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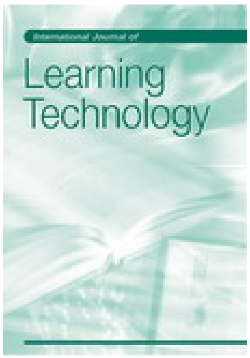

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A framework for co-designing effective LADs supporting sensemaking and decision making

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Abstract: Learning analytics dashboards (LAD) deserve increasing attention, yet their adoption remains limited. Designing effective LAD is a difficult process, and LADs often fail in turning insights into action. We argue that providing explicit decision-making features in a participatory design process may help to develop LADs supporting action. We first examine how the decision-making process is reflected on LADs. Second, we review the literature to identify major design space dimensions and examine how to include decision-making features. Third, we propose the DEFLAD design framework to synthesise this review which provides explicit decision-making features in three dimensions: *goal* expression as a situation awareness level, *visualisation* and related *interactions*, as support of decision-making process. Fourth, we consider how this framework is involved through every stage of a human-centred design (HCD) process to express and manage such features. The main contribution of this paper is to provide a framework integrating the decision-making features in a participatory design process of LADs. Furthermore, we demonstrate the implementation of our proposals through the development of a card-based toolkit to assist in the ideation phase of participatory design, and present feedback from participants of a workshop utilising this tool as a proof of concept.

Keywords: learning analytics; learning analytics dashboard; design space; sensemaking; decision making; participatory design; human-centred learning analytics.

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1 Introduction

Learning analytics (LA) research aims to leverage human judgement (Siemens and Baker, 2012) and to empower learners and teachers with actionable knowledge to allow them to make informed decisions (Jivet et al., 2017). Learning analytics dashboards (LADs) are tools used to represent and display the results of a learning analytics process in a meaningful way. By incorporating visual and interactive features, they amplify human natural abilities to detect patterns, establish connections and make inferences. Different indicators related to the learner(s), the learning process(es) and/or the learning context(s) are combined within a single display into one or more visualisations using different modalities, from textual and graphical representations to complex artefacts such as alerts and notifications that prompt action (Schwendimann et al., 2017). Recent work underlines that the term 'dashboard' does not pick out a unique method of organising, presenting, and using data, but rather covers a diverse set of practices (Sarikaya et al., 2019).

Although LADs have received increasing interest in recent years, there is a general agreement that they are still under-researched and under-explored (Alhamadi, 2020), widespread dissemination to their stakeholders remains limited. We argue that this is due to several reasons:

- Because of their relatively recent emergence, studies on their design principles are still relatively few (Echeverria et al., 2018; Sedrakyan et al., 2019).
- Designing effective LAD is a difficult process, in which stakeholders need to be involved. Indeed, LA tools may impose assumptions that do not meet the stakeholders' needs (Dawson et al., 2016).
- Users are lacking experience of LAD use and data literacy. Many dashboard designs fail to measure the appropriateness of the incorporated visualisations for their visual literacy levels (Schwendimann et al., 2017). Some authors (e.g., Chatti et al., 2020; Jivet et al., 2017) emphasise the importance of empowering the stakeholders.
- LADs often fail in turning insights into action since the processes by which people use these representations for insight seeking and decision making are still not well understood (Verbert et al., 2020).

LADs can only make an impact if they successfully influence a thought process or a decision (Meyer et al., 2010). Their design should thus focus on enhancing awareness and reflection to drive shifts in cognitive, behavioural and emotional skills (Jivet et al., 2017). This requires design researchers and practitioners to build on theoretical foundations drawn from several fields, ranging from data visualisation to human cognition and human-computer interaction (Yoo et al., 2015; Alhadad, 2018).

Drawing defensible conclusions from available information using LAD can be facilitated by designing LADs so that they support human sensemaking and reasoning processes. Designing dashboards as effective communication tools depends on a thorough understanding of the way humans see and think (Few, 2006). Our objective in this paper is to specify a design space that enables decision-making support. We advocate for a human-centred design, an approach that is becoming very popular for emphasising human factors (Chatti et al., 2020). More specifically, research found that involving end-users in the design loop ensures appropriate design responses that are well-aligned with their requirements and expectations (Taffe, 2015; Holstein et al., 2017).

By pursuing this objective, we aim to answer the following research questions:

RQ1 How can the decision-making process be reflected on a learning dashboard?

RQ2 How can we design LADs that make explicit the associated decision-making processes?

- RQ2.1 How can we make explicit the associated decision and meaning-making processes during LADs design?
- RQ2.2 How to manage decision-making features through the design process?

In the first part, we will examine how sensemaking and decision making can be supported by LADs and reflected by user interaction. The second part of this paper is devoted to the definition of a framework that makes the design space of dashboards explicit and that includes decision-making functions. We also describe PaDLAD, a toolkit we built for the participatory design of LADs that implements the proposed framework. The final section explains how this design space framework provides relevant support for the human-centred design process of LADs.

2 Decision making and LADs

2.1 Designing effective LADs

As instruments of communication, the LAD design spans several fields, such as human cognition and perception, human-computer interaction, and visualisation technologies (Yoo et al., 2015; Alhadad, 2018). Therefore, any design process needs to account for several factors, sometimes of different nature. One important yet challenging multidimensional dimension within this context is the choice of appropriate visual representations, suitable for the current data and the task at hand, and consistent with the potential user's level of visual literacy. The effectiveness of a LAD depends on the use of appropriate visualisations of the data. Ineffective visualisations can cause unnecessary exploration, inaccurate or false knowledge, wasted time or lack of use due to frustration and confusion (Yalçin et al., 2016). Visual representations transform data into a form that relies on the human visual system to perceive its embedded information (Gershon and Page, 2001). By doing so, it aims to amplify cognition and generate insight, allowing humans to observe, understand, and make sense of the information, and to complete tasks more efficiently (Gershon and Page, 2001; Yi et al., 2007). By giving data a tangible form, visualisations allow humans to generate insights, make decisions, and formulate actions that may otherwise be impossible or difficult to do (Few, 2006).

Despite a growing popularity of LADs, more research needs to focus on design principles that are able to guide and justify design choices (Bodily and Verbert, 2017; Echeverria et al., 2018). As stated by Gašević et al. (2015), without careful considerations, the design of dashboards can result in the implementation of fragile and undesirable instructional practices by promoting ineffective feedback types and methods. In this section, we thus aim at answering our first research question (RQ1) related to investigating ways to model and represent the decision-making process within learning dashboards.

2.2 Sensemaking and decision support with LADs

A related aspect is supporting people to reflect, make sense of and react upon LAD visualisations. The process of stimulating and enabling human reasoning using interactive visualisation tools is an under-explored field (Meyer et al., 2010). From a meta-cognitive perspective, one of the important roles of dashboards and visualisations is to support sensemaking. This stands for an information integration process, sensemaking, that gives rise to a final decision or action. Pirolli and Card (2005) refer to sensemaking as the way in which humans process and interpret information about the world, resulting in the creation of new knowledge or insight as a basis for future action.

Sensemaking is a process of collecting, organising and analysing information to generate knowledge and inform action. The use of visualisations leverages the human visual system to support this process. Many authors attempted to describe and analyse sensemaking with LADs. Proposed models break the process down into phases that go from perceiving the dashboard to taking and implementing pedagogical actions and decisions. For instance, Wise and Jung (2019) elaborated a sense-making framework of instructor analytics using dashboards, in which the process starts by identifying the educational questions that lead to investigation and interpretation of the dashboard, followed by pedagogical responses. The model proposed by Campos et al. (2021) evolves from one or more pedagogical events to its multiple data representations. These representations are used by a set of sense-making sub-processes (emotional, analytical, and intentional dimensions) to produce an interpretation of the events. The authors' assumption is that sensemaking, by itself, may not lead to action. Yet, even if no action per se is taken, pedagogical knowledge and reflection are generated by the process. Thus, the model places pedagogical decision making along with reflection as external but connected processes to sensemaking.

2.3 LADs as cognitive tools

Existing process models of LA/LAD are designed around making sense of the data, gaining insight from that data and planning actions that impact teaching and learning.

Nevertheless, these models are evasive on how these cognitive activities are related to and correlated with the user's experience with the LAD.

Interaction is the means by which humans can explore visual representations to generate insight. It is an essential glue that tightly binds analysis, visualisation and the human analyst (Endert et al., 2014). To examine how users engage in sensemaking supported by LADs, we propose to investigate interaction beyond its technical and modality aspects, to consider it in terms of the discourse that occurs between users and LADs during sensemaking. Such a perspective is compliant with the view of interaction within the *distributed cognition* theory (Hutchins, 1995). According to this theory, cognition is inherently distributed, and results from the propagation of representations of information across various media. It is a property that emerges and builds up over time as an individual interacts with his or her environment; it develops through perception and action (Liu et al., 2008). These media include human minds but also the knowledge represented within the tools that encode information. The cognitive activity depends on the interaction between the elements in the overall context. From the perspective of distributed cognition, users and LADs form a single system built on coordination and causal influence. One of the primary attractions of such a perspective is that it can help us observe and reason about cognitive processes by watching the interchange of representations as they are passed between agents in the system.

2.4 Data/frame theory of sensemaking with LADs

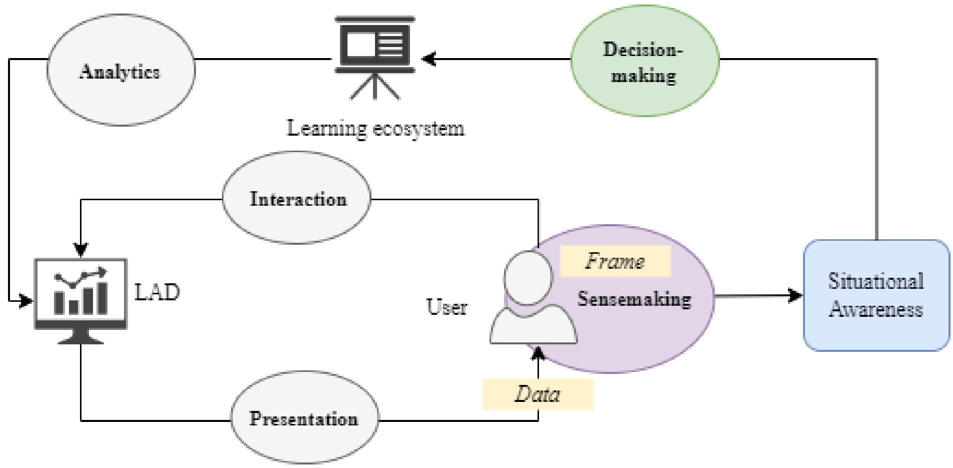
Sensemaking is a process of searching for a representation and encoding data in that representation to answer task-specific questions (Russell et al., 1993). By approaching sensemaking with LADs from the perspective of distributed cognition, we view internal representations as being formed in the head of the user as the result of his intrinsic factors (background, knowledge, emotional state, etc.) and from the perception and interaction with the external representations that are rendered by the dashboard.

Many models are proposed to analyse the sensemaking process. To account for LAD-based sensemaking, we adopt the *data/framework* (D/F) theory (Klein et al., 2006), which most clearly delineates the underlying cognitive processes of sensemaking among existing models. Moreover, this theory flows from the realm of naturalistic decision making, which reflects the reality of most decision making using LADs. According to this model, two kinds of entities interact dynamically during sensemaking: *data* and *frame*. The data is the information that a person receives or seeks, and the frame is the mental structure that organises, interprets and explains the data. The frame extends beyond the data, using background knowledge and expectations to fill in gaps, and eventually creates gaps into which the data can fit.

2.5 Interaction model for sensemaking

Figure 1 depicts a model of sensemaking supported by LADs. In this model, dashboards are seen as cognitive tools that enable users to visually identify patterns, trends, and anomalies in data to guide them to effective decisions (Brath and Peters, 2004). The proposed model addresses the first research question (RQ1 – 'how can the decision-making process be reflected on a learning dashboard?'), by providing a detailed schema that illustrates the relationship between the various steps involved in the decision-making process and the interactions with a learning dashboard.

Figure 1 Sensemaking supported by LADs interaction model (see online version for colours)



We envision sensemaking as the cognitive process that provides both a means of interpreting data from the environment and a trigger and catalyst for action to be taken accordingly. In pursuit of his goal, the user interacts with the dashboard to gain insights and perform actionable data. Starting from an initial frame, the user engages in an active process of sensemaking that can be described as the nesting of two tasks:

1 *Interacting:* During this task, the user interacts with the LAD to seek, search, filter, read and extract information. This data is provided by the representations displayed by the LAD. This interaction triggers background processes that recompute the graphic layout of the LAD, by adapting its view.

2 *Framing:* During this phase, the user integrates the data gathered from his interactions to his internal knowledge to construct, change or consolidate a frame.

The framing occurs in the user's mind. The interaction with a LAD allows the user to get necessary data that make it possible to evolve his current frame using sense-making activities. The framing is an iterative process: depending on the frame obtained, the user may need to interact again with the LAD. The D/F theory defines the following list of SM activities:

1 elaborating the current frame by adding it data and new relationships

2 questioning data that is incompatible with the current interpretation

3 preserving the interpretation regardless of the incompatibility, by relativising the significance or justifying the ignoring the incompatibility

4 comparing multiple interpretations that can explain the same set of data

5 reframing by looking for a solution that explains inconsistent data, possibly by reconsidering and reinterpreting rejected data

6 seeking a new interpretation of conflicting data, using for instance key data elements as anchors.

2.6 Decision-making process

Sensemaking is a prerequisite for many essential human tasks, especially decision making. Endsley (1995) described three levels of situation awareness (SA): *perception* of the elements in the environment within a volume of time and space, *comprehension* of their meaning, and *projection* of their status in the near future. This process leads to decision making and then to actions. According to Klein et al. (2006), the stages of knowledge represented by the levels of SA are only attainable through sensemaking.

Sensemaking is a cyclic process of gradually developing understanding of the present situation before eventually taking action. It brings the involved parts of LAD-based reasoning and decision making into a meaningful structure. Data provided from the learning ecosystem is processed by an analytics engine, and indicators are computed. These latter are presented to the user meaningfully by a LAD. The user makes sense of the data through interaction exploration. His interactions can result in the LAD updating its configuration and thus the associated representation. The insight gained by the user can push him to make some pedagogical decisions, which can impact the learning ecosystem.

3 LAD design framework

We propose a LAD design framework including sensemaking features 'DEFLAD'. This framework is based on literature analysis of design space proposals for dashboards (Sarikaya et al., 2019) and LADs (Sedrakyan et al., 2019), with a specific focus on sensemaking features. This framework aims to clearly outline the design dimensions of LAD, specifically those pertaining to decision-making processes, addressing our second research question RQ2 (how can we design LADs that make explicit the associated decision-making processes?).

The concept of design space has its roots in the theory of information processing developed by Newell et al. (1972), wherein a problem-solving activity is thought of as the act of searching in the state space of a well-defined problem. Solving a design problem is therefore the process of exploring the design space. A design space for a particular problem can be defined as the set of available solutions for the designed artefact and the alternative choices for these solutions (Shaw, 2011).

A common strategy for defining a design space is to extract common design principles from the existing techniques of the target domain (Schulz et al., 2011). In dashboard design, several authors have sought to characterise the design space. For instance, in the data visualisation field, Schulz et al. (2011) elaborated a design space by describing how designers can reason about tasks through six dimensions of task analysis: 'why' (task's goal), 'how' (task's means), 'what' (data characteristics), 'where' (the target and the cardinality of data entities within that target), 'when' (order of tasks), and 'who' (the user or type of user). Those dimensions may be found in Sarikaya et al. (2019), with an additional focus on user's visualisation literacy, and a refined analysis concerning interactions. The design space derived by the authors define four design dimensions related to different aspects of a dashboard: purpose (strategic, tactical, and operational decisions and learning), audience (circulation, required visualisation literacy, and required domain expertise), visual features (construction and composition, multiple pages, interactive interface, highlighting and annotating, and modifying state of the data or world), and data semantics (alerts and notification, benchmarks, and updating).

Some authors (e.g., Chatti et al., 2020) propose to use 5 W's questions to address such a design space, focusing on the object of interest, from visualisation to dashboards and learning process analysis. In the context of LADs, we formulate the 5 W's as follows:

1 *who?* depicts the audience and circulation between different users

2 *when?* permits to answer if usage is real-time or delayed

3 *why?* corresponds to the goal of the LAD

4 *what?* details the context of LAD's usage, and relevant data

5 *how?* focuses on visualisation, which is related to sensemaking with a LAD.

Table 1 summarises the properties we identified of each of these design dimensions. The next paragraphs detail and discuss each of these dimensions.

Table 1 Dimensions of the LAD design space

Dimension	*Elements*	*Values*
Who?	User	Governance, institution, curriculum, teacher/tutor, learner
	Circulation	Public, organisational, social, individual
When?	Real-time	Y/N
Why?	Focus	Learning process (cognitive, outcome-oriented, process-oriented, behavioural, meta-cognitive, social, emotional)
		Management (people, resources, activities, experience)
	Situation awareness level	Perception (or monitoring, awareness, support), comprehension (or analysis, reflection), action (or projection, decision, intervention, feedback, assessment)
What?	Data	List of relevant data
	Data scope	Learner, teacher, classroom, institution
	Data source	Classroom, learning management systems, curriculum, profile, other
	Data duration	One session, one semester, one year, whole schooling, lifelong
HoW?	Visualisation	Type of diagram
	Interaction	Zoom, filter, details-on-demand, relate, history, extract

3.1 Who? Identify the audience

Two dimensions are related to the audience:

1 LAD users' identification, which is classical in LA

2 dashboard circulation, which acknowledges dashboards as potential communication tools.

3.1.1 Users

LADs can target different stakeholders: administrators, instructors, learners or all of them. Previous work associates four levels of stakeholders: mega-level (governance), macro-level (institution), meso-level (curriculum, teacher/tutor), and micro-level (learner) (Sedrakyan et al., 2019; Ifenthaler and Widanapathirana, 2014). Acknowledging that dashboards may be a communication tool between different stakeholders, the target audience concept broadens the notion of user (Sarikaya et al., 2019).

3.1.2 Circulation

Related to the audience, interpersonal circulation of a dashboard can be detailed based on four groups: *public*, *organisational*, *social* and *individual*; each becoming more specific and requiring more contexts (where the necessary context might not be included in the dashboard itself) (Sarikaya et al., 2019). A public dashboard is intended for general consumption, and may describe societally-relevant data. Dashboards for organisations are broadly relevant within an organisational construct for many different individuals who share a common goal (say, validating diplomas). Social circulation captures contexts in which an individual restricts the access to the dashboard to individuals of their choosing, identifying scenarios of sensitive data or analysis. Individual circulation captures dashboards that quantify the individual and are generally not shared, except with trusted individuals (e.g., a teacher for a learner).

3.2 When?

This aspect of the design space depicts the time of use of the dashboard. Associated with the audience is the idea that users and data come together. It is possible to determine whether the communication is based on real-time data processing, i.e., whether the communication is based on what is currently happening or is based on historical data.

3.3 Why? Refining LAD goals

This dimension is broadly related to the intended purpose of the dashboard. Although this is a central aspect of LADs that provides the rationale for the design, it remains unclear when referring to the existing literature. Some authors refer to purpose, others to goals, or even objectives. We retain the term goal. Most articles only provide lists of goals derived from the work of Park and Jo (2015).

3.3.1 Focus

Most works on dashboard goals provide one or more lists of examples (Jivet et al., 2017; Sedrakyan et al., 2019). Sedrakyan et al. (2019) analysed students' objectives under the perspective of aimed intervention (or feedback), and proposed the following focuses on learning process:

1 cognitive

2 outcome oriented (e.g., achievement level)

3 process-oriented

4 behavioural

5 meta-cognitive.

As social presence is a key element of educational experience (Garrison et al., 2003), we propose to add to this list:

6 the social aspect, that relates to group-work or learner relations (for example in forums)

7 interventions of emotions (Ez-Zaouia et al., 2020) should complete this list.

Teachers' goals include interventions concerning the students' learning process, and the same focus list as students apply. They are also concerned by course management, and their goals may focus on:

1 people (e.g., students at risk)

2 resources (management or improvement)

3 activities (including assessment)

4 experience.

Other stakeholders at mega- or macro-level may be interested in additional focus objects, but this list remains to be proposed.

3.3.2 Situational awareness level

Typically, a goal can be expressed as a verb followed by an object. When browsing goal lists, the expression may be related to a situation awareness level or state (Endsley, 1995), that can take different names depending on the context:

1 monitor or awareness

2 analysis, or reflection

3 action, or projection, decision, intervention, impact, feedback, assessment.

We argue that the goals of LAD refer to two dimensions of the design space: focus and situation awareness level. These two dimensions allow all existing options to be integrated and new ones to be considered. Concretely, they:

1 open new opportunities for design

2 encourage designers to go beyond simple options like 'monitoring', and to explore higher levels of situation awareness.

Table 2 positions the list of goals elaborated by Park and Jo (2015) according to their *focus* and the targeted *situational awareness* level. It covers most learning process options, but not corresponding SA levels. Users should be encouraged to examine other SA levels, with a special attention to feedback. On the management options, many options remain to be explored.

Table 2 Expressed goals related to focus and SA level

Goal	*Focus*	*SA level*
To improve retention and performance outcomes	Learning process cognitive	Awareness
To provide a visualisation of learning performance with a comparison whole class group	Learning process performance	Comprehension
To provide feedback on students' learning activities and performance	Learning process performance	Action
To keep track of learners' interaction in e-learning systems	Learning process behavioural	Comprehension
To promote reflection and awareness of their activity	Learning process meta-cognitive	Awareness
To enable students' self-reflection and awareness of what and how they are doing	Learning process meta-cognitive	Comprehension
To visualise the evolution of participant relationships within discussion forums, to help students see how well they are contributing to the group	Learning process social	Awareness
To identify and treat at-risk students	People management	Awareness → Action

According to the goal defined and the intended audience, a collection of data will be necessary to support the sensemaking (i.e., comprehension) process of targeted users. Data scope must be defined, as it is decoupled from the audience. It may concern a learner, the classroom (or a whole cohort) or even the institution, but it may also concern the teacher. Including the teacher in this dimension encourages investigating teacher analytics (Bienkowski et al., 2012) where the goal is to improve the learning process itself.

Data source and data scope are also important features of the design. Data may be collected in the classroom (classroom analytics), from classical learning management systems, from the institution (transcripts of the curriculum, profiles of the learners, …) or from other sources (multimodal analytics). Duration can be as short as a session, or as long as a lifetime. Listing the different data needed is also required to define the dashboard.

3.4 How? Visualisation and sensemaking in LADs

How is a central question for dashboards, as relevant visualisations are required to gain insights (Sarikaya et al., 2019; Chatti et al., 2020). As identified in the 'why' section, the dashboard may support a sensemaking process, where the user(s) may navigate across different levels of sensemaking and may need to analyse some data. Multiple panels, interactions, and additional features such as alerting and notifying are relevant to qualify the dashboards.

Regarding interactions, a simple but supportive taxonomy is proposed in Shneiderman (2003). Known as the information-seeking mantra, this taxonomy summarises the essential elements of interacting with graphically presented information by defining a high-level set of tasks:

1 *overview* task purpose is to provide the user with a global view of the available data and to display aggregated, summarised and less targeted representations of this data

2 *zoom* task is executed to investigate a part of the data by allowing to select this part and to interact to select the focus and the zoom factor

3 *filter* task reduces the amount of data and/or visual objects displayed, and helps the user find and focus on specific items of interest

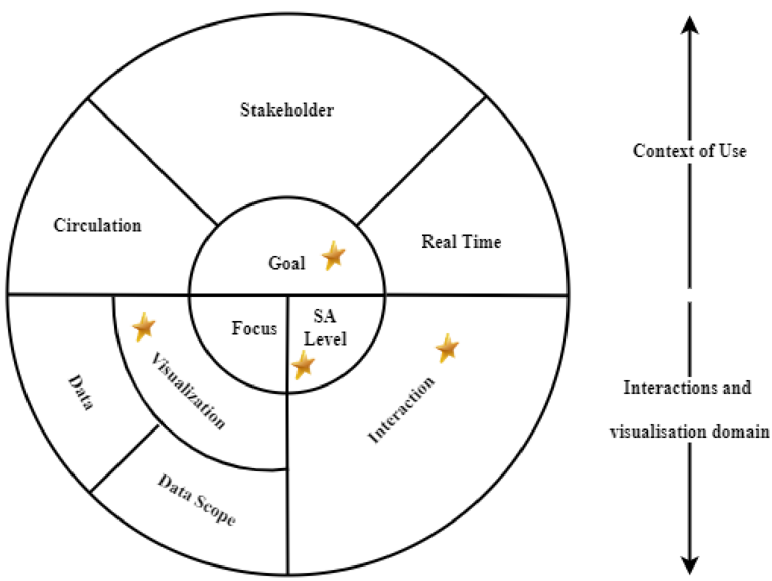
4 *details-on-demand* task refers to the use of techniques to obtain more precision on the data in order to obtain a better insight

5 *relate* task allows users to view relationships between data points

6 *history* task allows keeping a record of actions to support undo, replay, and progressive refinement

7 *extract* task allows users to visualise a part or sub-collection in order to focus only on the data that is necessary for immediate use.

Figure 2 LAD design framework 'DEFLAD' with sensemaking related features (star) (see online version for colours)



3.5 DEFLAD framework

Based on the refined design space, we propose ‘DEFLAD’, a LAD design framework that incorporates sensemaking capabilities, depicted in Figure 2. In addressing RQ2 (*how can we design LADs that make explicit the associated decision-making processes?*), the framework explicitly includes design dimensions related to decision-making, effectively providing an answer to RQ2.

In DEFLAD, the design space is divided into two main parts. The first part, comprising the first three questions, focuses on defining the context of use for the LAD. The second part, comprising the remaining two questions, addresses the visualisation and interaction aspects of the device. This framework aims to provide a comprehensive approach for designing LADs that effectively support sensemaking tasks.

We reify *goal* as the core of the LAD design framework. This goal is composed of two sub-dimensions, *focus*, which guides the *visualisation* and associated *data* on one hand, and *situation awareness level*, which is closely related to *interaction* with the dashboard. As previously discussed, *goal*, *situation awareness level*, *visualisation*, and *interaction* are all features that play a crucial role in the sensemaking process. This clearly defines the LAD design space with a strong emphasis on sensemaking features, addressing our second research question (RQ2).

4 Human-centred learning analytics

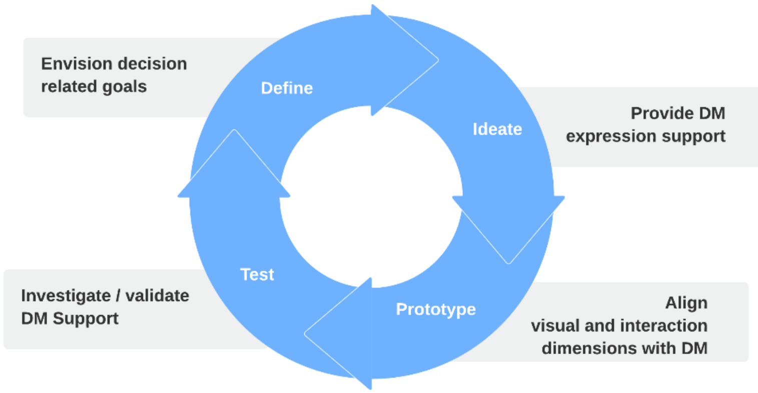
Current research found that the success of dashboards in terms of acceptance and adoption, and more globally of any LA innovation, greatly depends on the degree to which its stakeholders have been involved in the design process (Holstein et al., 2017). This has motivated the increasing focus of the LA research community on human-centred design (HCD) approaches and the emergence of the human-centred learning analytics (HCLA) (Shum et al., 2019; Dimitriadis et al., 2021). In this section, we provide a precision of our proposed solutions to our research questions. Specifically, we show how our model of LADs that support the decision-making process can be implemented during a design process that engages various stakeholders, including users and designers.

Participatory design has recently emerged as a growing trend in education. *Participatory design* or *co-design* derived from user-centred design as a particular case of co-creation where designers who are trained in creativity work together with non-designers during the design process. According to Sanders and Stappers (2008), the concepts of ‘participatory design’, ‘co-creation’ and ‘co-design’ refer to the same idea and associated practices of involving stakeholders throughout the design process.

Although LA academics and practitioners are increasingly acknowledging the relevance of HCD methods such as participatory design, their integration into learning analytics has been slow and is still not yet widespread (Sarmiento and Wise, 2022), and approaches to achieving this remain unclear (Dollinger et al., 2019; Alvarez et al., 2020). Prieto-Alvarez et al. (2018) proposed a co-design process adapted to LA, where activities are iterated, so as to refine the needs and get closer to the desired solution. Our aim is to instrument this process more specifically for LADs.

Following the approach used in Chatti et al. (2020), we focus on the central HCD stages, but retain the terminology used by Prieto-Alvarez et al. (2018): define, ideate, prototype and test, and consider how our DEFLAD is progressively explored and refined, as depicted in Figure 3.

Figure 3 Human-centred design with decision-making features (see online version for colours)



4.1 Define goals

Identifying the why? is the first stage of the HCD process providing a good understanding of users and the needs that the design is intended to meet. Our refined definition of goals makes explicit extensive options for development, and confronts the user with the ultimate design goal of turning ideas into action, through the expression of situational awareness.

Who? (audience and circulation) and when? provide additional information of users' needs and clarify the context of use.

4.2 Ideate

Ideation is a central stage in HCD design as it involves users to collaboratively derive design ideas. Some tools like La-Deck (Alvarez et al., 2020), PaDLAD (Sadallah et al., 2022) and LADStudio (Sadallah and Gilliot, 2023) provide guidance for the generation of such ideas. They typically provide:

1 *Cards:* To provide a common basis for understanding and communication in a team and support creative combinations of information and ideas (Roy and Warren, 2019). They thus provide convenient summaries of useful information and/or methods such as visualisation guidelines.

2 *Sketching:* Sketching is a second important feature to ideas' generation. This making process allows constructing visual representations, engaging co-designers beyond the ideation process. Prototyping allows participants to communicate in a non-traditional way, by inviting them to communicate their needs and expectations (Gaver et al., 1999). Reflection and interpretation are the primary objectives in building the first prototype that helps all learners involved understand what they are looking for in visual representations (Luckin et al., 2013). Sketching also

provides opportunities to specify interactions, which are central for decision making.

4.3 Prototype

During this stage, visualisation and interactions are implemented in a prototype, visualisation idioms and interactions options proposed in the ideate stage are examined and refined according to data available, and relevant guidelines. Additional options may be proposed by visualisation experts when available.

4.4 Test

The final stage is to get feedback from potential users on the LAD prototype. The aim is to verify that these prototypes effectively provide insight at the aimed situation awareness level defined as a goal. Whether the prototype provides relevant satisfaction, a new iteration may be necessary.

5 An illustrative implementation for ideation

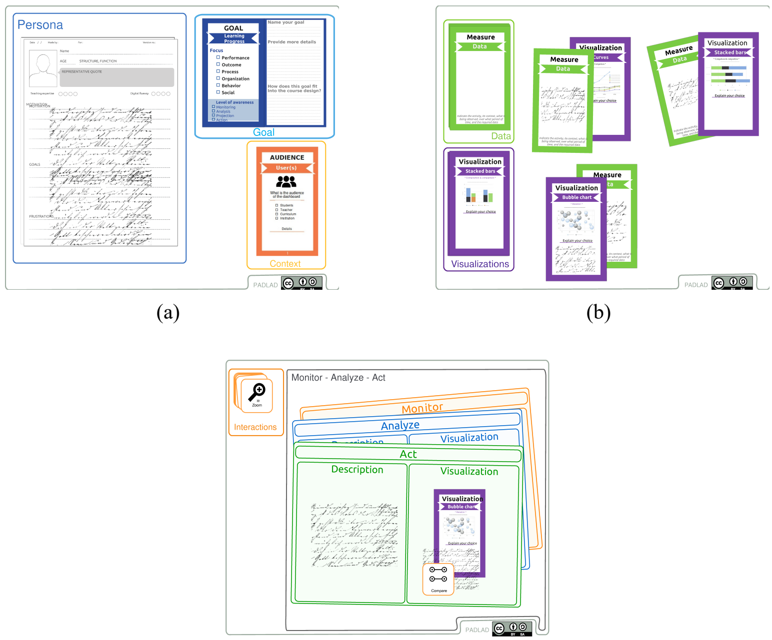
In this section, we demonstrate the practical application of the DEFLAD framework by presenting the development of a card-based toolkit that utilises the refined design space to enhance the ideation phase of participatory design workshops. The toolkit includes a set of tools that promote a high level of collaboration and creativity among stakeholders, effectively exemplifying the proposed human-centred design approach. To provide further validation, we present the results of using the toolkit in an educational setting through a design workshop, including feedback and insights gathered from the participants.

5.1 The PaDLAD toolkit

The PaDLAD toolkit (Sadallah et al., 2022) is built around the concept of personas, exploration maps, and various sketching and panelling tools that provide a variety of ways for users to express themselves. Its goal is to foster creativity while highlighting the different aspects of the design space. The design process using this toolkit involves three main stages, represented by specific panels (Figure 4).

The *identification board* provides a place for a persona form, a goal form, and a set of context cards. The persona form can be used to personify stakeholders and gather their information. The objective form is used to establish the problem that the dashboard aims to solve. This goal is defined according to the level of awareness of the situation sought (monitoring, analysis, action). The context cards describe the expected use of the dashboard: the audience cards define the field of analysis; the data cards define the targeted data source and the observation time.

Figure 4 PaDLAD toolkit panels, (a) identification panel (b) DataViz panel (c) sketching panel (see online version for colours)



(a) (b) (c)

The data and visualisation (DataViz) boards answers the question ‘what?’ and includes a placeholder for tuples constructed from data and visualisation cards. The data cards (or measurement cards) identify the relevant data and indicators to achieve the dashboard objective. Visualisation maps are a set of technology maps that provide traditional visualisations and are relevant to represent the information contained in the data maps.

The purpose of the sketching board is to allow design actors to create views and graphical representations by sketching the intended LAD, and to define interaction options. We distinguish three types of views:

1 views *perception* allow to monitor the state of the environment

2 views *understanding* comprise representations aiming at providing the necessary lighting to analyse and understand a given situation

3 views *projection* allow to prepare the user to act on the situations discovered and analysed in the previous levels.

Using this board, sensemaking is supported in three ways. First, in order to foster browsing of the different levels of SA, mockups of different colours are provided: red for *monitoring*, blue for *analysing*, and green for *action*. Participants are invited to associate data and visualisations to the different mockups. Second, technology cards of the main interaction options are provided to help participants express how they wish to interact with the LAD. Third, a storyboard form is attached to each mockup inviting them to express how they imagine the sensemaking process.

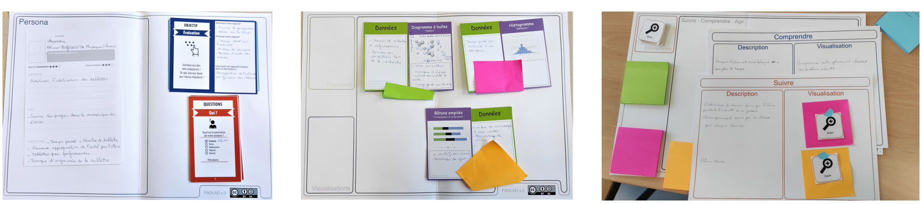
5.2 *Ideation workshops with teachers*

To experience with the proposed design toolkit in a real educational setting, we organised codesign workshops. Email invitations explaining the purpose and goal of our project and inviting participation in ideation workshops were sent to French high school teachers and instructional designers. Fifteen (15) persons agreed to participate, among which seven were teachers and eight were instructional designers. We (the authors) acted as facilitators whose task was to introduce the context and objectives of the workshop, explain the components of the toolkit, ensure that the instructions and protocol were followed, and answer participants' questions. The workshop took about one hour and a half.

5.2.1 *Description of the workshop run*

The participants were divided into three groups of five, with each group containing individuals from different backgrounds. Each group worked independently using a provided toolkit. While no specific order was required for the design steps, all three groups followed the suggested order. Using the appropriate cards and forms, they started by completing the identification board, which included defining a goal, describing a persona, and establishing the targeted use context. They then discussed which data and visualisations were necessary to achieve the identified goals before defining tuples of data/visualisation. These sets were then used to create a sensemaking storyboard that reflected the reasoning flow. This collaborative work resulted in various design options for the LADs, illustrated in Figure 5.

Figure 5 Examples of some produced *identification*, *DataViz*, and *sketching* panels (from left to right resp.) during the workshop (see online version for colours)



5.2.2 *Feedback from the participants*

The participants emphasised the importance of considering the needs and expectations of end-users when designing these tools and incorporating them into the design process. Their feedback during the workshop was globally positive, with many praising the benefits of the participatory design approach. They found the participatory design process to be highly valuable, leading to engaging discussions and the generation of creative ideas for improving classroom learning. Regarding the card-based approach, one participant noted "these cards, while not exhaustive, offer a wide range of possibilities and their categorization by intended goals helps clearly define design options".

During goal definition, the participants of one group decided to consider *learning progress*, to focus on the *process* with a *situational awareness level* going from monitoring to planning actions. Their aim was to adapt their teaching according to the obtained feedback and to develop equality among students. Nevertheless, as stated by a member of this particular group: "a dashboard can have a goal, but sometimes this latter is much more related to a use than to the dashboard: one can divert for another use a dashboard preconceived for a specific goal".

The use of the identification board effectively guided the groups in constructing a clear understanding of their target through the utilisation of the DataViz board. However, variations in participants' visual literacy skills resulted in discussions surrounding the most appropriate visual representations to use. Participants conveyed a desire for additional support during this phase, as reflected in the feedback of the majority of the participants, summarised by one participant's statement: "it is essential to involve an expert graphic designer in the codesign process to ensure that the visualisations chosen effectively represent the data. Without their expertise, it may be challenging to select the appropriate visualisations without compromising the clarity and effectiveness of the data representation".

The design of the dashboard views, which aligned with different levels of awareness, was perceived as intuitive by participants. They appreciated the reasoning behind it and found it easy to understand. This approach also helped participants envision actual usage scenarios, as it reflected and physically represented the thought process. This was acknowledged by one participant who stated: "what is interesting here is the focus on the story that you want to tell through maps, which is a very interesting, even innovative perspective". Another participant, while agreeing with this position, also raised the challenges inherent in the need to construct the panels associated with the different levels of awareness: "the ability to project the reasoning process into visual display is engaging, although it makes it more complex to determine the different steps and build the corresponding screens. In addition, sometimes one screen is sufficient for all the steps".

We observed that utilising different screens to depict the design process can enhance the organisation and clarity of ideas. However, some participants encountered difficulties in breaking down their reasoning into separate stages and connecting various visualisations to each stage. Nevertheless, when working in collaboration, conversations and explanations between participants frequently took place, enabling one participant to aid others in comprehending and utilising the tools more efficiently.

6 Conclusions

Designing effective LAD is a difficult process, and LADs often fail in turning insights into action. We argue that making decision-making features explicit in a participatory design may help to develop LADs supporting action.

Our first research question (RQ1) aimed to investigate the ways in which the decision-making process can be reflected on a learning dashboard. To answer this question, we first examined how the data frame theory (Klein et al., 2006) and distributed cognition theory (Hutchins, 1995) can provide relevant support for this task. We then developed an interaction model that relates the sensemaking process within the user's mind to their interactions with the learning dashboard. Our proposed approach for reflecting the decision-making process on a learning dashboard involves utilising a combination of data frame and distributed cognition theories, as well as incorporating a human-centred design approach that explicitly describes sensemaking and decision making throughout the design process. In this way, the decision-making process can be reflected on a learning dashboard by providing explicit support for it at the design stage.

Our second research question (RQ2) aimed to address the need for explicit decision-making features in a design process. To answer this question, we proposed a framework that synthesises a design space and provides explicit decision-making features in three dimensions: *goal* expression as a *situation awareness* level, *visualisation* and related *interactions*, to support the decision-making process by expressing perceived distributed cognition. To further elaborate on this answer, we examined how these features can be implemented and managed during different stages of a human-centred design (HCD) process. Specifically, the *define* stage enables goal expression, the *ideate* stage provides support for precise users' needs expression and solution generation, the *prototype* stage gives the opportunity to validate solutions according to good practice guidelines, and finally the Test stage evaluates and potentially validates the design.

To provide evidence of the answers for our research questions, we designed an ideation toolkit for the participatory design of LADs that implements the DEFLAD framework in a HCD context. The toolkit is based on the proposed refined design space. It promotes a more precise decomposition of the intended goals, including sensemaking depicted through SA levels. Moreover, it combines personas profile to express user needs, ideation cards to promote domain needs, and sketching to enable prototyping. The toolkit, as a means of expression, translates the transient aspects of the exchanges between participants and transforms them into a persistent representation. The evaluation of the toolkit with LAD stakeholders showed that its ability to capture the sensemaking dimension allows them to discuss aspects that are beyond the scope of data and representations. Thus, through the design of dashboards, the aim will be to design cognitive tools that support human reasoning.

In this paper, we aimed at defining a global framework. The next steps will consist in proposing relevant supporting tools for each HCD process stage. The *define* stage may benefit from an extensive collection of goals examples, which still need to be reviewed. The *ideate* stage should be supported with a participatory process that explicitly captures decision-making features. We illustrated with *PaDLAD* how this step can be supported. The *prototype* stage will take advantage of a generative approach, based on a collection of examples and based on good practices rules that will help the users and designer to explore fruitful alternatives. Finally, an experimental procedure should be defined for the test phase.

To conclude, as stated by DiSalvo et al. (2017), in participatory approaches, learning is both an implicit and explicit desired outcome, and if used well, can advance the development, implementation, and sustainability of learning innovations. We hope that providing relevant tools will contribute to empower users and foster LADs' dissemination.

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