in the context of a particular course and its specific learning context. This step depends on the teacher’s pedagogical knowledge and experience (i.e., tacit knowledge about the course design, the enrolled students, classroom practice, etc), which allow for critically evaluating the analytics results. It should be noted that the steps of *Sense making* and *Interpreting* are closely related and, in practice, are often indistinguishable, that is, happen almost simultaneously. This is because, having

[1] https://adlnet.gov/projects/xapi/
[2] https://github.com/LearningLocker

detected patterns in the data, teachers spontaneously ‘activate’ their knowledge of the course design and class dynamics to interpret the identified patterns.

Insights from the ISILA pilots suggest that the sense making and interpretation of learning analytics can be further supported by grouping recurring patterns of student behavior and learning-related indicators into a small set of learner profiles. Rather than interpreting analytics signals in isolation, instructors found it useful to consider combinations of behavioral, performance-related, and self-regulated learning indicators when making sense of student activity.

The use of learner profiles during the interpretation phase helped instructors distinguish between superficially similar patterns that required different pedagogical responses. For example, low engagement may reflect external constraints, emotional factors such as anxiety, or difficulties with learning strategies. Making such distinctions explicit during the “So What” phase supported more consistent and pedagogically grounded interpretations of analytics results.

Importantly, these profiles are not intended as fixed student categories, but as dynamic heuristics that support reflective interpretation. As new data become available over the course of the semester, students may shift between profiles, requiring updated interpretations and responses.

Finally, **Phase 5** pertains to the **Now What** question and is about making decisions based on the insights derived, in the previous phase, through data analysis. The decision-making process is mostly shaped by the context of a learning activity (learning modality, timing, cost, etc.) and the pedagogical goals of the activity. Depending on these aspects, a teacher should choose an appropriate intervention from a repertoire of available intervention approaches (e.g., reflect on pedagogy, wait-and-see, whole-class scaffolding, targeted scaffolding, course revisions) (Saar et al., 2022). The chosen intervention has to be integrated into the current pedagogical practice, goals, and expectations (Wise, 2014).

Findings from the ISILA pilots indicate that effective decision-making in the “Now What” phase benefits from viewing interventions not as isolated actions, but as part of a tiered and iterative process unfolding over the duration of a course. Rather than relying on single interventions triggered by specific analytics signals, instructors found it more effective to plan multiple intervention points that respond to evolving student data and learning conditions.

The pilots showed that different types of interventions tend to be effective at different stages of the semester. Early interventions often serve a preventive or orienting function, mid-semester interventions support adjustment and recovery, and late-stage interventions can play a crucial role in re-engaging students and supporting completion of outstanding learning tasks. Treating these intervention points as interconnected rather than independent supports more coherent and realistic pedagogical decision-making.

In this iterative approach, decisions made in the "Now What" phase are revisited as new data become available, allowing instructors to adapt interventions to shifts in learner profiles and contextual conditions. This reinforces the cyclical nature of the inquiry process and positions learning analytics as an ongoing support for reflective teaching practice rather than a one-time trigger for action.

3.2 Applying the guidelines: an illustrative example

This section presents an illustrative example of the teacher inquiry process, based on the model introduced in the previous section and using a subset of the (anonymised) data from the ILEDA[3] Erasmus+ project that many of the ISILA partners participated in.

In particular, the data used in this example originates from a graduate (master) course on advanced data management systems. In the year of the data collection (2023), the course enrolled 75 students and followed a flipped classroom design. The students had to complete a set of learning tasks before each week's face-to-face session with the teacher, which was devoted to practical work (exercises). More precisely, in each course week, the online component of the course included course slides, a video, and a quiz; the latter served for students' self-assessment, to check if they properly understood the topics introduced through the slides and the video. In class, the students worked, with the instructor's support, on a part of the assignment, and they had to submit the rest of the assignment before the end of the course.

The teacher's inquiry process was motivated by the interest in getting an insight into students' engagement with the online learning resources. This was especially important considering the course's flipped classroom design, where timely and proper preparation for the class (i.e., face-to-face session) is essential. Specifically, being aware of the relevance of early interventions, the teacher wanted to explore the students' engagement with the online resources already in the second week of the course, when the first course topic, namely entity-relationship (ER) diagrams, was covered. The inquiry process into the students' engagement with this course topic was driven by the following questions: a) How engaged the students are with the online activities available for the topic of ER diagrams? b) What is the dynamic of their engagement with distinct activities related to this course topic? c) How easy / difficult the self-assessment items (on the ER diagrams topic) are?

The data available for the inquiry originated from the university's learning management system and were related to the students' interactions with the course online learning resources: page views, including slides and lecture videos, answering self-assessment items, and assignment submission. After transformation into the xAPI format, the data was loaded into Learning Locker and several distinct

[3] https://ileda.eu/

data visualisations were created and combined into a custom, course and topic specific dashboard (Figure 1), to facilitate the teacher's inquiry process.

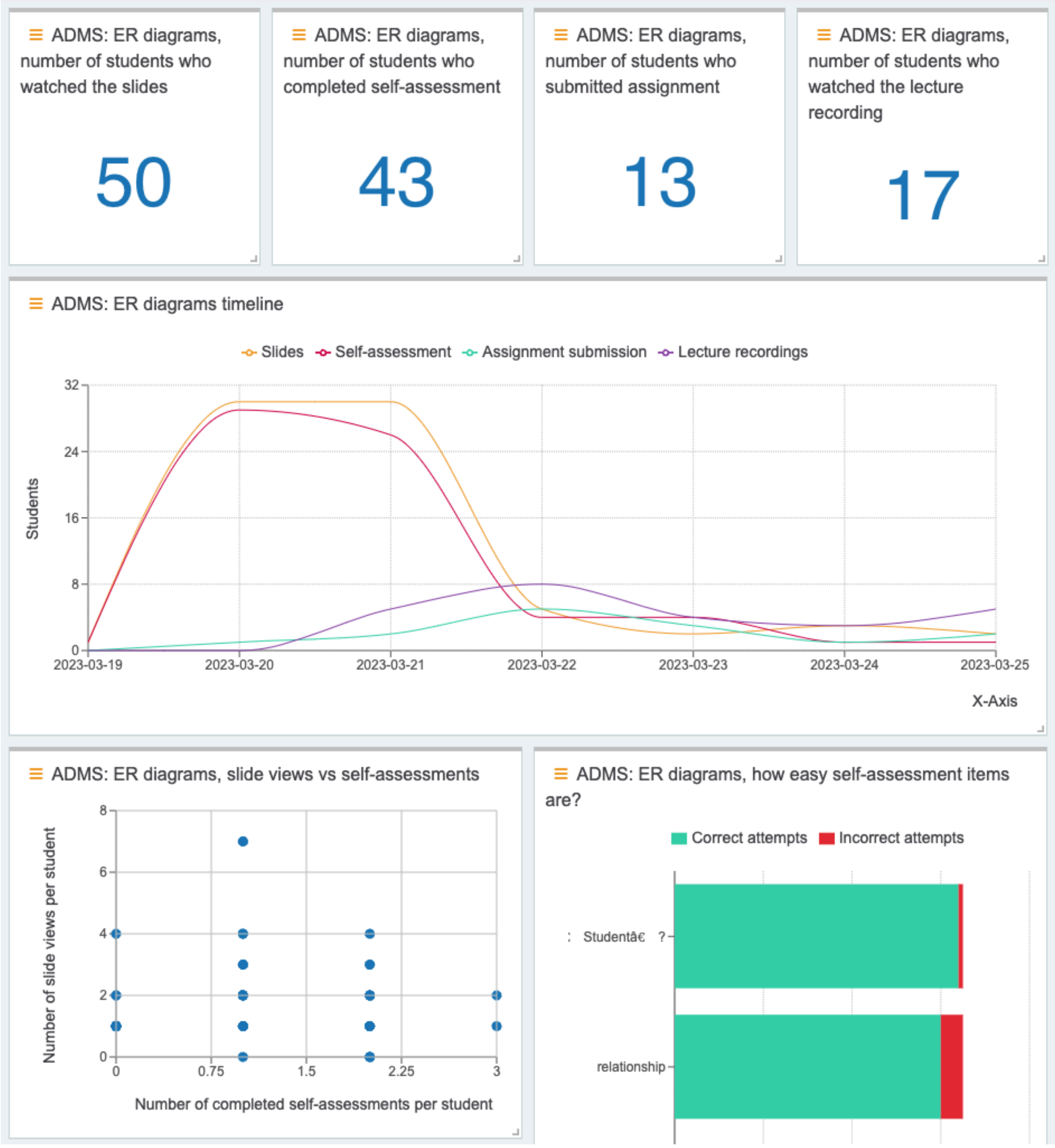

Figure 1. LA dashboard custom created, in Learning Locker, for the course on Advanced data management systems (ADMS) and its topic on ER diagrams

Through visual exploration of the data, the teacher could obtain information required for answering the inquiry questions. For example, the first question - How engaged the students are with the online activities available for the topic of ER diagrams? - may be answered based on the data presented in the four widgets at the top of the dashboard (Figure 1), as they present the number of students who engaged with each of the online activities. Furthermore, the line plot, in the middle, offers a temporal perspective on the student engagement. Considering that this inquiry relates to the second week of the course and already many students were not completing the online learning tasks (recall that there were 75 enrolled students), this information serves as a warning sign for the teacher that an intervention is needed. A typical intervention in such a case would be to reach out to students who showed no engagement with the online activities (Wong & Li, 2018; Herodotou et al., 2019), via a direct contact and explore if they would need any assistance. In addition, the teacher might reconsider the materials made available to students through slides, as not only 25% of students didn't access the slides, but there was also an absence of correlation between access to slides and completion of self-assessment quizzes (Figure 1, bottom left corner), whereas self-assessment were supposed to follow slides (i.e., after getting conceptual knowledge from slides, students were supposed to check their understanding of those concepts through quizzes). Yet another intervention may be related to self-assessments, since visual exploration of the number of correct and incorrect responses to individual self-assessment items (Figure 1, bottom right corner) suggests that some items had almost perfect (successful) completion rate (i.e., probably are overly simple), whereas others proved to be much more challenging to students.

In addition to getting an insight into the level and dynamics of engagement with online materials of the overall student cohort, the teacher may also further investigate the online engagement of individual students by, for example, focusing on those students whose behaviour notably differs from the majority. For example, looking at the diagram that juxtaposes the number of slides views and the number of self-assessment attempts per student (Figure 1, bottom left), the teacher may notice that one student 'visited' the slides just once, but completed the self-assessment three times. Such a behaviour pattern may suggest learning through trial and error, but may also suggest a spaced repetition study approach (Kang, 2016) if the student completed the self-assessment quiz over a couple of days. To explore this further, the teacher may "drill-down" the dashboard views (using the filtering mechanism) to focus on that particular student. The resulting dashboard views (Figure 2) suggest that the student used the self-assessment quiz to learn via a trial-and-error approach, as all the interactions with the quiz happened in one day. Then the student watched the lecture recording and completed the assignment. As the student completed all the tasks, an intervention may not be needed at this point, but if this pattern repeats in the following course week, the teacher may want to talk to the student and point out general weaknesses of their learning strategy.

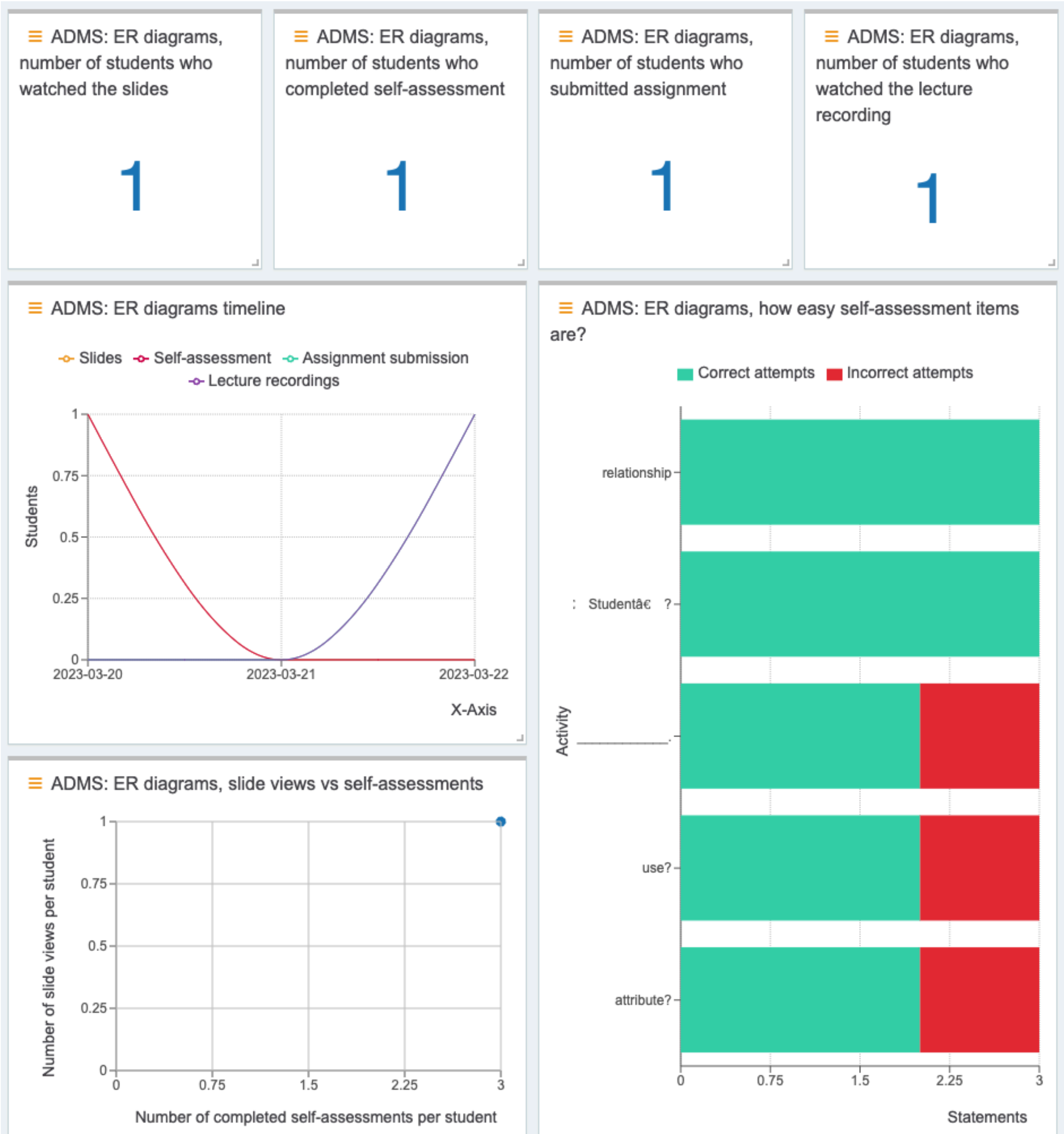

Figure 2. The same LA dashboard as the one shown on Figure 1, now with the focus on one particular student.

While this example illustrates a focused, early-stage application of the inquiry model, the ISILA pilots demonstrated that similar analytic approaches can be applied iteratively across the semester and adapted to different learner profiles and contextual conditions. The following section synthesizes these lessons learned from applying the framework in a variety of real course settings.

3.3 Lessons learned from the ISILA pilots

The piloting activities conducted within the ISILA project provided several cross-cutting insights that informed the refinement of the intervention framework and guidelines:

- **From analytics signals to pedagogical interpretation.**
  One of the main lessons learned from the ISILA pilots is that learning analytics signals require careful pedagogical interpretation before triggering interventions. Behavioural indicators such as low activity or late submissions proved insufficient on their own to explain students' learning situations. Instructors consistently relied on their pedagogical knowledge and contextual understanding to interpret analytics results meaningfully. The integration of multiple data sources, including behavioural data, performance indicators, and SRL measures, supported richer sense-making and reduced the risk of oversimplified interpretations. This reinforced the role of learning analytics as a support for reflective teaching rather than as an automated decision-making mechanism.
- **The role of learner profiles in supporting interpretation.**
  Across the pilots, instructors identified recurring combinations of learning behaviours, performance patterns, and SRL indicators that informed their interpretation of student engagement and learning progress. These recurring patterns effectively functioned as learner profiles that supported more consistent and pedagogically grounded interpretations of analytics results. Importantly, these profiles were not used as fixed student categories, but as dynamic interpretive tools that allowed instructors to revisit and adjust their interpretations as new data became available over the course of the semester.
- **Timing and iteration of interventions.**
  The ISILA pilots highlighted the importance of viewing interventions as part of a tiered and iterative process rather than as isolated actions. Interventions delivered at different points in the semester served distinct pedagogical purposes. Early interventions primarily supported orientation and prevention, mid-semester interventions facilitated adjustment and recovery, and late-stage interventions played a critical role in re-engaging students and supporting completion of outstanding learning tasks. These findings challenge the assumption that only early interventions are effective and emphasize the need for flexible intervention planning that responds to evolving learning conditions and student needs.
- **Contextual constraints and limits of course-level interventions.**
  Finally, the pilots demonstrated that the effectiveness of analytics-informed interventions is shaped by broader contextual conditions. Institutional policies, course design choices, learning modality, and external disruptions influenced both student engagement patterns and responsiveness to interventions. In addition, a subset of students remained disengaged despite

repeated outreach efforts, underscoring the limits of course-level interventions and highlighting the need for complementary institutional mechanisms, such as academic advising or program-level support, to address persistent disengagement.

3.4 Refined intervention guidelines based on learner profiles

Building on the insights gained from the ISILA pilots, this section presents refined intervention guidelines organized around recurring learner profiles. These profiles emerged from the interpretation of combined behavioural, performance-related, and SRL indicators across different courses and institutional contexts. Rather than serving as fixed student categories, the profiles are intended as dynamic heuristics that support pedagogical decision-making during the interpretation and intervention planning phases.

The learner profiles presented below should be understood as interpretive heuristics rather than diagnostic categories. They are intended to support instructors during sense-making and intervention planning, not to label students or prescribe fixed responses. Students may shift between profiles over time as learning conditions and engagement patterns evolve. Table 1 shows a summary of these profiles.

Table 1. Learner profiles and intervention guidelines derived from the ISILA pilots

Learner profile	Typical signals	Intervention focus	Recommended intervention strategies	Typical timing
P1 – No activity / dropout risk	No or minimal LMS activity, no submissions, no SRL data	Detection, outreach, referral	Personalized contact; clarification of expectations; referral to advising or institutional support if non-responsive	Early detection; late-stage re-engagement if context allows
P2 – Average activity, no SRL data	Moderate engagement, missing SRL responses	Data completeness, reflection	General reminders; low-threshold SRL prompts; explanation of benefits of SRL-informed support	Early to mid-semester
P3 – Late starter with high anxiety	Delayed engagement; high anxiety; adequate or high effort	Emotional reassurance, barrier reduction	Empathetic communication; flexible arrangements; task prioritization	Mid to late semester
P4 – Below-average performance with high SRL	High effort and SRL; low assessment results	Academic scaffolding	Targeted feedback; additional resources; strategy-focused consultations	Mid-semester
P5 – High performance with high anxiety	Strong performance; elevated anxiety or stress	Well-being, reassurance	Supportive feedback; normalization of challenge; optional well-being resources	Any stage, especially assessment peaks
P6 – Fully active, high performance, high SRL	Consistently high engagement and outcomes	Monitoring, enrichment	Minimal intervention; optional enrichment or peer-support roles	Ongoing

A more detailed explanation of the profiles is done in the next subsections

3.4.1 P1 – No activity / dropout risk

Typical signals

Students show no or minimal activity in the learning management system over extended periods, fail to submit assignments, and often do not respond to outreach efforts. SRL data, when available, is typically absent.

Intervention focus

Detection and outreach, combined with an assessment of whether course-level intervention is feasible.

Recommended interventions

- Early personalized contact to clarify expectations and offer support
- Clear communication of course requirements and consequences of non-engagement
- Referral to academic advising or institutional support mechanisms when repeated outreach fails

Timing considerations
Early detection is important; however, pilots showed that late-stage re-engagement attempts may still be effective when contextual constraints are resolved.

3.4.2 P2 – Average activity, no SRL data

Typical signals
Students show moderate engagement with course activities but do not provide SRL data, limiting insight into their motivational or emotional state.

Intervention focus
Encouraging reflection and data completeness rather than direct academic support.

Recommended interventions

- General reminders highlighting the value of SRL data for personalized support
- Low-threshold prompts or short reflective activities embedded in the course
- Group-level interventions explaining how analytics-informed support benefits students

Timing considerations
Early to mid-semester interventions are most appropriate, before patterns of disengagement or underperformance become entrenched.

3.4.3 P3 – Late starter with high anxiety

Typical signals
Delayed engagement with learning activities combined with SRL indicators of high anxiety and adequate or high effort.

Intervention focus
Emotional reassurance and reduction of perceived barriers to re-engagement.

Recommended interventions

- Personalized, empathetic communication acknowledging anxiety
- Flexible arrangements (e.g., adjusted deadlines, additional guidance)
- Clear prioritization of tasks to support manageable re-entry into the course

Timing considerations
Mid- to late-semester interventions proved particularly effective for this profile in the ISILA pilots.

3.4.4 P4 – Below-average performance with high SRL

Typical signals
Students demonstrate strong self-regulation, motivation, and effort, but achieve below-average performance in assessments.

Intervention focus
Academic scaffolding and strategic feedback rather than motivational support.

Recommended interventions

- Targeted feedback on learning strategies and task approaches
- Additional learning resources or practice opportunities
- One-to-one consultations focused on aligning effort with effective strategies

Timing considerations
Mid-semester interventions allow sufficient time for improvement while leveraging students’ existing self-regulation skills.

3.4.5 P5 – High performance with high anxiety

Typical signals
Strong academic performance combined with SRL indicators of elevated anxiety or stress.

Intervention focus
Emotional support and reassurance to sustain engagement and well-being.

Recommended interventions

- Supportive messages acknowledging effort and progress
- Normalization of challenge and uncertainty in learning
- Optional well-being or stress-management resources

Timing considerations
Interventions may be beneficial at any stage of the semester, particularly during high-stakes assessment periods.

3.4.6 P6 – Fully active, high performance, high SRL

Typical signals
Consistently high engagement, strong performance, and positive SRL indicators.

Intervention focus
Monitoring rather than direct intervention.

Recommended interventions

- Minimal intervention beyond standard feedback
- Opportunities for enrichment or peer support roles, if appropriate

Timing considerations
Ongoing monitoring throughout the semester is sufficient; no targeted intervention is typically required.

3.4.7 Concluding remarks on profile-based interventions

The profile-based perspective presented in this section illustrates how learning analytics can support differentiated and context-sensitive intervention planning in higher education. Rather than focusing exclusively on the early identification of at-risk students, the ISILA pilots demonstrated the value of recognizing a wider range of learning situations that call for distinct forms of pedagogical support.

By combining learner profiles with a tiered and iterative intervention logic, the refined guidelines support instructors in translating analytics insights into proportionate and pedagogically grounded actions across the semester. Importantly, the profiles are intended to guide reflective decision-making rather than prescribe fixed responses, allowing instructors to adapt interventions to evolving learner needs and contextual conditions.

Together, these refined intervention guidelines aim to enhance the practical applicability and transferability of the ISILA framework to courses beyond the piloting contexts, supporting sustainable and evidence-informed teaching practices in diverse higher education settings.

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