The teacher in the loop: customizing multimodal Learning Analytics for blended learning

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ABSTRACT

In blended learning scenarios, evidence needs to be gathered from digital and physical spaces to obtain a more complete view of the teaching and learning processes. However, these scenarios are highly heterogeneous, and the varying data sources available in each particular context can condition the accuracy, relevance, interpretability and actionability of the Learning Analytics (LA) solutions, affecting also the user's sense of agency and trust in such solutions. To aid stakeholders in making use of learning analytics, we propose a process to involve teachers in customizing multimodal LA (MMLA) solutions, adapting them to their particular blended learning situation (e.g., identifying relevant data sources and metrics). Since measuring the added value of adopting an LA solution is not straightforward, we also propose a concrete method for doing so. The results obtained from two case studies in authentic, blended computer-supported collaborative learning settings show an improvement in the sensitivity and F1 scores of the customized MMLA solution. Aside from these quantitative improvements, participant teachers reported both an increment in the effort involved, but also increased relevance, understanding and actionability of the results.

CCS CONCEPTS

• **General and reference → Measurement**; *Empirical studies*; • **Information systems → Data analytics**; **Personalization**; *Multimedia and multimodal retrieval*;

KEYWORDS

Multimodal Learning Analytics, Blended Learning, Customization, Personalization

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1 INTRODUCTION

Learning is a complex process that happens in the physical world (inside and outside the classroom) and, increasingly often, in virtual spaces [11]. To explore what happens in such blended learning experiences [30], there is a need for gathering evidence about physical and digital interactions and products, obtaining an integrated view of the learning situation [8, 23, 26]. Although learning analytics (LA) applications tend to focus on computer-mediated interactions and productions [36], recent work in multimodal learning analytics (MMLA) also collects evidence from physical spaces [29].

Advances in using MMLA techniques to better understand blended learning experiences are, however, still scarce (since most MMLA work focuses on face-to-face, co-located settings [4, 28]). Indeed, the heterogeneity of the scenarios and the variability of data sources available in each particular blended situation greatly conditions the applicability, accuracy, relevance, and actionability of any LA effort [12, 31]. Furthermore, most existing MMLA proposals are still exploratory and oriented towards researcher understanding of learning (not direct use by teachers or students).

One potential path to successfully apply (multimodal) LA for the end users' benefit in blended settings is to involve those end users more intensively, as they could help adapt the LA solutions to their specific context of use [9]. However, user involvement in the configuration of LA solutions (especially, MMLA) is currently minimal [13]. This limited involvement also impacts on the interpretation and contextualization of LA outputs, as well as on the sense of agency and trust in those outputs [3, 40]: users are often not aware of how the results apply to their learning context, how accurate they are and, therefore, what can be done with such information.

While in our previous work teachers were engaged in the co-design and assessment of an MMLA solution [34], this paper focuses on the added value of engaging the teacher in the *deployment* of the solution. More concretely, we propose an "a priori" reflection process for the deployment of MMLA in blended learning, which involves end users in the customization of the data gathering and analyses, making decisions about what to analyze and how.

We have applied this reflection process in two case studies carried out in blended computer-supported collaborative learning (CSCL) settings in higher education, supported by an MMLA system. To help us in the evaluation of this approach, we propose a method to quantify the added value of adopting the LA solution for the teacher. This way of measuring added value to better understand the costs and benefits involved in an LA-based innovation, can also be considered a secondary contribution of this paper.

2 USER INVOLVEMENT IN LEARNING ANALYTICS

As it happens in other disciplines, involving stakeholders in the design, deployment and assessment of LA solutions may contribute to the success, adoption and sustainability of such solutions [2, 9, 15]. Despite these envisioned benefits, looking at literature reviews in the area of LA [31, 36, 38, 39], the cases of user engagement in the design of LA proposals [20] are still in clear minority. Examples of user involvement in the evaluation of LA proposals (like [25]) are somewhat more frequent, albeit often the focus is more on usability aspects than on the added value to learning outcomes or teaching practice [38]. This low involvement may be due to the increased time and effort required in user-centered approaches [1], and the early stage many LA proposals are in (i.e., not yet tested with end users in real settings) [36, 38].

Multiple conceptual models have been proposed to describe the LA phases in the deployment and implementation of LA solutions [7, 8, 10], spanning from data gathering to decision making. However, in this cycle, often the role of end users is limited to providing data and getting the results of the analyses (and, hopefully, acting upon them), without paying attention to the specifics of each particular context, local user needs, and ethical consequences of not involving users [3, 17, 35, 40]. There is, hence, *a need to adopt a more participatory and personalized LA approach that engages end users*, to better tailor solutions to their needs [9, 27].

Taking a cue from current teacher observation processes (either for professional development or for classroom orchestration), observation protocols require certain teacher decisions to be made in advance, namely defining the areas of focus, the indicators to be obtained in order to illuminate such areas, and the specific events to be observed [18]. Then, the evidence gathered is analyzed and interpreted according to those initial decisions. Following this approach, there exist examples in the LA literature that show the benefits of enabling personalized solutions, e.g., where teachers integrate different data to be analyzed [14, 32], or even define concrete indicators, datasets, and visualization techniques [27].

However, many obstacles hinder the end-user configurability of current MMLA solutions for blended learning settings, such as the complexity of current solutions (e.g., involving sensors or multiple data sources that need to be integrated) and the low level of the indicators obtained (e.g., device's vibration or acceleration forces), which are hard to use by non-experts [12]. As a recently-emerged area of research, MMLA is still focusing on exploratory studies carried out with limited sample sizes and often reporting context-bound findings [4]. Yet, this research area could greatly benefit from end-user configurability, to increase the chances of successfully being applied, adopted and transferred to other contexts, and to better understand the impact of such proposals.

In addition, the application of LA to blended learning contexts also implies challenges, deriving from the need of gathering evidence from digital and physical spaces (a requirement for achieving a holistic view of the teaching/learning process [21, 26]). Thus, there is also *a need to identify which data sources are suitable for the different spaces* involved [21, 26].

From this related work we can see that the involvement of end users (e.g., teachers) in the deployment of LA solutions has been under-explored, especially in blended, across-spaces contexts. Furthermore, as a community we also need systematic ways to evaluate the added value of such solutions (customized by end-users or not), to understand whether the benefits outweigh the costs of these more complex MMLA setups [28]. This issue only recently has come to the foreground of LA research [37].

3 MMLA CUSTOMIZATION PROCESS

To ameliorate the aforementioned stakeholder problems (i.e., interpretation, contextualization, trust and agency), we propose to *include teachers in customizing the MMLA solution to be deployed* in their particular blended learning scenario. The following four phases (see also Figure 1) guide teachers in the reflection on those aspects that affect the MMLA solution, so that they can adapt it to the contextual constraints and the teacher's own needs:

1. Understanding of the MMLA solution. A first step towards customizing a MMLA solution is to understand its purpose, the context where it should be used, and the expected inputs and outputs. To reach this goal, MMLA technology providers (e.g., researchers that developed the LA systems, in our case studies below) have a crucial role in documenting and presenting the solution to the teacher.

2. Definition of the questions to be answered by the MMLA solution. Each stakeholder may have different questions about the learning scenario [9, 27]. It is thus necessary that the teacher states what are the questions to be answered by the MMLA solution (e.g., is there participation in the distance activities?), and which indicators or metrics should be used (e.g., editions in the reports to be written by students).

3. Reflection about the contextual constraints and the MMLA affordances. In many blended learning settings, due to the across-spaces nature of the scenario (e.g., interactions occurring face-to-face not being registered in the digital world), the data gathered by the default LA solution may be insufficient to obtain meaningful and actionable data. An MMLA expert (be it a researcher or, later on, a technological support system) identifies and informs the teacher about information gaps in the current solution, together with recommendations about potential customizations to ameliorate them. Using this information, the teacher reflects on whether a change in the scenario or in the MMLA solution is needed.

4. Refinement of the scenario and customization of the MMLA solution. Aware of the expectations (questions and metrics, step 2) and the limitations of the default/current MMLA solution (step 3), the teacher should be able to adapt the data gathering and analysis by including additional data sources (e.g., introducing additional or alternative informants, MMLA solutions, or learning tools that expose more LA data), selecting the metrics to be obtained from them, defining concrete time-spans for the data gathering, etc.

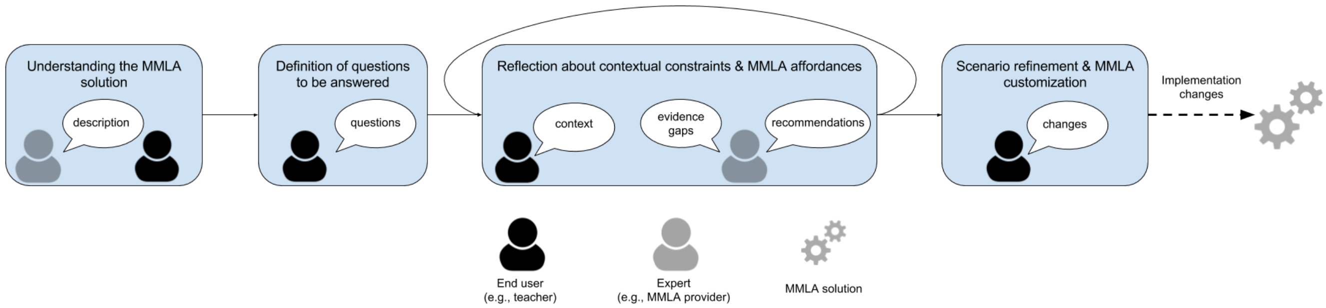


Figure 1: Proposed MMLA customization process.

As a result of this customization process, we expect to keep teachers aware of the impact that their decisions have on the MMLA solution's results, avoiding well-known undesired effects such as decontextualized results that are not actionable, or the lack of trust on the results [17, 35, 40]. Furthermore, we foresee that involving teachers in the LA configuration will contribute to better fit their needs, as different authors have already envisioned [5, 27, 34].

4 METHODOLOGY

In order to understand the added value of user customization in the deployment of MMLA solutions, we need to consider both its intangible impact (e.g., on the teacher sense of agency, or trust in the analytics outputs) as well as more tangible, even quantifiable ones (e.g., on the accuracy of such outputs). As a first step in this direction, and to lay down potential methods to be used in the evaluation of such an approach in other contexts, we illustrate this added value through two in-depth, mixed-methods case studies (presented below). The research question addressed in the two studies can be formulated as: *what is the added value of the personalized MMLA solution for the teacher, versus the non-customized solution, or versus the teacher's usual praxis without LA?*

It is worth noting that these two case studies are part of a larger design-based research [41] process to develop an MMLA solution to detect deviations between the teachers' scenario design and its enactment by the students, in blended CSCL scenarios. Hence, even if our overall research process featured user involvement also in the design and assessment of the LA solutions (as described elsewhere [34]), here we will focus on the added value of involving teachers during the *deployment* of the solution (see Figure 2). We have chosen these two studies because they both used an identical MMLA technological solution and a similar pedagogical approach (CSCL), including learning designs that were specially challenging to be monitored manually by the teachers. The differences between the two studies (mainly, in the scale of the cohorts and level of expertise of the teachers, see Table 1) would enable the exploration of different kinds of MMLA added value in the face of varying teacher orchestration styles.

Data gathering and analysis. In order to obtain all the needed information about the actual problems that occurred, the teacher's awareness about these deviations before consulting the LA solution, and the performance and usefulness of the information provided by the default and customized MMLA solutions, we used a mixed

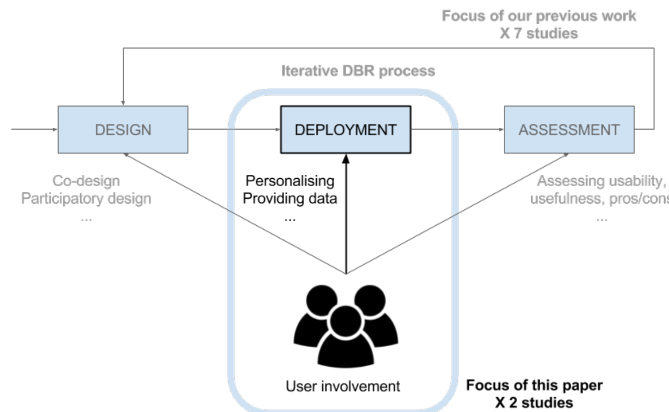


Figure 2: Potential user involvement in the MMLA solution lifecycle and focus of this paper.

methods approach [16], combining multiple informants (i.e., the two teachers, one researcher/observer, a total of 165 students, and the ICT tools used during the scenario). These informants provided a variety of quantitative and qualitative data which was gathered using multiple techniques (analysis of the learning designs, teacher interviews, researcher observations, student questionnaires, system logs, and student-generated artifacts). Figure 3 shows an overview of how these data sources were exploited to answer the different aspects of the research question. All these elements provided multiple perspectives and allowed for triangulated evidence [19] about the problems appearing during the learning scenario and whether they were detected by the LA solution. Besides, through the aforementioned qualitative data sources, we gathered feedback about the teachers' experience using the MMLA solution. While the intangible aspects of the solution's usage are derived quite directly from sources like the teacher interviews, the method to calculate quantitatively the added value of the MMLA solution (in terms of detecting deviations from the planned scenario) deserves more careful explanation (see next).

Quantifying the added value. Our approach towards quantifying the added value of the customized MMLA solution in terms of teacher awareness of potential problems/deviations from the expected unfolding of the scenario, relies on gathering data that enables us to build three different models of reality: (1) teachers' awareness during the scenario enactment, if they would follow their usual praxis (without any LA solution); (2) teachers' awareness if they had used the default, non-customized MMLA solution; and (3) teachers' awareness as they used the customized MMLA solution.

These three counterfactuals can be modeled as binary "problem detectors" that try to detect whether a deviation with respect to the scenario design has occurred. Hence, our evaluation requires specifying what kinds of deviations can occur, to be extracted from the scenario design in the form of condition checks (e.g., whether a concrete student has provided his review to a peer's document, as planned). It also requires gathering data about the problems that actually occurred during the enactment, what the teacher already knew about the progress of the scenario *before* the MMLA reports were visualized (i.e., what the usual teacher praxis would have detected), as well as the problems detectable by each of the available data sources (to build the non-customized MMLA detector). This enables us to build the three hypothetical binary classifiers or "MMLA detectors" mentioned above, as well as their performance in terms of true positives (a problem was detected in this activity, and there was actually a problem), false positives (we detected a problem but there was actually no problem), etc.

By comparing the detected problems, false positives, and false negatives of each of these "detectors" with the actual problems that occurred during the enactment, we can build performance metrics like accuracy, precision, recall, F1, etc. Comparing such metrics with estimations of the time and effort that each of these additional data sources (and the whole MMLA customization process in section 3) requires from the users, can be a first step to establish the added value of the solution in its different possible incarnations, so that teachers (and researchers) can make informed decisions about what flavor of MMLA most suits their needs.

5 CASE STUDIES

5.1 Contexts

The proposed MMLA customization process was evaluated in two authentic scenarios with a common profile [34]: blended CSCL scenarios spanning 3-4 weeks, supported by distributed learning environments (DLE, a virtual learning environment complemented with additional web 2.0 tools [24]). Both scenarios were composed of a sequence of inter-related collaborative activities (e.g., generation of a report by a student group which would be reviewed by another group in a later activity), making it crucial for the orchestration of the scenario to monitor the student-generated resources (i.e., to assess how deviations from the plan could impact later activities). Despite these commonalities, however, each study posed different monitoring challenges regarding the volume of students and resources, and the risks due to interrelated activities occurring in a short period of time. Table 1 offers an overview of the studies.

The first study (CS1) was carried out during March and April 2013 during a course on "Psycho-pedagogical Bases for Attention to Diversity" of a bachelors degree in Early Childhood Education. The scenario involved a non-CSCL-expert teacher and 150 students (out of 165 students enrolled in the course). The learning scenario spanned four weeks and consisted of various distance, face-to-face and blended activities combining individual and collaborative work. The purpose of these activities was to help students understand the Spanish educational legislation related to student disabilities. To support the learning activities, the students used Moodle and Google Drive applications. Between the teacher-provided materials and the student-generated artifacts (e.g., shared documents, wiki pages), the scenario included a total of 316 resources. Hence, the main challenge of this scenario for the teacher was to cope with the monitoring of a high number of students and resources.

The second study (CS2) took place from April to May 2013 in a course on "Educational Research" of a master's degree for Preservice Secondary Education Teachers. An expert teacher (both in terms of general teaching experience and in enacting CSCL scenarios) and 15 students were involved in this study. Over a period of 3 weeks the students worked on the definition of a proposal for an educational research project. The students' proposals were developed through several individual, group and class-wide activities, including both face-to-face and distance learning situations. The learning process was technologically supported by means of a wiki (MediaWiki) and Google Drive applications (involving a total of 77 resources). The main difficulty of this scenario was for the teacher to monitor a complex scenario design with many interrelated activities occurring in a short period of time, hence demanding much attention from the teacher to avoid problems that could jeopardize the scenario down the road.

5.2 MMLA solution

The MMLA solution deployed in both studies was the same: a design-aware monitoring solution that enabled teachers to detect deviations between the scenario design (or "desired state") and its actual enactment (or "current state") [34]. This MMLA solution builds an up-to-date history of the learners' actions, within the blended context of the activities of the learning scenario, that would serve to tailor teachers' subsequent interventions.

Data collection. Instead of gathering all the available data (coming from learning tools, sensors, self-reported data, etc.), the MMLA solution selects a priori the data to be included in the analysis, based on the information provided by the teacher at design time (i.e., the learning design in computer-interpretable form).

Model construction. The selection of indicators to be analyzed by the MMLA solution is linked to the learning design and its goals (e.g., promote collaboration among students). We have identified two types of indicators: low level indicators such as *participation* (involvement of an individual or group in the activity) and *use of resources* (participants' actions on the monitored resources); and more abstract indicators that build on the previous ones, dealing with the *collaboration* (interactions among groups and/or group members), the *group formation policies* (requirements that groups should accomplish in terms of criteria such as size or type of participants), and the *activity flow dependencies* (activity parameters that affect other activities, e.g., reuse of resources generated in previous activities). These indicators are then used to define the current and desired state of the learning situation. The main role of the aforementioned indicators is to detect a lack of evidence of a specific type of expected activity taking place (e.g., one student has not submitted its assignment). This is complemented by showing the teachers simple data (e.g. number of accesses to a tool), that they

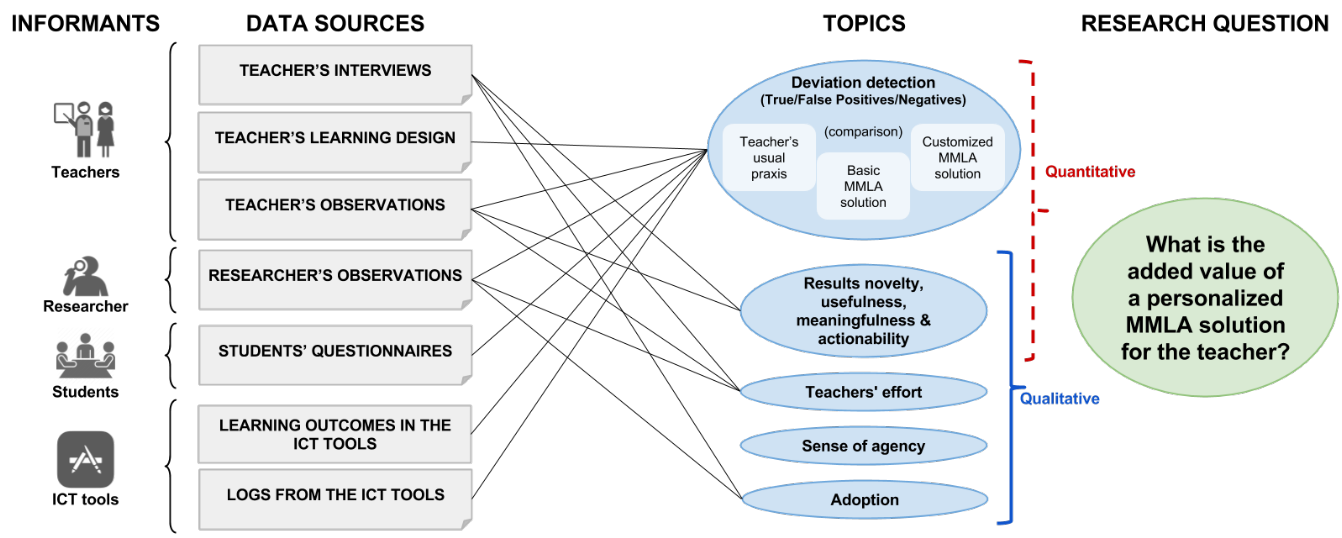


Figure 3: Informants and data sources used to inform the different topics of our research question.

Table 1: Main aspects of the case studies

Study	Duration	Teacher profile	Nr. Students	Nr. Activities	Nr. Resources	Main technologies used
CS1	4 weeks	Non expert	150	4	316	Moodle and Google apps
CS2	3 weeks	Expert	15	9	77	MediaWiki and Google apps

are expected to interpret in their own contexts. The indicators we have chosen are purposefully minimalistic since the available data is often very simple in heterogeneous, decentralized environments like DLEs, in blended learning scenarios [22].

Current and desired states comparison. For each monitoring period, the system compares current and desired states of the learning situation, checking the constraints. In those cases where the evidence does not satisfy the expected values, warnings are triggered highlighting the problem (e.g., lack of participation, lack of collaboration, lack of resource usage). Once the state of each activity is analyzed, its impact on future activities is also checked (e.g., the current situation leading to unavailable resources or unstructured groups).

Advice/Guidance. Finally, the system informs the teacher about the conformance/discrepancies between the current and the desired states of the learning situation, pointing out whether there is no evidence of expected participation, collaboration or use of resources. The dependencies in the flow of learning activities enable the system to predict the impact of the observed deviations in future activities (i.e., the lack of individual outputs endangering a future group activity). Figure 4 shows an example of the system's monitoring report (to be explained in more detail below).

By framing the learning analytics in the learning design, this MMLA solution aims to address the contextualization problems identified in the literature [3, 40]. Thus, contributing to provide teachers with relevant, understandable and actionable information to eventually intervene and adapt their plans during the enactment of the learning design.

However, this default MMLA solution ignores the impact that the context specifics may entail. For example, the participation in a certain activity or the usage of available resources may not always be mandatory. In addition, the data exposed by the ICT tools included in the learning design maybe insufficient to build the indicators. In those cases, the MMLA solution may encounter multiple false positives. The following section shows how the teacher may contribute to minimize these problems by customizing the solution.

5.3 Customization of the MMLA solution

In both case studies, we proceeded in the same way: the teacher and a researcher (expert on the MMLA solution) worked together through the customization process outlined in Section 3, during two face-to-face sessions each.

To ensure their understanding about the MMLA solution, in the first session the teachers received a tutorial about the MMLA solution. Then, they were provided with worksheets and forms that guided them through the second step of the customization process. Since the teachers' goal was to know whether the learning design was properly enacted, the question to be answered by the MMLA solution was: *is there any deviation between the learning design - "desired state"- and the enactment of the learning design -"current state"?* Then, for each learning activity, the teachers specified which constraints of the scripts should be monitored and which data sources and monitorable actions they wanted to use (among the ones mentioned in the learning design).

Based on the outcomes from the first session, the researcher extracted the constraints of the learning design and, taking into account the spaces where the activities should take place and the data sources selected by the teacher, assessed whether there was monitorable evidence to provide relevant results. The results of this assessment, together with recommendations pointing to complementary data sources, were presented to the teacher as the main inputs of the second session. The teachers reviewed the feedback about the evidence available in the learning tool ecosystem they had chosen, for the different constraints to be informed (related to the individual participation, the social level, the expected use of resources, and the activity flow). Even though the customization was not mandatory, this feedback led both teachers to modify the learning design (e.g. the selection of third party tools was influenced by their catalog of monitorable actions) and to extend the data sources with data gathered directly from teachers and students (e.g., controlling the attendance to the lab sessions) so that there was relevant evidence to inform about the accomplishment of the scenario constraints. It is noteworthy that this customization process led the teachers from the use of a monomodal LA solution based exclusively on system logs, to an MMLA one (including logs, attendance lists, questionnaires, etc.).

Once the definitive (paper-based) scenario design was ready, we used a number of technologies to create a computational representation of the scenario's collaborative learning script in an authoring tool (WebCollage[1]), implement the design into the selected learning environment (GLUE!-PS[2]), and integrate the third-party tools into the virtual learning environment (GLUE![3]).

Then, during the enactment of the scenario activities, teachers were provided with monitoring reports generated by the customized MMLA solution, like the one presented in Figure 4. In this learning activity, three groups of students (horizontal sub-tables) had at their disposal the description of the activity to be done (fifth column, in the horizontal sub-tables). Each group of students had to work on a different document (fourth column, 'final research proposal' in the horizontal sub-tables) and, later on, report how they had distributed their workload (third column, 'workgroup report' in each horizontal sub-table). Also, during the activity, the teacher kept track of the attendance to the face-to-face session and noted whether the group had satisfactorily submitted the proposals (column, 'teacher observations'). Based on the data sources selected by the teacher (student participation extracted from the workgroup report, logged accesses and editions to the proposals, logged accesses to the activity description, and teacher's observations) the MMLA solution obtained the deviations between the desired and the current state of the learning scenario. The last column ('Warnings') shows that there was no evidence of *Student6* interacting with the 'final research proposal', which was mandatory. These reports were obtained by a system designed to automate the data gathering, integration and analysis of data from learning activities enacted with DLEs (both the process and software architectures used are described in [34]).

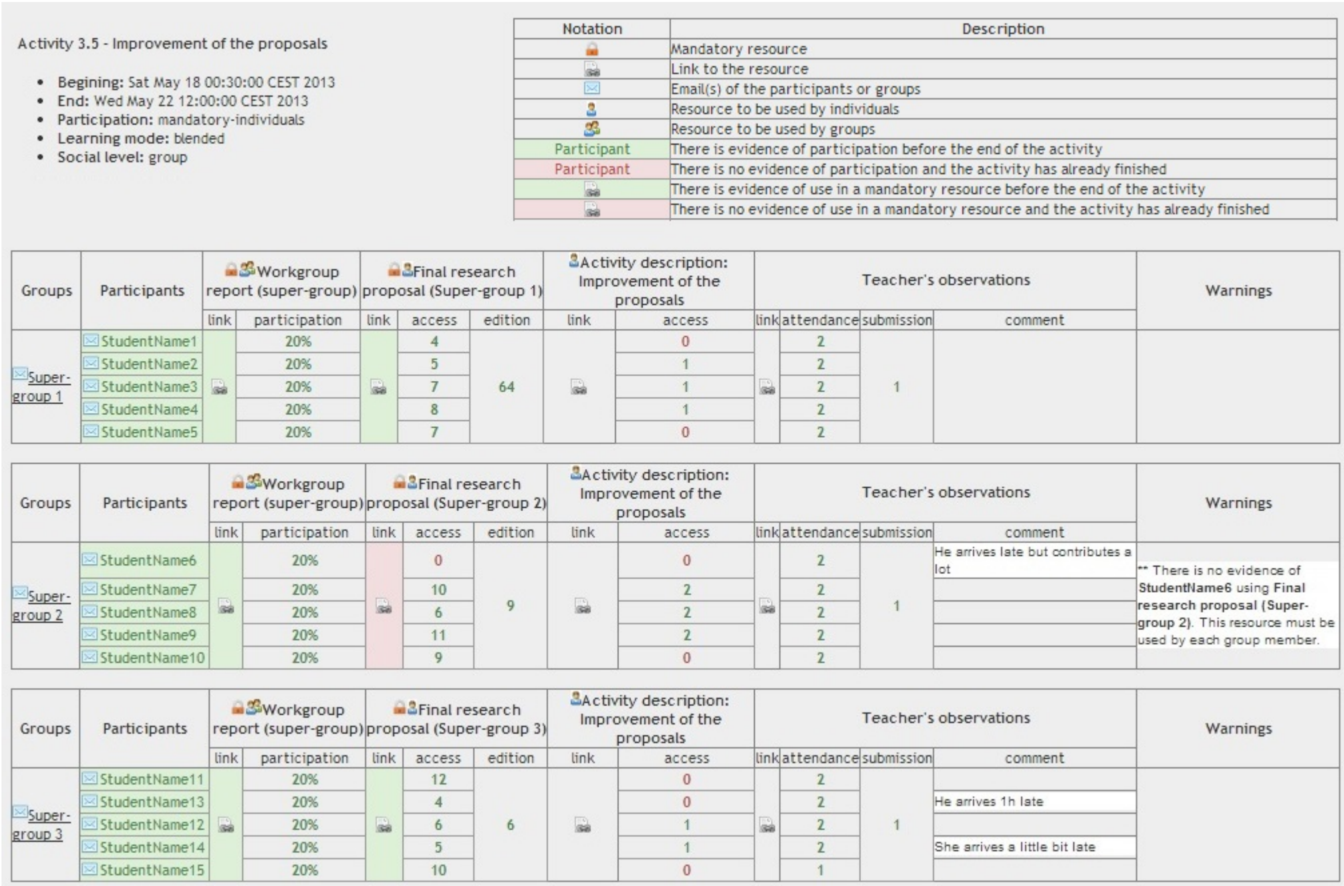
[1]https://www.gsic.uva.es/webcollage
[2]https://www.gsic.uva.es/glueps
[3]https://www.gsic.uva.es/glue

5.4 Quantifying the added value

As mentioned in Section 4, to understand the added value in terms of teacher awareness of potential deviations from the planned learning activities, we evaluated the success of three potential problem detectors listed in Table 2. In the concrete context of these two case studies, the problem detectors were built as follows:

- *Teacher detector.* To understand the information that the teacher would have gotten, had she followed her usual practices to enact the scenario (e.g., wait for students to explicitly flag problems), we asked the teacher about her current awareness of deviations from the planned scenario *before* the visualization of each monitoring report generated by the customized MMLA solution. This teacher awareness was compared with the different kinds of constraints that the learning activities had to fulfill (based on the teachers' questions to be answered, which entailed 1217 and 300 'indicator checks' in CS1 and CS2, respectively), and with the actual problems that occurred (from post-hoc questionnaires to students, interviews, observations, and the learning outcomes as reflected in the tools used by students). Following the decision heuristic that the teachers reported as their usual practice (i.e., if they had no evidence of a problem, they assumed everything was going according to plan), the number of true/false positives/negatives were calculated.
- *Basic MMLA detector.* To provide a quantified approximation to the added value of customizing the MMLA solution, a hypothetical problem detector was built considering the teacher-generated scenarios, data sources and monitorable actions that the MMLA solution had before customization (i.e., the system logs from the different learning technologies involved). Thus, this basic MMLA detector would ignore which resources are mandatory or optional to interact with, considering all of them as potential sources of trouble (hence the larger number of 'indicator checks').
- *Customized MMLA detector.* Finally, the deviations reported in the monitoring reports during the actual enactment (generated by the customized MMLA solution that included additional teacher-defined data sources) were also compared with the number of conditions to be checked -those used for the teacher detector- and with the post-hoc data about how many problems had actually happened during the enactment of the scenarios (as above).

To better understand what we mean by these conditions or 'indicator checks' and how they were evaluated, we can take a look at the example monitoring report shown in Figure 4. In this activity, 27 conditions (out of 300 in CS2) were verified by the customized MMLA solution, namely: the individual participation of the 15 students; the evidence of collaboration in each of the 3 groups; the usage of the 3 workgroup reports and the 3 research proposals by all the corresponding group members; and the impact that the (lack of) usage of the 3 improved proposals may have on the activities scheduled afterwards. To check these indicators, the customized MMLA solution used evidence provided by the teacher (the students attendance to the lab sessions), students (their answers to the workgroup reports), and ICT tools (accesses and editions in the reports and research proposals). While usage and impact indicators



Activity 3.5 - Improvement of the proposals

- **Begining:** Sat May 18 00:30:00 CEST 2013
- **End:** Wed May 22 12:00:00 CEST 2013
- **Participation:** mandatory-individuals
- **Learning mode:** blended
- **Social level:** group

Notation	Description
	Mandatory resource
	Link to the resource
	Email(s) of the participants or groups
	Resource to be used by individuals
	Resource to be used by groups
Participant	There is evidence of participation before the end of the activity
Participant	There is no evidence of participation and the activity has already finished
	There is evidence of use in a mandatory resource before the end of the activity
	There is no evidence of use in a mandatory resource and the activity has already finished

Groups	Participants	Workgroup report (super-group)		Final research proposal (Super-group 1)			Activity description: Improvement of the proposals		Teacher's observations				Warnings
		link	participation	link	access	edition	link	access	link	attendance	submission	comment	
Super-group 1	StudentName1		20%		4	64		0		2	1		
	StudentName2		20%		5			1		2			
	StudentName3		20%		7			1		2			
	StudentName4		20%		8			1		2			
	StudentName5		20%		7			0		2			

Groups	Participants	Workgroup report (super-group)		Final research proposal (Super-group 2)			Activity description: Improvement of the proposals		Teacher's observations				Warnings
		link	participation	link	access	edition	link	access	link	attendance	submission	comment	
Super-group 2	StudentName6		20%		0	9		0		2	1	He arrives late but contributes a lot	** There is no evidence of **StudentName6** using **Final research proposal (Super-group 2)**. This resource must be used by each group member.
	StudentName7		20%		10			2		2			
	StudentName8		20%		6			2		2			
	StudentName9		20%		11			2		2			
	StudentName10		20%		9			0		2			

Groups	Participants	Workgroup report (super-group)		Final research proposal (Super-group 3)			Activity description: Improvement of the proposals		Teacher's observations				Warnings
		link	participation	link	access	edition	link	access	link	attendance	submission	comment	
Super-group 3	StudentName11		20%		12	6		0		2	1		
	StudentName13		20%		4			0		2		He arrives 1h late	
	StudentName12		20%		6			1		2			
	StudentName14		20%		5			1		2		She arrives a little bit late	
	StudentName15		20%		10			0		1			

Figure 4: Example of monitoring report sent to the teachers at the end of each learning activity. This anonymized version corresponds to one of the learning activities of the second study (CS2).

were assessed only using the actions retrieved from logs, participation and collaboration ones also took into account attendance and reported participation from students. Out of these 27 conditions, the MMLA solution detected one problem. While 26 results were true negatives, the problem detected was a false positive since *Student6* had worked in the research proposal as mentioned in the qualitative data of the workgroup reports (maybe using someone else's credentials).

With these data about the true/false positives/negatives, we calculated not only the accuracy of the different detectors, but also the problem prevalence (how frequent the actual problems are in comparison with the whole population of indicator checks) as well as other common metrics of performance for diagnostic tests [33]: sensitivity (the detector's ability to correctly detect problems when they actually occur), specificity (its ability to correctly detect non-problem instances), or the detector's F1 score (the harmonic average of the detector's precision and sensitivity). Coming back to the illustrative monitoring report shown in Figure 4 and the specific activity of CS2, the problem prevalence was 0, accuracy and specificity 0.926, and finally sensitivity and F1 could not be calculated since no problem emerged during this activity. The summary of the aforementioned performance metrics for the two case studies can be seen in Table 2. For further information, a more detailed analysis[4] per learning activity and the R source code[5] used to analyse the data are available on-line.

5.5 Findings

Coming back to the research question posed in this paper (*What is the added value of a personalized MMLA solution for the teacher?*), below we discuss our findings according to the topics depicted in Figure 3. Tables 2 and 3 contain a summary illustrating the evidence obtained from these two studies.

Deviation detection. As we can see in Table 2, the teacher's own knowledge of the potential problems was quite good in terms of accuracy (even better than the hypothetical non-customized MMLA detector). However, the reasons behind this become rapidly clear by looking at the problem prevalence: in both case studies there were actual problems only in 2–6% of the cases (i.e., heavy class imbalance), so just by assuming that "everything always is OK" (as was often the teachers' heuristic due to the time-consuming nature of manual monitoring) one can achieve easily over 90% accuracy.

[4]Detailed performance analyses: http://bit.ly/2xPWyyE

[5]R code: http://bit.ly/2fKvyfa

Table 2: Performance metrics of the different 'problem detectors' in the two case studies

Study - Detector	Indicator checks	Problem prevalence	Accuracy	Sensitivity	Specificity	F1 score
CS1 - Teacher detector	1217	0.037	0.969	0.156	1.000	0.269
CS1 - Basic MMLA detector	2171	0.021	0.681	1.000	0.674	0.115
CS1 - Personalized MMLA detector	1217	0.037	0.997	0.911	1.000	0.953
CS2 - Teacher detector	300	0.060	0.940	0.000	1.000	NA
CS2 - Basic MMLA detector	639	0.042	0.837	1.000	0.830	0.342
CS2 - Personalized MMLA detector	300	0.060	0.980	1.000	0.979	0.857

Table 3: Examples of qualitative and quantitative evidence collected during the case studies

Topic	Illustrative evidence	Case study	Source
Data novelty & usefulness	*"In many cases I was not aware of what was happening. Without help, I could not have a clear perspective of what was happening with so many students (one does not remember any more what students have told you, who told you, or what emails they have sent you)."*	CS1	Teacher interview (post deployment)
Meaningfulness & actionability	*"Interpreting the reports was simple and immediate. The information that is provided is clear and does not lead to misinterpretations."*	CS2	Teacher interview (post deployment)
Teachers' effort & actionability	*"I dedicated 10 minutes at most: 5 minutes to read everything, plus another 5 minutes to take the corresponding measures."*	CS1	Teacher interview (post deployment)
Teachers' effort	*"I would have had to dedicate a lot of time to very mechanical and daunting tasks (e.g., opening the "thousands" of documents to note down who had performed the task), especially in very large cohorts."*	CS1	Teacher interview (post deployment)
Teachers' effort	*"It automates a low-level task that requires a lot of time, but which is very useful for the management."*	CS2	Teacher interview (post deployment)
Sense of agency	*"It has helped me and it has provided more confidence."*	CS1	Teacher interview (post deployment)
Sense of agency	*"Knowing that the activity was being monitored and having evidence that the work was being done gave a sense of order and control on which you can build up."*	CS2	Teacher interview (post deployment)
Adoption	*"Now that I am more aware of the benefits for the teacher, I will try to look for learning tools with similar characteristics, but which provide me with evidence of some kind (access, edition, etc.)"*	CS1	Teacher interview (post customization)
Adoption	*"In case that the tools that I had in mind did not provide monitoring information, I would have substituted them by other tools (provided they have similar functionalities)."*	CS2	Teacher interview (post customization)

Paying attention to the other performance metrics, we can see that the personalized MMLA detector provided great gains in terms of sensitivity (i.e., the ability to detect those infrequent deviations from the plan), with little or not cost in terms of specificity (i.e., few false positives of detection where no actual problem had occurred). The F1 score, which tries to provide a balanced measure between the detectors' sensitivity and precision in the detection, shows large gains for the user-customized MMLA detector, over both the basic MMLA detector and the teachers' own knowledge in usual praxis (except for CS2, where the fact that the teacher detected no problem at all makes the calculation of F1 impossible). The results of this kind of evaluation shows how teachers' knowledge of the local context helps them get by reasonably well even in these complex blended learning situations (as they have been doing before the advent of LA), and how LA solutions that do not exploit such contextual knowledge may easily end up providing little or no added value.

Novelty, usefulness, meaningfulness and actionability of the results. Although the teachers had a certain idea of what was happening based on the face-to-face sessions and students actively contacting them, in many cases (98,44% and 68.60% in CS1 and CS2, respectively) the teachers were not aware of the status of the learning activities before seeing the monitoring reports (see Table 3). Indeed, they considered that the customized MMLA information was almost invariably useful (99.67% and 97.26% of the provided indicators, respectively) – except for the cases of false positives and negatives. Besides, based on the feedback gathered during the interviews, the teachers highlighted that the selection of metrics and data sources from the different spaces contributed to provide relevant and reliable input for the management of the learning scenario. Finally, according to the teachers, the monitoring reports were easy and fast to interpret (taking less than 10 minutes to review the reports and regulate the scenario accordingly).

Teachers' effort. The added value of the customization process has to be compared with the additional effort involved in customizing the MMLA solution, gathering data (e.g., by means of observations), interpreting and acting upon the analytics results.

The teachers devoted, respectively, 85 and 105 minutes to the design process (including the customization). Comparing the decisions that the teachers made at scenario design time with the ones during the customization of the MMLA solution, we see that there are relatively few additional decisions (e.g., select the actions to be monitored, or define the expected use of the resources). Indeed, some customization aspects helped them better reflect on what they expected from the students, and to be more explicit about it in the description of the activities. Thus, the teachers pointed out that the customization process did not increase significantly the effort devoted to prepare the scenario, as the majority of this effort was devoted to the initial design of the learning situation (previous to the customization).

Regarding the monitoring effort, the teachers stated that their daily monitoring activity relied normally on the students feedback, complemented by the awareness gained during face-to-face sessions. Although they also tried to have a look to the students' work, the fact that it was very time-consuming often led to it being skipped, despite its importance. Teachers reported that configuring the MMLA solution reduced the their workload thanks to the systematization of data gathering and integration. Besides, the customization also decreased the computational load due to the reduction in the number of constraints to be analyzed (see the difference between the indicator checks of the basic and customized MMLA detectors in Table 2). Finally, the teachers remarked that the monitoring reports decreased the time and effort required for a proper management of the CSCL scenario, contributing to a more efficient use of the time available (see Table 3).

Sense of agency. As we can see in Table 3, teachers considered that reflecting on the MMLA customization had benefits on their awareness about problems that could jeopardize the scenario, enabling them to think in advance about potential solutions to avoid/minimize them. Also, the transparency and trust on the MMLA solution increased thanks to reviewing and selecting the data sources used to build the different indicators. Finally, because of the time saved in the monitoring process and the increased actionability of the results, the regulation of the scenario was easier, thus releasing even some time to assess the students' work in more detail. Such control of the situation entailed an improvement in the teachers' sense of agency.

Adoption. The observation of the customization process and the teacher interviews reveal that, even though the customization tasks were optional, both teachers went carefully through the four phases of it, taking into consideration the feedback provided by the MMLA expert and adapting both the MMLA solution and the learning design to better satisfy the needs of the learners.

At the end of both studies, teachers were asked whether they would adopt this customization process in their practice. Both confirmed that, given the aforementioned reported benefits (in terms of performance, results understanding and actionability, monitoring effort and sense of agency), it was worth customizing the MMLA solution. Indeed, they mentioned that it would be useful also for other teachers, especially in highly demanding scenarios like the ones presented in this paper (where the effort invested in the design and customization is clearly compensated with the time and effort saved by using the customized MMLA solution).

6 CONCLUSIONS

In order to get a realistic view of blended teaching and learning processes through LA solutions, it is necessary to gather and integrate evidence from digital and physical spaces, resulting in multimodal datasets and/or requiring multimodal analyses. So far, LA (and MMLA) has focused mainly on solutions designed and configured by researchers. However, to promote the generation of relevant results in practice, there is a need to include users in more phases of the LA lifecycle, allowing them to be aware of the limitations that the solutions have in their particular learning contexts, and giving them the chance to customize the solutions to their needs.

In this paper, we have presented a reflection process that allows teachers to customize MMLA solutions and fosters user involvement in the data gathering. Our results from two studies with two teachers in blended CSCL scenarios, show a positive impact on the sensitivity, F1 scores, novelty and relevance of the analyses, as well as on the teacher ability to interpret and react according to the analyses' results. However, the application of this approach, especially in MMLA, is still in its infancy: in our case studies, multiple supporting technologies were in place to aid teachers in the design, deployment and monitoring of the scenario (see Section 5.3), but most of them still require a researcher to be present or to perform certain steps of the process (i.e., teachers were not really autonomous). Also, the kind of LA being performed in our case studies (basically, an early warning system for the teacher) were admittedly quite basic.

On a different level, the two case studies presented above also highlight another open question that has much to do with the adoption of LA solutions: what added value are we providing as we propose solutions for teachers and students (especially, in blended learning settings)? By looking at a variety of performance metrics (beyond just accuracy), and comparing with the teachers' praxis in the absence of LA, we have gained a detailed view of the benefits (increased sensitivity to the relatively infrequent problems), but also the costs associated with our customized MMLA proposal. In this sense, we have taken a very different approach to other LA evaluation proposals such as the Evaluation Framework for Learning Analytics (EFLA) [37], which provides a low-cost assessment of the users' subjective impression of using an LA system. Our approach can provide a more diagnostic view of an LA tool (since subjective user assessments are only one component of a tool's evaluation [6]), in a local context of application in which certain teacher practices are in place – but it does so at a higher cost of implementing the evaluations. Nevertheless, we see these two approaches as complementary, both part of our repertoire as researchers, to be used at different stages in the development of an LA innovation.

In any case, we believe this line of work towards increasing the involvement of teachers in the LA process has enormous potential. In the most immediate future, we aim to perform more detailed analyses of the added value of the different user decisions and elements of the multimodal solution (e.g., the added value of each particular data source). The broader question of measuring the added value of MMLA solutions (and LA solutions in general), and their associated tangible and intangible costs, is still an open problem for our community. We hope that the method proposed in this paper will spark a much needed conversation about this topic, and about how to operationalize it in learning analytics practice.

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