Generating LADs that Make Sense

Madjid Sadallah[a] and Jean-Marie Gilliot[b]
IMT Atlantique, Lab-STICC UMR CNRS 6285, F-29238 Brest, France
{*madjid.sadallah, jm.gilliot*}*@imt-atlantique.fr*

Keywords: Learning Analytics Dashboard, Codesign, Generative Design, Dashboard Generation.

Abstract: Learning Analytics Dashboards (LADs) deliver rich and actionable representations of learning data to support meaningful and insightful decisions that ultimately leverage the learning process. Yet, because of their limited adoption and the complex nature of learning data, their design is still a major area of inquiry. In this paper, we propose to expand LAD codesign approaches. We first investigate how the user makes sense of the data delivered by LADs and how to support this sensemaking process at design. Second, we propose a generative tool, supporting sensemaking and decision making process, that extends end-users participation during the prototyping phase and empowers LAD designers. We also present an evaluation of the tool, including usability and user experience, demonstrating its effectiveness in supporting the design and prototyping of LADs.

1 INTRODUCTION

Learning analytics dashboards (LADs) are visualization tools that report on student learning in educational contexts as a result of a learning analytics (LA) process (Schwendimann et al., 2017). By incorporating visual and interactive features, they amplify human natural abilities to detect patterns, establish connections and make inferences. Being the most visible face of LA, their successful design is critical to the adoption of LA solutions by the educational community. Despite numerous reviews showing an increasing interest in LADs (see, e.g., (Schwendimann et al., 2017)), large-scale diffusion to their stakeholders remains limited. This lack of adoption can be attributed to issues related to (1) their poor design, resulting in a failure to incorporate pedagogical underpinnings (Jivet et al., 2018), (2) a poor alignment with users' needs and expectations (Chatti et al., 2020), and (3) failure to measure the appropriateness of embedded visualizations to users' visual literacy levels (Schwendimann et al., 2017).

LADs can make an impact only if they successfully influence a thought process or a decision (Meyer et al., 2010). Yet, their design as instruments of communication is challenging (Echeverria et al., 2018) and calls for theories from several fields, ranging from data visualization and human cognition to human-computer interaction (Yoo et al., 2015; Alhadad, 2018). We argue that their design should focus on supporting sensemaking and decision-making, and enhancing awareness and reflection as a means to drive shifts in cognitive, behavioral and emotional skills (Jivet et al., 2018). From a practical standpoint, creating effective LADs is complex not only in terms of design, but also of implementation. Capturing LAD design and delivering it for end-users are a highly demanding, time-consuming and challenging task requiring expertise in data analysis and visualization (Deng et al., 2022). Our objective is to propose a complete design and delivery methodology capable of creating meaningful LADs at affordable costs.

To fulfill our objective, we advocate for a codesign approach to ensure design responses that are well-aligned with users' requirements and expectations (Holstein et al., 2017). We also focus at the design stage on creating LADs that are centered on sensemaking to best support decision making. Moreover, literature reports that effective co-design of LA systems with stakeholders requires generative design tools and techniques to overcome potential barriers (Holstein et al., 2019). Thus, to support the production of co-designed LADs, we follow a generative approach for providing functional prototypes without requiring a significant development effort.

In this paper, we aim to address two research questions: *How can the decision-making process be reflected on a learning dashboard?* (RQ1) and *How to support the designer in the prototyping phase to design LADs that make explicit the associated decision-making processes?* (RQ2). We propose a generative

[a] https://orcid.org/0000-0001-9118-0235
[b] https://orcid.org/0000-0003-4569-3552

co-design approach and tool to address the research questions. Our approach and tool integrate generative design and participatory design to identify the desires, needs, values, and constraints of LAD designers and stakeholders, and to generate prototypes that support the decision-making process. The remainder of this paper begins with a review of relevant research (Section 2). Section 3 presents a framework of interaction for sensemaking in LADs, and details our proposed generative co-design approach. Section 4 describes LADStudio, a tool we built to illustrate the implementation of our proposals; it also reports on the studies carried out to evaluate the usability and the user experience of the tool before concluding (Section 5).

2 BACKGROUND AND RELATED WORK

2.1 Factors of Effective LAD Design

Because LAD design spans several fields, any design process needs to account for several factors, sometimes of different nature (Yoo et al., 2015; Alhadad, 2018). To translate data into a form that effectively leverages the human visual system, it is crucial to select visual representations that are consistent with the available data and relevant to the task at hand. The use of appropriate visualizations has the potential to amplify cognition and facilitate insights, decisions, and actions that may otherwise be difficult or impossible to achieve (Van Wijk, 2005). Conversely, failure to associate effective visualizations with data can lead to unnecessary exploration, inaccurate or false knowledge, wasted time or lack of use due to frustration and confusion (Yalçin et al., 2016).

The process of stimulating and enabling human reasoning using interactive visualization tools is still an under-explored field (Meyer et al., 2010). LAD design choices are often based on assumptions about how users will make sense of the information and their capacity to reach a shared understanding of the analytics presented (Clow, 2012). Beyond these assumptions and expectations, the process of making sense of a LAD and the factors that impact the user's sensemaking remains largely unknown (Jivet et al., 2020). Research needs to focus on design principles that are able to guide and justify design choices (Bodily and Verbert, 2017; Echeverria et al., 2018).

2.2 LAD Codesign

The success of any innovation in LA depends largely on the degree of stakeholder involvement during the design phase (Holstein et al., 2017). Therefore, *codesign* (or *participatory design*), derived from user-centered design, has recently become a subject of a growing trend. In LA, it is defined as *an approach where learners, educators, institutions, researchers, developers and designers are all included across different stages of the design process, from exploration to actual implementation* (Prieto-Alvarez et al., 2018). Examples of successful use for co-design of dashboards are reported in the literature (Sarmiento and Wise, 2022). Yet, the LA community still lacks tools specific to the needs of its stakeholders to effectively communicate and understand the design components (Alvarez et al., 2020). In addition, most research on participatory approaches has focused on the ideation phase. In this paper, we aim at extending discussion through the prototype phase, by providing tools for the designer that facilitate user requirements translation, supporting sensemaking features and providing relevant guidelines.

2.3 Sensemaking and Decision Support

From a metacognitive perspective, LADs play a crucial role in supporting the process of sensemaking, an information integration process that that involves interpreting and processing information, allowing individuals to construct meaning and derive insights that inform future actions and decisions (Pirolli and Card, 2005). To describe and analyze 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. Nevertheless, these models remain evasive on how these cognitive activities are related to and correlated with the user's experience with the LAD.

To account for LAD-based sensemaking, the data/framework (D/F) theory (Klein et al., 2006) defines a model that most clearly delineates the underlying cognitive processes. It flows from the realm of naturalistic decision-making (Beach et al., 2014), which reflects the reality of most decision-making using LADs. According to the D/F model, two types of entities interact during sensemaking: *data* and *frame*. The data is the information that a person receives or seeks, and the frame is the mental structure that organizes, interprets and explains the data. Also, 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. The D/F model identifies the different types of framing 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 relativizing 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; and (7) *seeking* a new interpretation of conflicting data, using for instance key data elements as anchors.

Sensemaking is a prerequisite for many essential human tasks, especially decision-making (Zhang and Soergel, 2014). The naturalistic approach for exploring human decisions focuses on the early process of building ''situation awareness" (SA) using sensemaking strategies through which a course of action is developed (Beach et al., 2014). Three levels of SA are defined in (Endsley, 1995): *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. The stages of knowledge represented by the levels of SA are only attainable through sensemaking (Klein et al., 2006).

2.4 Dashboards Generation

The systematic literature review presented in (Vázquez-Ingelmo et al., 2019) identified three main approaches regarding generating tailored dashboards, namely *customization*, *personalization*, and *adaptation*. Customization solutions are driven by the explicit user requirements and actively involve the user by requiring him to perform explicit tailoring actions (Mayer and Weinreich, 2017). Personalized solutions infer an appropriate configuration from implicit data on users, tasks or objectives and goals. Some authors (e.g., (Kintz et al., 2017)) use the business process and goals model, adding user roles to the process for further tailoring. Adaptive dashboards are able to adjust and adapt themselves in real time according to environmental changes. For instance, the solution described in (Belo et al., 2014) restructures itself given user-profiles and behaviors extracted from the dashboards' analytical sessions.

A major drawback of all these solution approaches is the fact that, although the end user is the primary source and target of the generation process, the design does not explicitly follow a user-centered approach. Existing solutions are focused on data properties, usage context description, and user profiles. These dimensions are crucial for the design and generation processes. Yet, human factors related to intended dashboard use and decision-making are not explicitly integrated to dashboard design and generation.

3 THEORETICAL FRAMEWORK

In this section, we introduce a framework that explicitly outlines the user-centered design dimensions, including sensemaking. We also show how this framework guides our codesign approach to create LADs that are aligned with users needs and expectations.

3.1 LAD Design Space

A design space provides a comprehensive guide for a class of applications emphasizing the freedom to choose from different options and to explore alternatives in the target domain (Schulz et al., 2011). According to (Shaw, 2012), it identifies and organizes the decisions to be made, together with the alternatives for those decisions. In dashboard design, several authors have sought to characterize the design space. Combining insights from previous works (e.g., (Yigitbasioglu and Velcu, 2012; Schulz et al., 2011)), we propose to describe the LADs design space through four dimensions: Goal, Usage Context, and Data, representation & Interaction (Gilliot and Sadallah, 2023). These dimensions were established based on existing literature and are intended to be adequate and sufficient for characterizing the LAD design space and evaluating the effectiveness of LADs in supporting awareness, sensemaking and decision making.

Goal. The *goals* can be classified based on the competence they aimed to affect in learners: metacognitive, cognitive, behavioral, emotional and self-regulation (Jivet et al., 2017). In (Sedrakyan et al., 2019), the authors analyzed students objectives in terms of targeted intervention and suggested focusing on the following aspects of the learning process: (i) cognitive, (ii) outcome oriented (e.g., achievement level), (iii) process-oriented, (iv) behavioral, (v) metacognitive. The social presence being a key element of any educational experience (Garrison et al., 2003), we add to this list (vi) the social aspect, that relates to group-work or learner relations.

Usage Context. This dimension describes the learning *context* (classroom, online, or outside the classroom), and the *scope* or target of the dashboard (a learner, a group of learners, the entire class, or at the school, department, academy, or intermediate level). It also precises the focus of the analytics (the people, their activity, their results, the context, the content, the exchanges). More generally, a LAD can be designed to be used or shared by several stakeholders with different perspectives, objectives and expectations.

Data, Representations & Interaction. This dimension defines the data and their properties, associates visual representations with the data, and adds interaction features to them. While data and representations provide insights for sensemaking, specifying interactions helps to better sustain the underlying process.

3.2 Interaction for Sensemaking

Interaction is the means by which humans explore visual representations to generate insight. It is an essential glue that tightly binds analysis, visualization and the human analyst (Endert et al., 2014). To explore how users engage in sensemaking supported by LADs, we propose to investigate the interaction beyond its technical aspects, to examine it in terms of the discourse that occurs between users and LADs. This 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 between the user and the environment. It is a property that emerges and builds up over time as an individual interacts with his environment: it develops through perception and interaction (Liu et al., 2008). This perspective is useful for observing and reflecting on the cognitive processes involved by examining the exchange of representations during their transmission between the user and the environment.

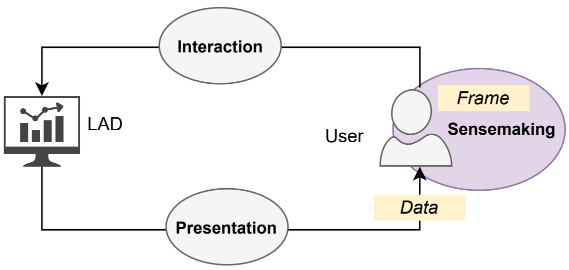

Figure 1: Loop of Interaction-Sensemaking with LADs.

Derived from this conceptualization of LADs as cognitive tools, we propose the *Interaction-Sensemaking* loop (depicted in Figure 1) to account for representation propagation through interaction. According to this model, the user makes sense of the data rendered by a LAD through interaction exploration. His interactions may lead to an update of the LAD configuration and thus of the associated representations. The insight gained by the user can push him to make some pedagogical decision, which can impact his environment. Framing occurs in the user's mind as data derived from his interactions is integrated with his internal knowledge to evolve his current frame. This process is iterative: depending on the resulting frame, the user may need to interact again with the LAD. The interaction-sensemaking process is cyclic, and provides both a means of interpreting data from the environment and a trigger and catalyst for action to be taken accordingly. It thus brings the involved parts of LAD-based sensemaking and decision-making into a meaningful structure.

3.3 A Generative Codesign Approach

We propose a methodology for conceiving LADs that draws on two complementary approaches: *generative design* and *participatory design*. The approach is also interactive insofar as, throughout the process, a given design space is explored and a target design is evaluated on the basis of human judgment (Khan et al., 2019). Generative design approaches allow designers to use automated tools to generate valid design solutions for a given problem, specified by defining a set of goals and constraints (Keshavarzi et al., 2020).

3.3.1 Modeling Stakeholders

As part of a codesign approach, we advocate making explicit the definition of representative roles of the stakeholders involved in the development and use of LADs. We can distinguish several stakeholders: end-users, designers, developers, pedagogical team, administrators, etc. The latter can be combined under two key roles: *user* and *designer*. The *user* role refers to all the stakeholders from which the requirement expression originates and those who will be potential end-users. The *designer* role refers to the users whose role is to design and implement the dashboard specification. This role includes refining the user's specification, defining the indicators and associated visualizations, conceiving the user interface, and implementing the final LAD. The aim of the proposed approach is therefore to allow the user and the designer to fully describe the desired result, to generate candidates and to refine them

3.3.2 Process of Generative Design

Generative design is a process in which the human is given tools to describe his needs and intent, explore the design space, generate a set of target solutions and then select and refine the most appropriate one based on his own judgment. Following this approach consists in designing an LAD progressively, in several steps, by involving the different actors involved in the design process: user and designer. The user is also involved in describing the usage and evaluating the result, while the designer manages the whole generation process, translating the usage description, exploring different options, directing the generation and evaluating the result with the end user (Figure 2).

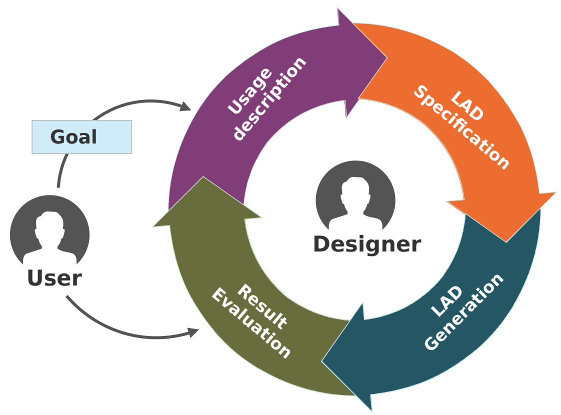

Figure 2: LAD Generative design approach.

Goal Definition. Defining the LAD goal is a core aspect of the design process. This characterizes the dashboard and its use, provides access to existing implementations and allows for future capitalization based on objectives. Therefore, this step is assumed to provide a static input into the design loop rather than being part of it.

Usage Description. This task is conducted by the designer in collaboration with the end user. It lays the foundation for the final LAD by making explicit the users' needs and expectations, and defining sharing options with other users, time of use, and observation time on which the decision is based.

LAD Specification. The requirement capture and understanding of the usage context are crucial in building a LAD that aligns with the user's expectations. This process is done through a progressive and iterative approach, which involves setting up the data sources, representations, and interactions that ultimately result in the desired dashboard composition.

- *Data Identification.* Based on the LAD specification, the designer needs to identify the indicators that are necessary to create effective dashboard components. This involves having expertise in data analytics and understanding the best practices of defining metrics that meet the user's expressed needs.
- *Definition of Visualization Components.* Having identified the relevant indicators, the designer must then determine the appropriate visualizations and define the interaction options that enable the user to understand the data. This requires a high level of visual literacy from the designer.
- *Supporting End-User Sensemaking.* The designer must structure the LAD components in a way that guides the user through the sensemaking process, providing different levels of awareness. For each level, he can define one or more relevant views. These views must be structured in a way that enables the user to interact within each view, and to navigate to other views in search of new insights, using the specified interaction options.
- *Fine-Tuning for Better Fit with Design Principles.* To ensure the LAD design follows established design guidelines and principles, the designer must bring his domain expertise and understanding of the cognitive process involved in using the dashboard. This step of the specification is crucial to the success of the design.

LAD Generation. From the specification produced in the previous step, the designer generates a testable dashboard prototype using available tools. To make this process more efficient, the designer can rely on automatic generators that interpret the specifications, which eliminates the need for technical work. This approach offers a high level of stakeholder involvement, allowing them to view and provide feedback on the prototype, and enables the designer to easily modify and refine the design. Additionally, automatic generators facilitate the identification of errors and inconsistencies in the design, which can be addressed before moving to the other phases.

Result Evaluation. This stage is initiated after the generation of a proof (i.e., a ready-to-use dashboard), as testing with high-fidelity prototypes provides more valuable feedback from the end-users. Through a series of user testing sessions, the designer validates the dashboard design with the user and solicits feedback for future iterations. This iterative process may lead to revisions of the original design specification and the incorporation of new features or improvements to better align with users' needs and preferences.

4 A TOOL FOR LAD GENERATION

4.1 Rationale and Overview

As a proof of concept of the proposed approach, we developed LADStudio for dashboard specification and assisted generation. It allows designers to build, with end-users, and implement potentially complex dashboards by providing only the highest level of information. The development of LADStudio takes part within a global project, PaDLAD [1], where the aim is to propose models and tools for LAD codesign for awareness, sensemaking and decision-support. A card-based codesign toolkit is proposed to collect participants' needs in terms of cognitive support and related interfaces (Sadallah et al., 2022). Using the toolkit, the designer collects user requirements and uses LADStudio as a tool to discuss, evaluate and refine the design with them. Specifications as entry of LADStudio are thus obtained from an ideation process, as described in (Prieto-Alvarez et al., 2018). LADStudio is dedicated to the next step identified, namely prototyping.

LADStudio is designed following a three-tier architecture in which presentation, application processing, and management are logically separated processes. We implemented it using modern technologies, the dashboard rendering is tested using an instance of the Grafana [2], an open source analytics and interactive visualization tool.

4.2 Component-Based Model

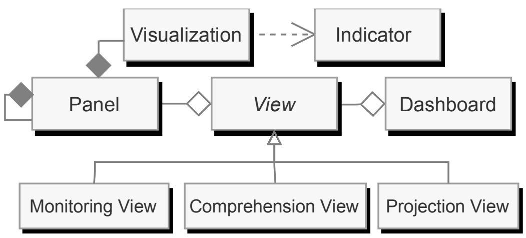

Figure 3: Dashboard component-based structure.

We follow a component-based approach for modeling the structure of LADs. The structure (and logical view) of a dashboard is thus constructed using a hierarchy of nested components. Such an approach eases the design of LADs by providing common, shareable and reusable components. New components can be created from scratch, by editing existing ones or from lower-level components. LADs components can be of different types (Figure 3): (1) *Indicators* are data components that describe a high-level measure of interest; (2) *Visualizations* are rendering components with visual manifestation; (3) *Panels* are the building blocks of the dashboard. They are containers of visual that define structuring relations between components. We define two types of panels:(a) basic panels define mapping functions between the indicators and the visualizations; (b) composite panel set out compositions of basic panels; (4) *Views* are high-level components intended to support levels of awareness. They provide the structural elements and define the interactivity needed to develop an understanding of the environment. We distinguish three types of views, according to the targeted level of situation awareness: (a) *Perception* views represent LAD configurations that allow the user to monitor his environment ; (b) *Comprehension* views represent LAD configurations aimed at providing the user with the necessary insight to analyze and understand a given situation; and (c) *Projection* views allow preparing the user to take action on the situations discovered and analyzed in the previous levels.

4.3 Interaction Model

As described in the *Interaction-Sensemaking loop* (Section 3.2), interaction plays a crucial role in users' engagement with the LAD, allowing them to develop their understanding through the framing functions proposed by the D/F model. To identify the types of interaction that would support sensemaking, we drew upon the *Visual Information-Seeking Mantra* (Shneiderman, 2003), a taxonomy of the essential elements of interacting with graphically presented information. Based on this taxonomy, we identified six types of interaction that are particularly relevant for LADs: (1) *Overview*, which provides a global view of the available data; (2) *Zoom*, which allows users to select and investigate a part of the data in more detail; (3) *Filter-Search*, which helps users to find and focus on specific items of interest by reducing the amount of data or visual objects displayed; (4) *Details*, which allows users to obtain more precise information about the data or a part of it to gain a better insight; (5) *Relate-Associate-Compare*, which enables users to view relationships between data points; and (6) *Change view*, which allows users to change their point of interest. The combination of these interactions with the D/F model framing functions provides a powerful framework for supporting sensemaking in LADs.

The user's interaction with a specific component (panel or view) triggers background processes that update the LAD. This can result in the display of new data that the user can integrate with his internal knowledge through *framing*, to construct, change or consolidate his current mental framework. By combining user interactions with the framing functions of the D/F model, our approach provides a powerful framework for supporting sensemaking in LADs.

[1] *Participatory Design of Learning Analytics Dashboards* project (https://padlad.github.io/)

[2] https://grafana.com/grafana/

4.4 Library of LAD Components

In order to promote the reuse and sharing of components, the library provides a way to define and store components that can be used for the composition of dashboards. The library contains five types of components: (1) indicator templates; (2) visualizations; (3) panels; (4) composite panels; and (5) views. A user can extend this library by defining new components from scratch or by using and reusing the existing ones. He can also modify existing components and, for some reason (e.g., redundancy), delete some others. Each component is associated with interactions that support the sensemaking process.

4.5 LAD Specification Wizard

This component of the tool allows a step-by-step specification of a dashboard (Figure 4). Five sequential screens compose a specification scenario:

1. *Target Use and usage description.* The first step of the process is the gathering of the information needed to characterize the dashboard, the type of learning environment it is intended to serve, the role of the user, and the sharing preferences;
2. *Goal Setting.* A predefined list of goals and their descriptions is provided. The designer can also introduce another goal if the list provided does not cover the desired LAD purpose;
3. *Monitoring and Perception Views.* These are screens that allow the user to monitor his environment, in relation to his goal. He can use existing views stored within the library, or define new ones by selecting or adding appropriate panels, defining data sources and setting interaction options;
4. *Analysis and Comprehension Views.* These views allow the finer analysis of a specific aspect. Their purpose is to allow the user to attain the comprehension and the projection levels of awareness regarding the aspect of interest. The user can define new views or reuse existing ones; and
5. *Dashboard Generation and Export.* Once the specification is completed, the user can generate a working prototype.

A specification can be re-edited, defining a cyclical process of editing and testing. In addition, the components (indicators, visualizations, panels, and views) produced during the dashboard specification are automatically saved, which simplifies the feeding of the LADStudio library for component reuse.

4.6 LAD Prototype Generation

By advocating a generative design approach, we acknowledge the need to prevent too much technical exposure to the user. Therefore, we designed LADStudio so as it generates running prototypes from LADs specifications without requiring technical skills. The user has the possibility to adjust the generated dashboard, to personalize it and to adapt it to his preferences and needs.

To render the LAD, the designer may generate a functional prototype and build it into the embedded Grafana instance or a remote installation (See example of Figure 5). He can also download the *JSon* description file.

4.7 User Evaluation

For evaluating LADStudio, we organized a design workshop to experiment with the proposed tool. The objective was to evaluate the usability and user experience of the tool. We report on a qualitative study to present the results of feedback on the use of the LADStudio tool and to collect the impressions and opinions of the participants.

4.7.1 Participants and Procedure

Considering the difficulty of finding experts in LAD design and development, we turned to communities with a background in educational tool design and development: interface design researchers, university teachers who have used educational dashboards, and software developers. We thus used in this study a non-probability and expert sampling, a subtype of purposive sampling. The inclusion criterion was experience in the use and the design of educational tools, and the exclusion criterion was unwillingness to participate in the study. Of those who received email invitations to take part in the study, thirteen (13) persons agreed to participate. The socio-demographics and general background of the participants were collected as part of the study (see Table 1 for key demographics).

The evaluation procedure is organized as follows. A presentation and demonstration session is held for all participants, explaining the context and objectives of the project, and describing the LADStudio tool. The participants were then invited to experiment with the tool independently, and then to attend a collective codesign workshop. Finally, they were asked to individually complete a questionnaire and answer open-ended questions aimed at gathering their opinions. The study took about two hours to complete.

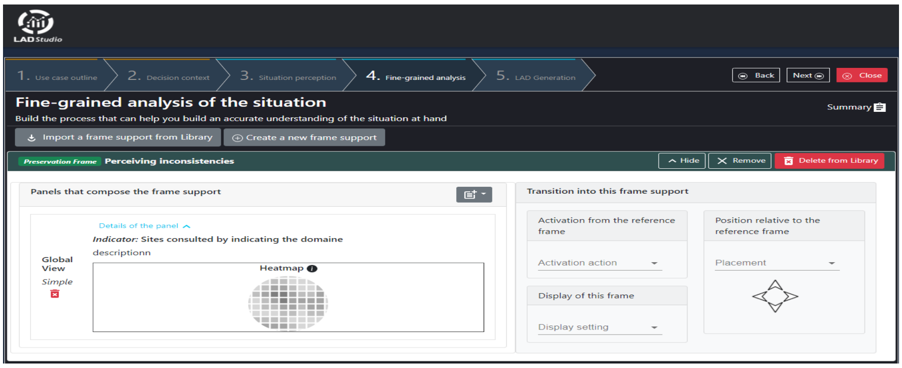

Figure 4: Dashboard specification.

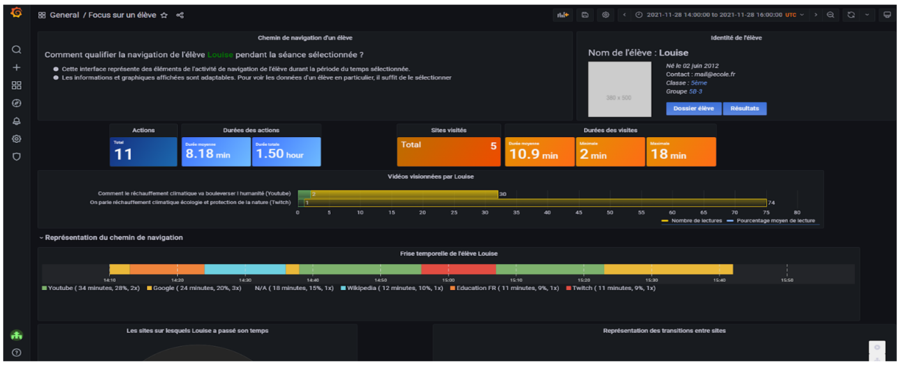

Figure 5: A generated LAD prototype.

Table 1: Participants' demographic data (N=13).

Variable	Category	n (%)
Gender	Male	8 (61.54)
	Female	5 (38.46)
Age	25–35	3 (23.08)
	36–45	7 (58.84)
	46–55	3 (23.08)
Staff	University Teacher	4 (30.77)
	Researcher	6 (46.15)
	Software developer	3 (23.08)

4.7.2 Instruments

As the LADStudio tool design is still exploratory, we followed a qualitative approach using standardized questionnaires. The tool usability was assessed by completing a System Usability Scale (SUS) questionnaire (Brooke, 1996), a well-researched and widely used questionnaire for perceived usability evaluation. According to (Tullis and Stetson, 2004), SUS provides a reliable usability measure even with a relatively small sample size. Based upon the general template of SUS, we designed a questionnaire containing the ten statements presented in Table 2.

User Experience (UX) evaluation provides an overview of the level of comfort to a person's satisfaction with a system, and determines areas of improvement. We used the User Experience Questionnaire (UEQ), a valid tool that serves as a means of comprehensively assessing the UX of interactive products (Laugwitz et al., 2008), applicable to small groups (Schrepp et al., 2014). The questionnaire groups a total of 26 items into six scale (Santoso et al., 2016): (1) *attractiveness* describes the general impression that

Table 2: SUS questionnaire items.

Q1	I think I would like to be able to use LADStudio frequently
Q2	I found LADStudio unnecessarily complex
Q3	I thought LADStudio was easy to use
Q4	I think that I would need support to be able to use LADStudio
Q5	I found the various components of LADStudio were well integrated
Q6	I thought there was too much inconsistency in LADStudio
Q7	I would imagine that most people would learn to use LADStudio fairly quickly
Q8	I found LADStudio very cumbersome to use
Q9	I felt very confident using the LADStudio tool
Q10	I needed to learn a lot before I could use the LADStudio tool

users had of the tool; (2) *efficiency* qualifies the possibility to use the tool quickly and efficiently; (3) *perspicuity* describes how easy it is to understand how to use the tool and to get familiar with it (4) *dependability* qualifies the user's feeling of being in control of his interaction and confident with the tool; (5) *stimulation* describes whether using the tool is exciting and motivating; and (6) *novelty* describes the extent to which the tool's design is innovative and creative, and attracts the user's attention.

4.7.3 Results

Usability. The results of the usability study are summarized in Table 3. To analyze them, we followed the procedure proposed by the author of the instrument (Brooke, 1996) to compute the SUS score based on the equation shown in Formula 1.

$$\overline{\text{SUS}} = \frac{1}{n}\sum_{i=1}^{n} norm.\sum_{j=1}^{n} \begin{matrix} q_{ij}-1, q_{ij} \bmod 2 > 0 \\ 5-q_{ij}, otherwise \end{matrix} \quad (1)$$

where n=number of subjects (questionnaires), $m = 10$ (number of questions), q_{ij}=individual score per question per participant, $norm = 2.5$

Table 3: Results of the SUS questionnaire (N=13).

Positive statements				Negative statements			
	A	N	D		A	N	D
Q1	9	2	2	Q2	0	1	12
Q3	10	2	1	Q4	7	3	3
Q5	11	1	1	Q6	0	0	13
Q7	2	4	7	Q8	1	0	12
Q9	10	3	0	Q10	3	6	4

A: Agree or Strongly agree; N: Neither agree nor disagree; D: Disagree or Strongly disagree

A SUS score ranges from 0 to 100, where a score of 0 implies that a user found a system absolutely useless while a score of 100 reflects that a user did find a system to be optimally useful. A score above 68 would be considered above average. The results of the assessment of the participants obtained a total value of the SUS score of 925 with the resulting average value of 71.15, a standard deviation of 6.15, and a median of 72.5. In (Bangor et al., 2009), SUS scores are mapped to a scale of adjectives in order to attach a more descriptive meaning to the SUS score assigned to a system. Using this grade ranking as shown in Figure 6, the SUS score on the tool of 71.15 means that the level of user *Acceptability Range* is *Acceptable*, the *Grade Scale* level is *category C*, and user *Adjective Rating* level is *Good category*. This indicates a satisfactory and an acceptable level of usability of the tool according to the participants.

User Experience. We computed the UEQ results after scaling participants' responses from -3 (negative extreme) to $+3$ (positive extreme) on a Likert scale. Scores ranging from -0.8 to 0.8 reflect a neutral evaluation of the corresponding dimension, while scores above 0.8 indicate a positive evaluation and those below 0.8 imply a negative evaluation.

Table 4: Results of the User Experience study (N=13).

Dimension	Mean	Variance	Rating
Attractiveness	2.04	0.13	Excellent
Perspicuity	1.13	0.73	Below average
Efficiency	2.27	0.12	Excellent
Dependability	1.64	0.17	Good
Stimulation	2.25	0.18	Excellent
Novelty	2.48	0.17	Excellent

As shown on Table 4 and represented on Figure 7, the overall rating is sufficiently high. The highest mean score was for *novelty*, with a mean of 2.48 (SD = 0.17), followed by *efficiency* (mean = 2.27, SD = 0.90) and *stimulation* (mean = 2.25, SD = 0.18). These scores were at an excellent level. Dependability has a good score (mean = 1.64, SD = 0.17). The less positive result was on *perspicuity* dimension (mean = 1.13, SD = 0.73), meaning that participants found some difficulties in understanding the use of the tool.

Participants' Feedback. The participants in the study acknowledged the innovativeness of the proposed approach and tool aimed at addressing two main challenges faced in creating effective LADs: lack of end-user involvement and the technical complexity of constructing LADs from scratch. Their evaluations of the user experience with the tool emphasized its usefulness and potential for producing meaningful LADs. Despite some initial difficulty in using the tool without understanding its background and rationale, the participants felt that with practice, they could effectively use it to improve their memory level. The participants also highlighted the tool's focus on supporting the sensemaking process in dashboard design. However, incorporating theoretical concepts related to decision and sensemaking into the tool presented challenges in its initial appropriation. The participants indicated a need for expert design support, and recognized that a lack of data and visual literacy was a hindrance in fully adopting LADs. This was reflected in their difficulty in associating the visual representation with the data. Given these insights, we believe that further improvements are needed to better inform and guide the designer in constructing the various components of the LAD.

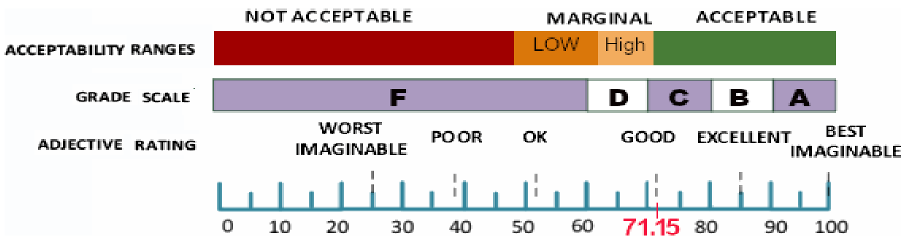

Figure 6: Grade rankings for SUS scores (Bangor et al., 2009). In red, the SUS score of LADStudio.

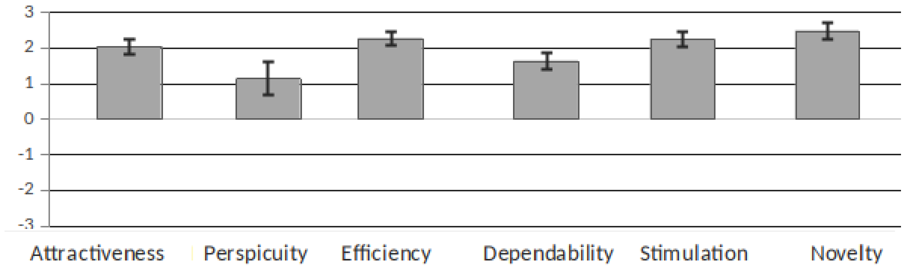

Figure 7: UEQ results of the LADStudio evaluation.

4.7.4 Discussion

The purpose of this study was to assess the usability and user experience of LADStudio, two critical aspects of system quality. The results of the SUS study indicated that LADStudio has good usability, with a global mean score of 71.15 and a high level of acceptability. The UEQ results revealed that the user experience of LADStudio is satisfactory, as evidenced by the sufficient average scores of each aspect studied. The *novelty*, *efficiency*, and *stimulation* scores were at an exceptional level, indicating that the participants found LADStudio highly creative, efficient, and stimulating. On the other hand, the *perspicuity* score was only moderate, which can be attributed to the relatively limited time participants spent on the tool compared to the amount of information available to them. We acknowledge that widespread adoption of such a tool would require significant efforts in dissemination and training for both designers and potential users.

The study has certain limitations, primarily due to the limited sample size of only 13 participants. This restricts the generalizability of the results and only provides preliminary insights into the effectiveness of the tool. However, it is noteworthy that previous research has demonstrated the reliability of using SUS as a measure of perceived usability, even with relatively small sample sizes (Tullis and Stetson, 2004). Also, UEQ is found applicable even with a limited group of participants (Schrepp et al., 2014). However, we believe that, in order to consolidate our results and ensure their validity, a more extensive investigation is required. In particular, a larger sample size is needed to mitigate the self-selection bias that is inherent in qualitative research methods, as those who responded to our survey and invitations may have a vested interest in LADs. Additionally, it is well established that qualitative research can also be subject to group think and the influence of dominant personalities, further highlighting the need for a more comprehensive study. Moreover, the current study focused solely on the quality of the tool used for LAD generation and did not assess the quality of the generated LADs themselves. Therefore, it is essential to conduct a larger-scale study to fully understand the potential and limitations of the LADs generated.

5 CONCLUSION

LADs are instruments of exploration, analysis and decision-support that allow users to gain insight and take well-informed actions. This paper sought to contribute to addressing their limited adoption by their stakeholders by focusing their design. We first proposed to improve the LAD design space, specifically by integrating elements related to the sensemaking dimension. This allowed us to answer our first research question RQ1 (*How can the decision-making process be reflected on a learning dashboard?*). We then defined a design methodology that enables stakeholders to be involved in the design of such LADs, and provides designers with means to rapidly obtain functional prototypes that comply with the specifications and requirements of end-users. This provided us with the possibility to answer the research question RQ2 (*How to support the designer in the prototyping phase to design LADs that make explicit the associ-*

ated decision-making processes?). The proposed approach combines generative and participatory design, leveraging the strengths and mitigating the limitations of both methodologies. By doing so, we were able to create a framework that supports a high level of stakeholder involvement while balancing it with the computational power and efficiency of the generative design process. This framework allows for a more comprehensive and adaptable solution that can be customized to fit the needs of different stakeholders.

To demonstrate the feasibility of our approach, we implemented LADStudio, a tool that enables designers to generate functional prototypes based on specifications developed through the co-design process. This tool is built within the proposed design space and instrumented with features to support the end-user sensemaking and decision-making process. The evaluation results showed that innovative proposals and LA adoption are possible with stakeholders, when using supportive and assistive design strategies. Our approach and tool have been streamlined to facilitate generative development of functional prototypes, enabling further exchanges focused on design adoption issues. We believe that this step is essential to ensure that LAD design leads to actual use. In conclusion, we believe that collecting LAD proposals from users and practitioners using LADStudio can reveal additional needs and lead to the identification of new usages. We are committed to capitalizing on and sharing these findings with the learning community to further advance the design and adoption of LADs.

REFERENCES

Alhadad, S. S. (2018). Visualizing data to support judgement, inference, and decision making in learning analytics: Insights from cognitive psychology and visualization science. *Journal of Learning Analytics*, 5(2):60–85.

Alvarez, C. P., Martinez-Maldonado, R., and Shum, S. B. (2020). La-deck: A card-based learning analytics co-design tool. In *Proceedings of the tenth international conference on learning analytics & knowledge*, pages 63–72.

Bangor, A., Kortum, P., and Miller, J. (2009). Determining what individual sus scores mean: Adding an adjective rating scale. *Journal of usability studies*, 4(3):114–123.

Beach, L. R., Chi, M., Klein, G., Smith, P., and Vicente, K. (2014). Naturalistic decision making and related research lines. In *Naturalistic decision making*, pages 49–56. Psychology Press.

Belo, O., Rodrigues, P., Barros, R., and Correia, H. (2014). Restructuring dynamically analytical dashboards based on usage profiles. In *International Symposium on Methodologies for Intelligent Systems*, pages 445–455. Springer.

Bodily, R. and Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, 10(4):405–418.

Brooke, J. (1996). A quick and dirty usability scale. In Jordan, P., Thomas, B., Weerdmeester, B. A., and A. I., M., editors, *Usability evaluation in industry*, volume 189, pages 194–101. Taylor & Francis.

Chatti, M. A., Muslim, A., Guliani, M., and Guesmi, M. (2020). The lava model: Learning analytics meets visual analytics. In *Adoption of Data Analytics in Higher Education Learning and Teaching*, pages 71–93. Springer.

Clow, D. (2012). The learning analytics cycle: closing the loop effectively. In *Proceedings of the 2nd international conference on learning analytics and knowledge*, pages 134–138.

Deng, D., Wu, A., Qu, H., and Wu, Y. (2022). Dashbot: Insight-driven dashboard generation based on deep reinforcement learning. *IEEE Transactions on Visualization and Computer Graphics*.

Echeverria, V., Martinez-Maldonado, R., Granda, R., Chiluiza, K., Conati, C., and Shum, S. B. (2018). Driving data storytelling from learning design. In *Proceedings of the 8th international conference on learning analytics and knowledge*, pages 131–140.

Endert, A., Hossain, M. S., Ramakrishnan, N., North, C., Fiaux, P., and Andrews, C. (2014). The human is the loop: new directions for visual analytics. *Journal of intelligent information systems*, 43(3):411–435.

Endsley, M. (1995). Toward a theory of situation awareness in dynamic systems: Situation awareness. *Human factors*, 37(1):32–64.

Garrison, D. R., Anderson, T., and Archer, W. (2003). A theory of critical inquiry in online distance education. *Handbook of distance education*, 1(4):113–127.

Gilliot, J.-M. and Sadallah, M. (2023). A framework for codesigning effective lads supporting sensemaking and decision making. Submitted for publication.

Holstein, K., McLaren, B. M., and Aleven, V. (2017). Intelligent tutors as teachers' aides: exploring teacher needs for real-time analytics in blended classrooms. In *Proceedings of the 7th international learning analytics & knowledge conference*, pages 257–266.

Holstein, K., McLaren, B. M., and Aleven, V. (2019). Co-designing a real-time classroom orchestration tool to support teacher–ai complementarity. *Journal of Learning Analytics*, 6(2).

Hutchins, E. (1995). *Cognition in the Wild*. Number 1995. MIT press.

Jivet, I., Scheffel, M., Drachsler, H., and Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. In *European conference on technology enhanced learning*, pages 82–96. Springer.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., and Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education*, 47:100758.

Jivet, I., Scheffel, M., Specht, M., and Drachsler, H. (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th international conference on learning analytics and knowledge*, pages 31–40.

Keshavarzi, M., Bidgoli, A., and Kellner, H. (2020). V-dream: Immersive exploration of generative design solution space. In *International Conference on Human-Computer Interaction*, pages 477–494.

Khan, S., Gunpinar, E., and Sener, B. (2019). Genyacht: An interactive generative design system for computer-aided yacht hull design. *Ocean Engineering*, 191:106462.

Kintz, M., Kochanowski, M., and Koetter, F. (2017). Creating user-specific business process monitoring dashboards with a model-driven approach. In *MODELSWARD*, pages 353–361.

Klein, G., Moon, B., and Hoffman, R. R. (2006). Making sense of sensemaking 1: Alternative perspectives. *IEEE intelligent systems*, 21(4):70–73.

Laugwitz, B., Held, T., and Schrepp, M. (2008). Construction and evaluation of a user experience questionnaire. In *Symposium of the Austrian HCI and usability engineering group*, pages 63–76. Springer.

Liu, Z., Nersessian, N., and Stasko, J. (2008). Distributed cognition as a theoretical framework for information visualization. *IEEE transactions on visualization and computer graphics*, 14(6):1173–1180.

Mayer, B. and Weinreich, R. (2017). A dashboard for microservice monitoring and management. In *2017 IEEE International Conference on Software Architecture Workshops (ICSAW)*, pages 66–69. IEEE.

Meyer, J., Thomas, J., Diehl, S., Fisher, B., and Keim, D. A. (2010). From visualization to visually enabled reasoning. In *Dagstuhl Follow-Ups*, volume 1. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik.

Pirolli, P. and Card, S. (2005). The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *Proceedings of international conference on intelligence analysis*, volume 5, pages 2–4. McLean, VA, USA.

Prieto-Alvarez, C. G., Martinez-Maldonado, R., and Anderson, T. D. (2018). Co-designing learning analytics tools with learners. In *Learning Analytics in the Classroom*, pages 93–110. Routledge.

Sadallah, M., Gilliot, J.-M., Iksal, S., Quelennec, K., Vermeulen, M., Neyssensas, L., Aubert, O., and Venant, R. (2022). Designing lads that promote sensemaking: A participatory tool. In *Educating for a New Future: Making Sense of Technology-Enhanced Learning Adoption: Proceedings of the 17th European Conference on Technology Enhanced Learning, EC-TEL 2022*, volume 13450 of *Lecture Notes in Computer Science*, pages 587–593. Springer.

Santoso, H. B., Schrepp, M., Isal, R., Utomo, A. Y., and Priyogi, B. (2016). Measuring user experience of the student-centered e-learning environment. *Journal of Educators Online*, 13(1):58–79.

Sarmiento, J. P. and Wise, A. F. (2022). Participatory and co-design of learning analytics: An initial review of the literature. In *Proceedings of the 12th International Learning Analytics and Knowledge Conference*, pages 535–541.

Schrepp, M., Hinderks, A., and Thomaschewski, J. (2014). Applying the user experience questionnaire (ueq) in different evaluation scenarios. In *International Conference of Design, User Experience, and Usability*, pages 383–392. Springer.

Schulz, H.-J., Hadlak, S., and Schumann, H. (2011). The design space of implicit hierarchy visualization: A survey. *IEEE Transactions on Visualization and Computer Graphics*, 17(4):393–411.

Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., and Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies*, 10(1):30–41.

Sedrakyan, G., Mannens, E., and Verbert, K. (2019). Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts. *Journal of Computer Languages*, 50:19–38.

Shaw, M. (2012). The role of design spaces. *IEEE software*, 29(1):46–50.

Shneiderman, B. (2003). The eyes have it: A task by data type taxonomy for information visualizations. In *The craft of information visualization*, pages 364–371. Elsevier.

Tullis, T. S. and Stetson, J. N. (2004). A comparison of questionnaires for assessing website usability. In *Usability Professionals Association 2004 Conference*.

Van Wijk, J. J. (2005). The value of visualization. In *VIS 05. IEEE Visualization, 2005.*, pages 79–86. IEEE.

Vázquez-Ingelmo, A., Garcia-Penalvo, F. J., and Theron, R. (2019). Information dashboards and tailoring capabilities-a systematic literature review. *IEEE Access*, 7:109673–109688.

Yalçin, M. A., Elmqvist, N., and Bederson, B. B. (2016). Cognitive stages in visual data exploration. In *Proceedings of the 6th Workshop on Beyond Time and Errors on Novel Evaluation Methods for Visualization*, pages 86–95.

Yigitbasioglu, O. M. and Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems*, 13(1):41–59.

Yoo, Y., Lee, H., Jo, I.-H., and Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In *Emerging Issues in Smart Learning*, pages 145–155. Springer.

Zhang, P. and Soergel, D. (2014). Towards a comprehensive model of the cognitive process and mechanisms of individual sensemaking. *Journal of the Association for Information Science and Technology*, 65(9):1733–1756.