

Multimodal Data Value Chain (M-DVC): A Conceptual Tool to Support the Development of Multimodal Learning Analytics Solutions

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Abstract—Multimodal Learning Analytics (MMLA) systems, understood as those that exploit multimodal evidence of learning to better model a learning situation, have not yet spread widely in educational practice. Their inherent technical complexity, and the lack of educational stakeholder involvement in their design, are among the hypothesized reasons for the slow uptake of this emergent field. To aid in the process of stakeholder communication and systematization leading to the specification of MMLA systems, this paper proposes a Multimodal Data Value Chain (M-DVC). This conceptual tool, derived from both the field of Big Data and the needs of MMLA scenarios, has been evaluated in terms of its usefulness for stakeholders, in three authentic case studies of MMLA systems currently under development. The results of our mixed-methods evaluation highlight the usefulness of the M-DVC to elicit unspoken assumptions or unclear data processing steps in the initial stages of development. The evaluation also revealed limitations of the M-DVC in terms of the technical terminology employed, and the need for more detailed contextual information to be included. These limitations also prompt potential improvements for the M-DVC, on the path towards clearer specification and communication within the multi-disciplinary teams needed to build educationally-meaningful MMLA solutions.

Index Terms—Data Value Chain, Multimodal Learning Analytics, Usefulness, Evaluation, Stakeholder communication, Conceptual tools.

I. INTRODUCTION

Learning Analytics (LA) aims at understanding and optimizing learning, using machine-readable data that is not feasible to process manually [1]. Most commonly, this is done by analyzing digital traces (i.e., logs) of educational platforms. Trace-based Learning Analytics, however, presents only a partial picture of the learning processes, outcomes and environments [2]. Multimodal Learning Analytics (MMLA), on the other hand, aims to present a more holistic picture through the collection, processing and analysis of multiple sources of evidence about learning [3], normally from the digital and physical spaces of a learning scenario [4]. Modalities, in this context, are the different communication channels that the MMLA system exploits to gather information about the

learning scenario [5]. Examples of modalities are the system logs which are traces of the students' mouse clicks, their voice if they are solving a task collaboratively face-to-face, or a video of their movements if the learning task involves some form of embodiment. These multiple data sources in turn reflect the multiple modes in which learning processes occur (e.g., visual, auditory, tactile, embodied, etc.) [6], as explained by different educational theories and pedagogies [7]. Recent technological advancements thus allow us to collect traces of multiple such modalities, leading to heterogeneous datasets [8].

MMLA is a data-intensive field, inheriting many properties from fields like Data Mining and Big Data [9]. In the process of multimodal analysis, there is a need of multiple data processing activities, such as preparing, organizing and fusing the data from different sources [10]. These different activities can be organized into what is called a Data Value Chain (DVC): "a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product (i.e., good and/or service) for the market" [11]. In the Big Data and Data Mining domains DVCs have been defined, including seven data processing activities: 1. Collect and Annotate; 2. Preparation; 3. Organization; 4. Integration; 5. Analysis; 6. Visualization; and 7. Decision making [12]. Each of these seven data processing activities, in turn, involves different sets of data processing steps, which often vary depending on the requirements of each particular case (e.g., how exactly to remove noisy or incorrect values, dealing with missing values, aggregation steps, etc.).

MMLA aims to find meaningful information and patterns in the heterogeneous datasets gathered from educational scenarios, which can support stakeholders (e.g., teachers and students) in evidence-based decision making during teaching and learning practices [13]. However, multiple system design decisions need to be made to go from the heterogeneous, raw multimodal evidence of learning to meaningful stakeholder support, from selecting which data processing activities are relevant [14], [15], sequencing them [16], or structuring the particular steps involved in each of those data processing activities [17]. Aside from making these decisions and systematically specifying them, prior MMLA research highlights the need to include contextual information of the learning scenario in the analysis, to aid in the correct processing and interpretation of the analyses [18], [19]. For example, information about how many students and groups were involved in a group

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Manuscript received November 09, 2019; revised January 16, 2020.

learning activity might be needed to correctly distinguish a case of an inactive student from that of an student being absent from the entire class; a teacher's note that the school's WiFi connection was down for 15 minutes during the lesson would help to understand why there was no log activity during that period; etc.

MMLA is still an emergent field, mostly dominated by research prototypes, and not widely adopted in educational practice. Aside from the inherent complexity of such systems (which can hinder adoption) [17], [16], recent literature also suggests that a lack of stakeholder involvement and the difficulties in communication (e.g., between teacher, researcher and technology developer) can play a crucial role in the lack of adoption of LA systems [20]. These different stakeholders often need to communicate to agree on the requirements of the MMLA solution, which can eventually be systematized into a Software Requirement Specification (SRS) – one of the main contractual documents of any software development product [21]. However, due to the novelty of the field, currently stakeholders have limited experience designing, implementing and/or using MMLA systems (which makes such communication difficult, even beyond the classic terminology gaps between educational research and practice, and software development).

This paper builds on our previous work [22], where we applied the aforementioned generic Big Data DVC [12] in four MMLA scenarios to understand the specificities of data processing activities in MMLA. In this paper we incorporate the lessons learnt modeling multimodal evidence of learning in those four scenarios using the DVC, and construct a more specific DVC for MMLA: the Multimodal Data Value Chain (M-DVC). To study the effectiveness of the M-DVC in supporting communication about the development of MMLA solutions, we applied M-DVC to three MMLA case studies. M-DVC was used to support the conversation between stakeholders at different stages during the development of MMLA solutions, themselves of varied complexity. More concretely, think-aloud protocols and interviews were conducted with a total of six participants (two per project, one with a developer/analyst profile and another with an educational researcher or teacher profile), looking at the support that the M-DVC provided in terms of communication, systematization, eliciting of contextual information and (system design) decision-making.

The rest of this paper is structured as follows: Section II briefly presents the state-of-the-art, whereas Section III briefly summarizes the four MMLA scenarios used to build the M-DVC, and describe it in more detail. Further, we describe the methodology of the evaluation study in Section IV, and its results are presented in the Section V. We discuss the implications and limitations of our study in Section VI. Finally, we report the main conclusions and the future work of this paper in Section VII.

II. RELATED WORK

The first pioneer LA researchers worked on some initial projects that led to the development of initial conceptual tools, such as sets of frameworks [23] and reference models [24].

These papers collected the experience obtained in the first LA pilots. They were of much help to the LA community as they defined the steps to follow in a LA project (e.g. [24]) and the aspects to be taken into account (e.g. [23]). Furthermore, these conceptual tools underlined the most important difficulties found and how they could be overcome. As an example, ethical issues when managing personal data from learning processes were initially seen as important problems without clear solutions [23], that were later on supported by several frameworks [25].

These synthesis works led to more advanced and more mature LA research projects, as well as their first adoption in educational institutions [26]. Right now the research community keeps working on aggregating the experience obtained in LA projects and their deployment in schools and universities with projects like Lace¹, SHEILA² or LALA³. In fact, we currently count on much more mature conceptual tools for researchers, teachers, software developers and institutional leaders [27] [28] on how to design and enact LA projects. Their positive impact has been translated in an increase of LA adoption by educational institutions during the last few years [28]. However, they mainly focus on LA processes that involve a single data source. Hence, the complexity of LA solutions that involve several data sources are out of their scope.

We can find Data Value Chains (DVCs) used in the Big Data domain as conceptual tools that abstract the complexity of data heterogeneity. In the LA field, DVCs are not widely used, but some proposals can still be found. For example, in [29] a DVC emerged from the analysis of several LA processes and was used to guide practitioners to scale-up LA processes in a national level. In a similar way, we used an existing DVC [12] in our previous work to guide our analysis of the MMLA infrastructure literature [17] and to model the processing of multimodal evidence of learning in four MMLA scenarios [22]. Interestingly, we conclude that none of the MMLA architectures support all the steps defined by the DVC [17], and that the DVC we employed (which came from the Big Data domain) did not address all the challenges that MMLA processes face [22].

Hence, as an emerging issue we detected the need of defining a DVC specialized to the MMLA domain.

- 1) Challenges in decision-making: Most software developers do not have experience of processing multimodal evidence of learning. They need to decide which data processing activities and steps are going to be involved in the analysis process [15]. Moreover, they need to reformulate their usual design decisions, which are based on their past experience for MMLA development [14]. Finally, there is a need to include contextual information about the learning process in the analysis, as otherwise analytical results can be misleading for the educational stakeholders [18], [19].
- 2) Challenges in process systematization: The processing of multiple heterogeneous datasets with contextual in-

¹<http://www.laceproject.eu/>

²<http://sheilaproject.eu/>

³<https://www.lalaproject.org/>

formation as a whole is complex. This complexity brings challenge in front of developers to arrange the data processing activities [16]. Recent MMLA projects break this complexity into modules where each of the modules need to be mapped to one data processing activity of DVC [17]. Moreover, the required information for each of the modules need to be classified in Input-, Output-, and Processing-related information which can ease the development process by following modular approach of software development [22].

- 3) Communication challenge: Educational stakeholders need to communicate the requirements of an MMLA solution to software developers. It is difficult to communicate for both of the stakeholders as they have their expertise in two different fields and in most of the cases, they do not have prior experience of MMLA requirement specification [30]. Moreover, the terms used in the communication for both of the stakeholders are not familiar to each other[20]. However, they do not want to waste their time and resources in the way to develop an MMLA solution [16]. Finally, there is a need of effective communication so that a clear understanding can be carried out where both the stakeholders agree on extracted requirements and expected outcomes from the development process [30].

III. MULTIMODAL DATA VALUE CHAIN

In order to propose a Multimodal Data Value Chain (M-DVC), we build over a currently-existing and widely employed DVC [12]. We propose an extension of this DVC to overcome its limitations when applied to a MMLA process. More specifically, in our previous research [17] we detected three characteristics of the MMLA field that should be taken into account:

- 1) MMLA deals with educational data rather than any business data where every decision must be backed up by the educational theories [31].
- 2) MMLA needs to meet the requirements of multiple stakeholders from a wide spectrum of educational hierarchy like from policy makers to students. Moreover, in order to develop an MMLA solution, it is required that those stakeholders from wide spectrum of education, they need to communicate with technical stakeholders [20].
- 3) MMLA involves heterogeneous learning scenarios. These learning scenarios are diverse among each other in many aspects like number of participants, type of learning activities, learning spaces, purposes and reasons to use MMLA, and modalities.

As a first step in the M-DVC proposal, we analyzed four real MMLA scenarios (which are summarized in Table I. We analyzed their heterogeneity and diversity in order to understand the specificities of MMLA. Out of this analyses, we extracted the following characteristics that distinguish MMLA processes from other Big Data processes that the DVC intends to support.

- 1) Need of defining goals, modes and modalities: Data processing in Big Data and Data mining holds true for

the reasons such as 1. there is no specific goal behind analysis rather than random mining to find meaningful patterns or trends and 2. the raw data is historical and was not collected with the same purpose as the analytical purpose. However, in MMLA, educational stakeholders have a clear and specific goal behind using the MMLA. This goal is based on the educational theory and underlying pedagogy of the learning context. The educational stakeholder define multiple modes in which learning processes occur. Further, educational and technical stakeholders (IT professional of the school or educational technologists) need to discuss about the setup of the learning scenario for the mapping of modes into modalities which can be further tracked to generate multimodal evidence of learning. Hence, the specialized DVC should handle these aspects.

- 2) Inclusion of the contextual information: Unlike business domain, education involves humans, and educational practices are cognitive practices. Therefore, there are some events which cannot be planned in advance. For example, the learning activity was planned for 12 students but two students fell sick and could not join at the time of learning enactment. Therefore, educational data involves contextual information which involves metadata from planning to enactment phases of the learning activities. The straight analysis of the multimodal evidence of learning without including contextual information might lead the stakeholders to misleading results. Hence, the specialized DVC should take the specificity of MMLA into account.
- 3) Feed back to educational stakeholders from decision making step: Educational stakeholders are required to take pedagogical decisions based on the analytical results in decision making activity of the DVC. Those pedagogical decisions should be fed back into the educational practices for taking necessary actions. Those actions might trigger some changes for the betterment in the involved practices. This might lead educational stakeholders to define new goal.
- 4) Sequence of data processing activities are not linear: Unlike the existing DVC, data processing activities are not linear and uni-directional. The main reason behind this dissimilarity in most of the MMLA cases that stakeholders are exploring the multimodal data (due to almost no experience and the data-intensiveness of MMLA). In their exploration, they jump from one data processing activity to another quite often.

We incorporated the four lessons learnt into the existing DVC and proposed a specialized DVC for MMLA (see Figure 1) called Multimodal Data Value Chain (M-DVC). First we incorporate the first lesson 'need of defining goals, modes and modalities' by adding three new steps as 1, 2, and 3 in M-DVC (blue boxes in Figure 1). The second lesson was incorporated into M-DVC by adding a connection between phase 1 and 5 which brings the contextual information in the processing of multimodal evidence of learning. The third lesson was applied by adding an arrow in step 10 which feed backs the phase 1

TABLE I
LEARNING CONTEXT AND MULTIMODAL FEATURES OF THE FOUR SCENARIOS USED TO PARTICULARIZE THE DVC TO THE CONTEXT OF MMLA.

Scen.	Learning Context			Multimodal Learning Analytics	
	Participants	Course Type	Spaces	Purpose	Data Sources
1	8 Teachers 3 Researchers 20 Students	Blended learning activities (open doors day)	Digital + Physical	To analyze the impact of innovative teaching practices on group engagement	Graasp logs Structured observation
2	1 Teacher 1 Researcher 150 Students	Online Course	Digital	To study the effect of gamification on student engagement	LMS logs 3rd-party tools logs Gamification platform logs
3	2 Teachers 20 Students	Treasure hunt activity	Digital + Physical	To adapt the student learning experience in real time	App logs Structured observation Sensors
4	1 Instructor 1000 Students	MOOC	Digital	To help the instructor identify struggling students in the course	Course forum posts Self-reported problems

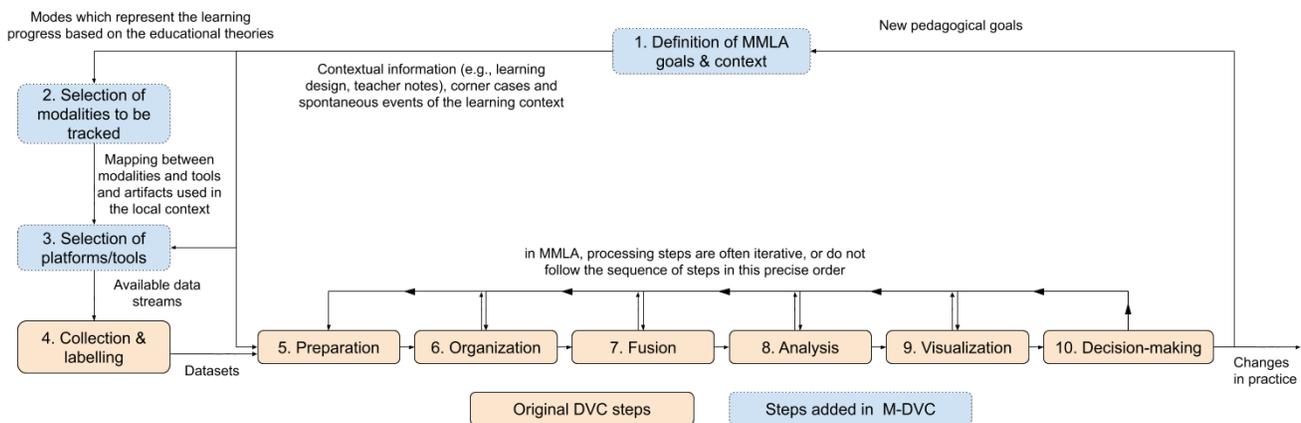


Fig. 1. Multimodal Data Value Chain (M-DVC).

with new pedagogical goals (see closed arrow between phase 10 and 1 in Figure 1) and another arrow from step 10 which leads to the change in the existing practice (if needed) based on the evidence from the analysis. Finally, we incorporated the fourth lesson by adding recursive arrows from step 5 to 10 which allows to jump from one data processing activity to another.

IV. METHODOLOGY

As part of our long-term Design-Based Research (DBR) [32] effort to support the development of MMLA solutions, we propose that the M-DVC described above could be a useful conceptual tool to support stakeholders communication during such development processes. To investigate this claim in a first iteration, we set up a study with the following main Research Question (RQ):

To what extent is the proposed M-DVC useful as a conceptual tool to support cross-disciplinary stakeholders communication during the development of MMLA solutions?

Our main RQ is investigated from the perspective of three main topics, related to the challenges found in the literature about the development of MMLA solutions (see Section II). Hence, our evaluation will target the usefulness of the M-DVC

to support system design decisions, systematization, and to ease communication between the involved stakeholders (who typically have different backgrounds). These three topics are further decomposed into ten sub-topics (see Figure 2).

In this iteration, we evaluate our proposal by following a mixed-method approach [33] in three real cases of projects developing MMLA solutions, at Tallinn University (Estonia). Table II summarizes these three cases. We involved two stakeholders from each of these projects: one with a more technical profile (e.g., developer or software analyst) and another one with a rather educational profile (e.g., educational researcher or teacher). We will denote these two stakeholders 'pairs' from now on (i.e., a total of six participants forming three pairs, one per case/project). The basic idea of the evaluation was then to ask every pair to discuss their MMLA project in order to specify the requirements of the MMLA solution (as a first step in the development process), using the DVC as a conceptual tool to guide the conversation.

To help the participant stakeholders in engaging with the M-DVC while communicating, we developed an instrument (a reflection and conversation guide, implemented using the Google Sheets spreadsheet service), which operationalizes the concepts and flow of the conceptual tool (i.e., detailing the involved data processing activities and concrete steps involved

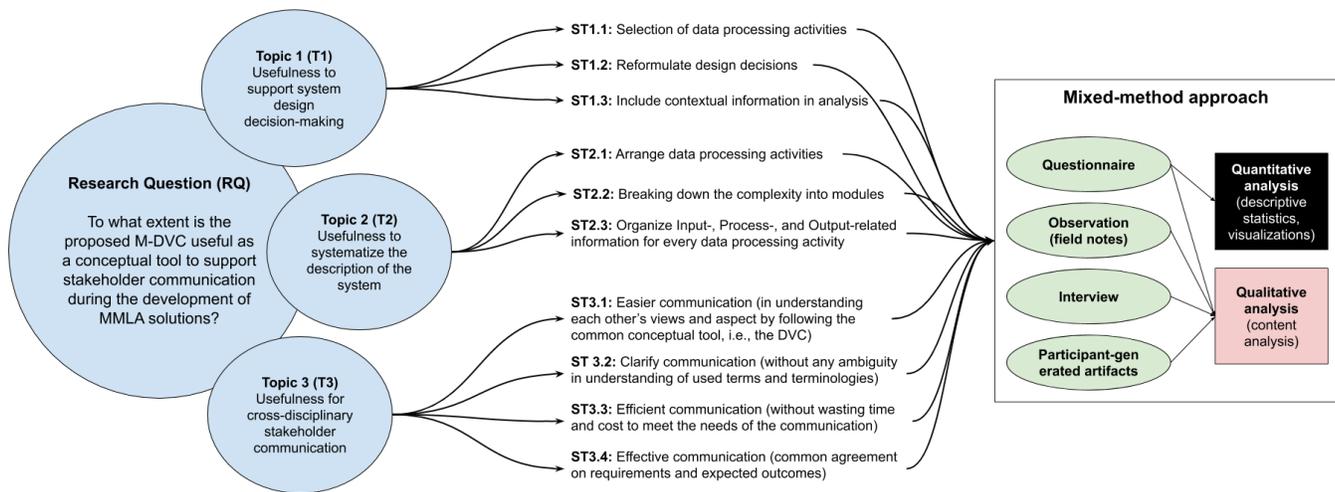


Fig. 2. Research question, addressed topics and sub-topics, and mixed-methods approach used for evaluation

TABLE II
DESCRIPTION OF MMLA CASES

Case	Role of Participant 1	Role of Participant 2	Research Goal(s) of the case	Educational Context	Goal of the MMLA Analysis	Current Project Stage (Educational)	Current Project Stage (Technical)
Case 1	Researcher (educational)	Developer (technical)	Is it possible to detect meaningful collaboration and dominance patterns using audio and log data?	Group work in secondary school classrooms	To visualize individual contributions and dominance within a group	Several pilot experiments with a prototype carried out	Working prototype available
Case 2	Researcher (educational)	Software Analyst (technical)	To help teacher to understand classroom activities in technology-enriched designs, including physical as well digital spaces	Primary school teachers inquiring about their practice using digital learning resources	To visualize multimodal data in a class monitoring tool	Learning resources already in use	Specification
Case 3	Researcher (educational)	Developer (technical)	How a teacher-cum-researcher can understand/compare teaching strategies in terms of learning (gain, correctness of tasks, time consumed) and student feedback?	Teacher professional development in primary/secondary schools (about the impact of teaching practice on student success)	Visualize/Compare multimodal data from different lessons in a self-reflection dashboard	Several data gathering experiments carried out	Specification

in each of the activities). Moreover, two of the authors of this paper performed a similar exercise (i.e., conversation and filling in) about a previous MMLA scenario/system, so as to provide a worked out example of the instrument ⁴, for stakeholders to use as a reference, if needed. For each of the cases studied, a face-to-face semi-structured interview was set up with the pair of stakeholders, in which the interviewer (one of the authors) presented the M-DVC, one blank copy of the instrument, and the filled-in example in about five minutes. Once the participants provided oral consent for participating in the research and for being audio recorded, the pair of stakeholders discussed how their proposed MMLA solution should work, by following and filling in the different phases of the M-DVC instrument (this exercise lasted for 90, 80, and 150 minutes in case 1, 2, and 3 respectively). During this discussion, the interviewer acted as an observer, taking field notes and answering any doubts of the stakeholders about the instrument.

After this discussion exercise, each of the stakeholders was

presented with a questionnaire⁵, which included 10 Likert-scale questions (responses from 1–Strongly disagree, to 5–Strongly agree), mapping to the 10 sub-topics (ST) of our evaluation (see Figure 2). The questionnaire also included three open-ended questions inquiring in more general terms about the rationale for the participant scores related with each of the topics (T). After these questionnaires were filled in, the interviewer asked further clarification or probing questions about their responses and rationale in the questionnaire, and about their general impressions of the usage of the conceptual tool.

The quantitative data from the aforementioned questionnaires was analyzed using descriptive statistics and basic visualizations, to unearth general trends in the stakeholders’ opinions (as, given the small sample size, statistical inferences would not be appropriate). The bulk of the analysis, thus, was of qualitative nature, consisting on content analyses of the open-ended questionnaire answers, interview remarks and field notes, coded along the topics and sub-topics of the evaluation. The stakeholder-generated artifacts (i.e., the M-

⁴Worked out example instrument: <https://tinyurl.com/yylf5wud>.

⁵Questionnaire available at: <https://tinyurl.com/y6y2vya2>.

DVC instruments filled in during the interviews) were used to better interpret the utterances in the audio recordings and the questionnaires.

V. EVALUATION RESULTS

Table III, IV, and V presents our main findings and their main supporting evidences respective to each topic and sub-topic in the evaluation. Qualitative evidence respective to our findings is labeled using the following scheme: '[Cn.R/D/SA]'. In this scheme, 'C' stands for 'Case', 'n' refers to 'number of the case study', 'R' stands for 'Researcher', 'D' stands for 'Developer', and 'SA' stands for 'Software Analyst' (for more details about case studies, see Table II). For example, if there is an evidence which has suffix code as [C2.D] which means that the evidence is provided by the **Developer of the Case 2**. A histogram is used to represent the quantitative evidence in each of the sub-topics, to give an idea of the distribution of stakeholder answers. Below, we summarize the main findings for every topic and sub-topic in the evaluation.

a) *Usefulness to support MMLA system design decision making (T1)*: When asked about how the M-DVC was supporting them in selecting data processing activities, including contextual information in the analysis and formulating design decisions, our participant stakeholders mentioned the following:

- Selection of data processing activities (ST1.1) Although the M-DVC was found generally useful to select data processing activities (5 out of 6 participants agreed to this statement), it also seems that developers may find it more useful given the fact that they are more knowledgeable about many of these pre-processing operations that happen before the actual data analysis [C3.R, C3.D].
- Reformulating design decisions (ST1.2) The M-DVC is useful for reformulating design decisions (5 out of 6 participants strongly agree and 1 agrees). However, participants did not finish the whole exercise. Hence, they did not have much opinion on this aspect because they did not discuss much about design decisions.
- Including contextual information in MMLA analyses (ST1.3) Participants had mixed responses (2 - strongly disagrees, 1 - disagree, 2 - agree, and 1 - strongly agree) about the usefulness of the M-DVC in including contextual information into MMLA. They mention that the M-DVC as a whole in its pictorial form presents the idea but when the participants start their discussion and filling-in exercise on the instrument then they forget about the idea [C3.D]. There is a translation gap from the conceptual tool to the instrument which does not explicitly inform this idea. Moreover, the cognitive load is high during discussion and they do not bother to read the instructions of the instrument carefully where the idea is presented in short [C3.R].

Overall, we can observe that the M-DVC was considered generally useful as a decision support tool, in terms of what kinds of data processing should be included, and in what sequence [C2.SA]. It also was reported to increase the

awareness about data processing activities to the educational stakeholders who have limited data literacy in most of the cases [C3.R]. Moreover, as a conceptual tool, M-DVC helps in the cognitive walkthrough of the stakeholders to think about decisions [C2.R]. However, M-DVC does not meet the requirement to include the contextual information into analysis in its current form where neither the tool nor the instrument pushes this aspect explicitly during their discussions [C3.D].

b) *Usefulness to systematize the description of an MMLA system (T2)*: Data collected about this topic yielded the following results:

- Arrange data processing activities (ST2.1) The M-DVC was found useful as a conceptual tool in structuring and arranging data processing activities in the process to develop MMLA solutions (3 out of 6 participants agree whereas rest of the three strongly agrees to this point) [C1.D].
- Organize input- process- and output-related information for every data processing activity (ST2.2) Regarding this point, all the six participants agreed with the statement that the M-DVC as a conceptual tool is useful to break-down the complexity involved in the development of an MMLA solution into chunks [C1.D, C2.R].
- Breaking down the complexity into modules (ST2.3) The M-DVC and the instrument were reported useful to discuss and note the relevant information about all the data processing activities involved in the process of MMLA. Only one participant neither agreed nor disagreed with this point. Additionally, the participants mentioned a need to classify the requirements of every data processing activity under the labels of Input/Process/Output-related information [C1.D].

In summary, M-DVC was found generally useful as a systematization tool in the process to develop MMLA solutions. However, as MMLA is not widespread yet, some participants without prior MMLA experience found it time-consuming [C2.R]. Moreover, two developers highlighted that they might have followed a different sequence for processing the multimodal evidence of learning in real practice without having the knowledge of such a conceptual tool [C1.D, C3.R].

c) *Usefulness as a systematization tool (T3)*: . The results related to this topic are the following:

- Clear communication (ST3.1) The M-DVC was reported to ease the communication (4 out of 6 participants strongly agree whereas rest of the 2 participants neither agree nor disagrees) when both of the participants of one case used the same conceptual tool during the discussion to specify the requirements. The participants said that the tool helped, even in the case where the educational scientist did not have experience in expressing the software requirements to developers [C2.R].
- Effective communication (ST3.2) Regarding this aspect, the M-DVC did not meet the expectation of being useful as a conceptual tool for clear communication (3 out of 6 participants neither agreed nor disagreed, 2 agree and rest of the 2 strongly agrees). Especially developers are doubtful about the term 'clear communication' itself in the context of requirement specification [C3.D].

TABLE III
TOPIC 1, SUBTOPICS, FINDINGS AND ILLUSTRATIVE EVIDENCE FROM THE THREE CASE STUDIES. LABELS IN BRACKETS DENOTE THE CASE/PARTICIPANT FROM WHOM THE UTTERANCE WAS TAKEN

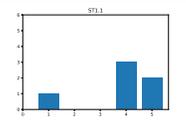
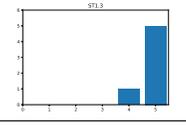
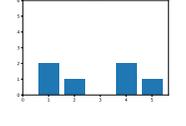
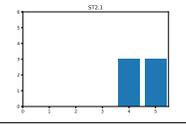
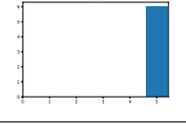
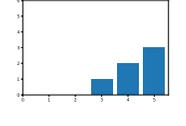
Topic / Subtopic	Finding	Qualitative evidence	Quantitative evidence
T1. Usefulness of the M-DVC as a decision-support tool	M-DVC is useful as a decision-support tool but there is a need of explicit focus on the aspect 'inclusion of contextual information into analysis' which can draw the attention of the stakeholders.	* 'Support of the contextual information can be helpful.' [C1.D] * 'This tool is useful in my cognitive walkthrough to take decisions related to multimodal data processing.' [C2.R] * 'DVC is very useful in decision-making for our case and informs me about the sequence of data processing activities.' [C2.SA] * 'It made me more aware of data processing aspects.' [C3.R] * 'It was VERY useful to unearth design decisions or operations that the other stakeholders may not be aware of them.' [C3.D]	(see histograms below)
ST1.1 Selection of data processing activities	Developer profile has more knowledge about data processing activities in general but steps involved in each of the activities need to be discussed with the researcher profile	* 'The DVC made me more aware about data processing activities but this time, my decisions and contribution in this conversation were very much dependent on the developer's queries.' [C3.R] * 'I was aware about the DVC and the instrument beforehand so it was a bonus for me. I used my previous knowledge to push hard in front of researchers to extract the requirements but the support of the tool as a common conceptual tool during the discussion was useful.' [C3.D]	
ST1.2 Reformulate design decisions	Stakeholders seem to agree that the M-DVC helped them reformulate design decisions		
ST1.3 Include contextual information in MMLA	Translation of the M-DVC into the instrument has some gaps which did not bring the aspect 'inclusion of the contextual information into analysis' clearly for the stakeholders	* 'Contextual information is not only needed in data preparation but also in other data processing activities. Researcher needs to discuss about the contextual information in cases where there is no LD involved.' [C1.D] * 'DVC and the instrument tries hard to include the contextual information in analysis but did not push hard the idea - to include contextual information into analysis' [C3.D]	

TABLE IV
TOPIC 2, SUBTOPICS, FINDINGS AND ILLUSTRATIVE EVIDENCE FROM THE THREE CASE STUDIES. LABELS IN BRACKETS DENOTE THE CASE/PARTICIPANT FROM WHOM THE UTTERANCE WAS TAKEN

Topic / Subtopic	Finding	Qualitative evidence	Quantitative evidence
T2. Usefulness of the M-DVC as a systematization tool	The M-DVC is useful for the systematization purpose but it is time-consuming for inexperienced MMLA stakeholders and there is a need of extra focus on 'I/O/P-related information for each of the data processing activity' aspect	* 'As per the DVC, visualization is after fusion but in some cases where researchers explore collected data then sequence can be different like having a preliminary visualization before fusion.' [C1.D] * 'This DVC is useful for our case in order to organize and arrange data processing activities. But, this exercise is very time-consuming and complex to answer especially in our case because we do not have past experience.' [C2.R] * 'I might have different sequence of data processing activities in order to meet my need but following this kind of a standard conceptual tool can be a good practice for systematization purpose.' [C3.R] * 'The structuring of I/O/P is not very explicit.' [C3.D]	(see histograms below)
ST2.1 Arrange data processing activities	The M-DVC as a conceptual tool helps in practical arrangement of data processing activities as well as in stakeholders' cognitive thinking	* 'Although we were following different data processing activities to meet our requirements but this tool helps us to structure and arrange the data processing activities and also sparks our cognitive walkthrough.' [C1.D]	
ST2.2 Breaking down the complexity involved in the development of an MMLA solution into chunks	The M-DVC handles this aspect well with its modular structure to present the overall concept involved in the processing of multimodal evidence of learning	* 'Although our approach was not modular in the past but the tool gives me a better view to work in a modular way to develop an MMLA solution.' [C1.D] * 'It helps to breakdown the bigger problem into smaller problems to support our conceptual thinking.' [C2.R]	
ST2.3 Organize information, process, and output-related information for each involved data processing activity	The phases of M-DVC help the stakeholders to extract the requirements for each of the involved data processing activity but there is a need to classify those requirements under the categories of I/O/P-related information for every activity	* 'DVC as a tool is helpful for me to extract the requirements from the researcher for every data processing activity.' [C1.D]	

- Efficient communication (ST3.3) We found that during the discussion the cognitive load was reported to be high for both of the participants and time-consuming. Hence, 4 out of 6 participants neither agrees nor disagrees with the concept that the M-DVC is useful as a conceptual tool in efficient communication in the process to develop an MMLA solution.
- Easy communication (ST3.4) The M-DVC was declared useful in effective communication as a conceptual tool [C2.DA] where 4 out of 6 participants strongly agree whereas 1 of them agrees and the other one neither agrees nor disagrees.

facilitating easy and effective communication during the specification of requirements for the development of an MMLA solution. This is true for all of the stakeholders, especially the educational stakeholders who had limited data literacy. However, it is not as effective as expected in clear and efficient communication because of the current state of the M-DVC and because the the current instrument uses technical terms which are not easy-to-grasp for most of the educational stakeholders.

It is interesting to highlight here that all the participants who belong to the researcher profiles in the three cases either agree or strongly agree with T3 except the efficiency aspect in case 3. Developers found that the tool is still not useful as a communication tool especially with the aspects related

Globally, the participants found the M-DVC model useful for

TABLE V
TOPIC 3, SUBTOPICS, FINDINGS AND ILLUSTRATIVE EVIDENCE FROM THE THREE CASE STUDIES. LABELS IN BRACKETS DENOTE THE CASE/PARTICIPANT FROM WHOM THE UTTERANCE WAS TAKEN

Topic / Subtopic	Finding	Qualitative evidence	Quantitative evidence
T3. Usefulness of the M-DVC as a communication tool	M-DVC is useful in easy and effective communication even the stakeholders have limited data literacy but there is a need to ease the technical terms so that non-technical stakeholders can better participate in the development of an MMLA solution by using the M-DVC as a conceptual tool	* 'It really eases my communication with the system analyst. But, still I am not familiar with the terms and terminologies used in this tool. The complete vocabulary is new for me.' [C2.R] * 'Every time there's humans involved, it's difficult to minimize all issues regarding to communication. Concept is great but not sure how it would work in real life situations (between researchers and developers).' [C2.SA] * 'It helped to negotiate the meaning between ourselves even having the limited data literacy.' [C3.R] * 'I think the terminology is still very technically-oriented. There are ambiguities (e.g., operations that could be classified as both organization and preparation). I think it is a very effective tool, not because of the end result, but from the discussions that it helped to carry out.' [C3.D]	(see histograms below)
ST3.1 Easy communication by following a single conceptual tool	M-DVC eases the communication because both the stakeholders use the same conceptual tool i.e., the M-DVC	'I have never thought about a conceptual tool for data processing. I had the fear of talking with technical people when I discuss the requirements for the asked tool. Using this DVC, I feel as a educational scientist that I can talk to the technical guys.' [C2.R]	
ST3.2 Clear communication without any ambiguity in understanding of terms and terminologies due to involvement of different profiles	Terms used in M-DVC are more inclined towards the technical side rather than educational side of the MMLA	* 'I am not sure about the clear communication aspect because there are many definitions and parameters involved in a clear communication.' [C3.D]	
ST3.3 Efficient communication without wasting time and cost to meet the expected outcomes	Educational researchers cannot judge the efficient communication aspect of the M-DVC because it takes time and cognitive load is also high in the discussion	'The exercise which includes the discussion, and filling-in the instrument especially in our case where we do not have any previous experience of MMLA, is time consuming. So, the tool itself does not save my time' [C2.R]	
ST3.4 Effective communication by agreeing on expected outcomes and requirements	The M-DVC is useful for effective communication in general, even in those cases where stakeholders did not have either the technical or educational experience of MMLA	'By using this tool, we can negotiate the expectations and requirements. Earlier, it was almost not possible but still skeptical whether it will work in every case.' [C2.SA]	

to *clear and efficient* communication. The strongest aspect in T3 is 'easy communication' where four out of six participants strongly agree with the statement. In this regard, the researcher of case 2 mentions that 'It really eases my communication with the system analyst. But, still I am not familiar with the terms and terminologies used in this tool. The complete vocabulary is new for me'.

VI. DISCUSSION

The previous section shows how our findings about the three topics defined in section IV. Now we discuss the main results and their implications for the MMLA field.

The analysis of our scenarios show the need of explicit focus on the inclusion of contextual information to avoid misleading analytical results [T1]. The practice of including the contextual information into analysis is sought from many researchers [19], [18]. In most of the learning scenarios, the contextual information is either not recorded or recorded in learning orchestration-related documents like the learning design or the teachers' notes. Moreover, in those cases where there is an explicit record of these documents, they are typically unstructured text that is very difficult to be processed by a technical system. This hinders the inclusion of contextual information into the LA analysis and increases the complexity for the stakeholders to take it into account. Hence, they need an external push in their usual practice through the conceptual tool like M-DVC which can explicitly draw their attention on this aspect.

We also showed that there is not a clear linear sequence of the data processing activities in a M-DVC [T1]. In most of the MMLA projects the stakeholders explore the heterogeneous

datasets to understand the multimodal evidence of learning [16]. In their exploration, they might perform data processing activities in different sequence than the presented in the M-DVC. For example, they might need to visualize each of the datasets before the data fusion activity. However, once the exploration phase is over then stakeholders might follow a standard sequence of data processing activities like the M-DVC.

There is also the need of better structuring and organizing I/P/O-related information for each data processing activity [T2]. In this sense, the M-DVC is a useful tool when structuring and extracting the requirements of a MMLA solution. This is especially true when several stakeholders are involved as it can also be used to guide their discussion. The time required to fill-in the instrument, and amount of data from the filled-in copies reveal that each of the data processing activities involve few relevant information which are extracted during the communication of stakeholders for requirement specification. The current version of the M-DVC classifies such relevant information into I/P/O-related information for each of the data processing activities. However, a more narrow focus on this aspect is needed where relevant information of every activity can be classified under the I/P/O labels.

Finally, we found the need to ease the technical terms involved in the M-DVC for the educational stakeholders [T3]. In most of the cases, MMLA stakeholders do not have prior experience with MMLA solutions and many educational stakeholders face data literacy issues, which sometimes hinders their understanding of the M-DVC. The participants - especially researchers who have the background in 'education science'- highlight that the terms involved in the proposed

M-DVC are too technical. For some of them, the M-DVC presents a whole new vocabulary that requires a significant effort to grasp. Moreover, a few terms are confusing even for the stakeholders with a technical background.

We should also be conscious of the limitations of our study: First, we collected evidence from only three cases which do not give enough evidence for all the topics and subtopics. Second, all the three MMLA cases are from Tallinn University which means that they share the same socio-cultural aspect. Third, we planned to conduct the study for one hour in each of the three cases but none of them could be finished within planned one hour. The exercise where participants were expected to communicate their MMLA case and fill out the information in the instrument require more time especially in those cases where participants do not have any prior experience of multimodal data processing. Fourth, we did not run other similar studies which could enable us to perform a comparative study. Last, both the participants of a case were asked to fill in the instrument with the information required in different phases of the proposed M-DVC. However, the instrument did not guide that who is responsible out of the two participants for which phase to fill out the instrument. This lack of guidance lead to some confusion between the participants which end up with some negative responses in the questionnaire. A kind of mapping of the participants (based on their role) with the data processing activity was required, where the instrument clearly states that who is responsible to fill in the information in a specific part.

VII. CONCLUSIONS AND FUTURE WORK

This paper is built on the paper [22] where we use the existing DVC of Big Data [12] in four MMLA scenarios to model the processing of multimodal evidence. From that study, we extracted the requirements for the purpose of specializing a DVC for MMLA. This paper present the specialized DVC called Multimodal Data Value Chain (M-DVC) by incorporating the lessons learnt from the previous study and reports its use as a decision-support, systematization and communication tool to support the development of MMLA solutions. M-DVC usefulness was assessed by using it in three real MMLA cases carried out at Tallinn University.

We formulate a RQ **To what extent is the proposed M-DVC useful as a conceptual tool to support cross-disciplinary stakeholders communication during the development of MMLA solutions?**. To answer our research question, we conduct evaluation study based on a mixed-method approach (see Section IV for more details). The overall findings show that the proposed DVC is useful as a decision-support, systematization and communication tool to support the stakeholder communication during the development of MMLA solutions. Results highlight that the M-DVC is useful as a conceptual tool for even those educational stakeholders who have limited data literacy. It empowers the educational researcher to communicate with the technical stakeholders by using a common conceptual tool in the process of development. Finally, the results also highlight that the M-DVC is useful for those stakeholders who do not have any prior experience of MMLA.

Our future work is in two folds. In first fold, we have short-term plan - to polish the instrument by incorporating three points - 1. an explicit focus to push the idea of 'inclusion of contextual information' 2. map the data processing activities and the underlying steps of the M-DVC to the stakeholders' profiles so that they do not get confuse while discussing and filling-out their case and 3. clarify and ease the technical terms used in the instrument for the educational stakeholders.

The second fold of our future work will focus on further supporting researcher, educators and technical staff to carry out MMLA solutions. We plan to build a MMLA infrastructure that follows the M-DVC as a conceptual tool to model the data processing activities and steps involved in every activity. This infrastructure will support the development of such MMLA solutions which can be reused in different learning scenarios and can be adapted in real practice. Once it is available, we will employ the infrastructure, together with the M-DVC, to support real MMLA scenarios in different institutions. Thus, we will collect more evidences of the usefulness of M-DVC.

ACKNOWLEDGEMENTS

This research has been partially funded by the European Union via the European Regional Development Fund and in the context of CEITER under grant agreements no. 669074. Also, by the European Regional Development Fund and the Regional Council of Education of Castilla y Leon under grant no. VA257P18 and by the ERDF and the National Research Agency of the Spanish Ministry of Science, Innovation and Universities, under project grant TIN2017-85179-C3-2-R.

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