
Design Considerations for Data-Driven Dashboards: Supporting Facilitation Tasks for Open-Ended Learning

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Abstract

Data-driven dashboards have been increasingly integrated into various contexts, particularly in educational settings. There is a growing need to understand how to design learning dashboards to help educators support learning experiences by providing real-time formative feedback. We are studying the design of a learning dashboard that can support educational facilitation tasks in a museum setting. In our approach, we use discrete facilitation tasks as the cornerstone of our design process. Using this task-based approach, we conducted pilot studies and participatory design sessions to better understand the context of design. In this paper, we offer preliminary findings and design considerations for supporting and digitally augmenting facilitation tasks in a highly interactive, open-ended learning environment.

Author Keywords

Participatory design; design; data-driven dashboards; learning analytics dashboards; socio-technical systems; method

CCS Concepts

•Human-centered computing → Participatory design; Contextual design;

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Figure 1: Screenshots of visitors interacting with the Connected Worlds exhibit.

Introduction

There is a growing attention to the design of learning dashboards¹ that can collect, process, and visualize data to support educator practices [8, 21, 23, 25, 27, 33], and enhance learner experiences [15, 31]. Classrooms often have rigid activity structures, resulting in dashboards that summarize progress towards known goals (e.g., by tracking grades and other scores). However, dashboard support is arguably most needed for open-ended collaborative learning activities, like team project work or group problem-solving, which are known to be educationally valuable but are notoriously difficult for educators to monitor and manage.

We are researching and designing a mobile learning dashboard to support learning in an open-ended learning activity in a museum exhibit. Our testbed exhibit² asks up to 50 simultaneous visitors to maintain the diversity of a simulated ecosystem via their water and forestry management decisions (Figure 1). Trained facilitators are present to help visitors use and make sense of the exhibit, a charge which currently entails a large amount of pragmatics (e.g., starting and managing sessions, explaining how to interact with the exhibit, enforcing the rules of conduct) but not as much engagement with visitors around the learning content as was intended when the exhibit was created [19]. In response to these challenges, and having access to over 90 variables that show the state of the simulated ecosystem at any give moment, we saw an opportunity for deploying a data-driven dashboard on the mobile tablet that the facilitators currently carry to manage the exhibit.

This is an interesting challenge because accepted classroom design practices like “backwards design” (starting with

the desired educational outcomes and working backwards to figure out how to highlight them) [24] are not easily applicable when there are a multiplicity of possible outcomes, demanding new design approaches. Typically, dashboard interfaces are designed by UI and learning analytics (LA) experts, but our approach is to embed design in context and to embed non-expert practitioners (i.e., facilitators) in the design process to co-evolve expectations for both UI design and the practices (i.e., facilitation tasks) incorporating that design. In other words, we are using a socio-technical lens in our work to take all the social and technical aspects into consideration in our interface-interaction decisions [14]. Recent literature documents other researchers taking a similar approach [1, 21], which suggests that “designing in context” is a promising new model for designing learning dashboards – systems that are highly dependent on both the environment and the user interactions.

By exploring dashboard design for an open-ended learning activity in a museum, which has always privileged learning processes over outcomes, we have special freedom to focus on this under-explored design space for educational dashboards. In this paper, we present some of our preliminary findings from a series of field observations, focus group sessions, and participatory design sessions with exhibit facilitators. Our work has surfaced a design perspective (using a task-based lens) and design recommendations that will be of interest to interaction designers who wish to support educators in providing real-time formative feedback for open-ended learning environments.

Background

Designing Formative Learning Dashboards

The majority of learning dashboards are intended to deliver summative feedback on learner engagement and performance to teachers, with over 90% designed for use in uni-

¹Few [11] defines dashboards as “a predominantly visual information display that people use to rapidly monitor current conditions that require a timely response to fulfill a specific role.”

²<https://nysci.org/home/exhibits/connected-worlds/>

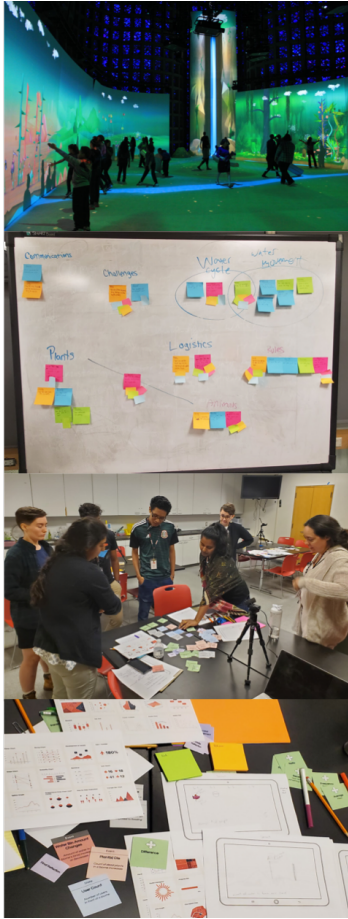


Figure 2: Screenshots of different phases of the design process, including observations, focus group sessions, and participatory design sessions.

versity courses [27, 32], but some researchers have started exploring how dashboards can provide “formative feedback” to teachers so they can intervene in real time and during ongoing learning activities [7, 20, 22]. However, a major facet of formative feedback often concerns the “correctness” of learner efforts [29], which is not readily defined or even useful for open-ended inquiry activities.

Dashboards in Informal Educational Settings

Classroom activities tend to court very specific and measurable learning outcomes, whereas informal educational settings like museums often support a flexible range of possible learning goals. This shifts informal dashboards away from the main classroom function of “monitoring learning attainment” towards the more formative goal of “identifying opportunities for deeper learning”. A handful of museums have attempted to use exhibit log data in a formative fashion to inform or improve the learning of the visitors at the exhibit itself (e.g., [13, 30, 17, 31, 21]). A main focus of these dashboards has been to help facilitators identify “teachable moments” in which they can approach visitors to deepen their learning [13, 31], and the attention demand they impose on museum facilitators was identified as an important design consideration for informal dashboards [13].

Design Process

We quickly realized that the kinds of facilitation tasks that facilitators mix and match to suit an ongoing dialogue with visitors (e.g., highlighting, explaining, questioning, challenging) may each have very different LA and UI requirements. For our context, and for open-ended learning environments in general, we thus propose that a “facilitation task”-centric design approach is essential. Adapting a “contextual design” approach [5], we used a variety of techniques to develop a deeper understanding of the problem space, centering our attention on: (1) tasks that are currently being

practiced (*existing tasks*) and (2) hypothetical future practices with the support of a dashboard (*desired tasks*). This process included *in situ* observations, focus groups and interviews, and participatory design sessions (Figure 2), which we briefly describe here.

Observations and Interviews

We first conducted around three hours of *in situ* observations to better understand the nature of practices performed by the facilitators and challenges they are facing when scaffolding the learning experience for visitors in the exhibit. To gain a complementary first-person perspective, we conducted a focus group with seven facilitators (4 females and 3 males; between the ages of 20 and 25 years old; 3 with high school diplomas, 4 with college degrees, and 1 with a graduate degree; with facilitator experiences ranging from 6 months to more than 3 years). We conducted two separate focus group sessions, one with a group of four *expert* facilitators (who had the most experience with facilitating the test exhibit), and one with a group of three *novice* facilitators (who had very little experience with the exhibit). The focus group structure was borrowed from the Socio-Technical Systems participatory design methodology [14], which situates participants in the social, physical, and intellectual aspects of using a new technological tool.

Participatory Design Sessions

We then conducted three participatory design sessions with one group of facilitators (the *expert* facilitators; 2 Male, 2 Female). Each session lasted two hours and was video recorded. Using our task-centric approach, we progressively concretized the facilitation tasks: (1) the first session was focused on expansively defining the design space according to the facilitators, by brainstorming tasks they would like to engage in if they had “any” additional support; (2) In the second session, we began focusing the task defi-

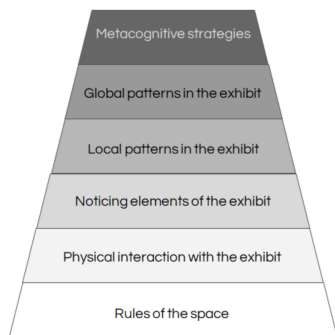


Figure 3: Diagram showing the progression in facilitative tasks, with the tasks that tend to be most common at the bottom, and the less-common tasks (which often build on lower-level ones) at the top. The lower three levels pertain to visitors’ physical engagement with the exhibit, while the top three mainly relate to visitors’ conceptual engagement.

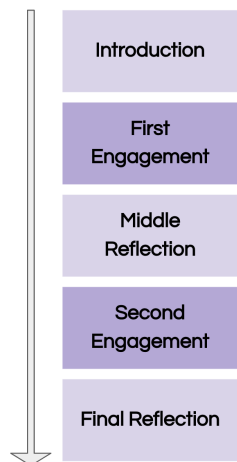


Figure 4: An example of a pragmatic sequencing.

nitions by prompting facilitators to adapt the tasks to be more directly linked to the exhibit learning content. We also prompted them to focus on tasks that might be possible with tablet interfaces and available exhibit data, and asked them to brainstorm design ideas for a dashboard tool that supports those tasks; (3) Building on the familiarity with tasks and scenarios created in the first two sessions, in the third session we integrated the exhibit data (and its possible transformations and visualizations). This session used a paired co-design model where each facilitator was paired with one researcher. Each pair worked on defining a task-centric scenario, through specifying a cohesive vision of what exhibit data would be used and how they would interact with the interface. At the end, they created a paper prototype, or in some cases sketches, based on the designed scenarios.

Preliminary Findings and Discussion

We studied our design process using our field notes, video recordings, the task elicitations and scenarios, and design prototypes. Here, we present our preliminary findings related to design considerations for developing a learning dashboard to facilitate open-ended activities in real time.

Supporting Task Management with Pragmatic Sequencing

The task elicitations map out a vast variety of facilitative tasks spanning the gamut of physical and conceptual engagement with the exhibit open-ended activities. We found six levels of tasks ranging from tasks that focus on physical engagement (e.g., asking visitors not to touch the screens) to tasks that attend more to conceptual engagement (e.g., calling visitor attention to events within a single part of the exhibit). Though these levels are not necessarily sequential, we found that facilitators performing in higher levels also performed lower level tasks: the lower levels appear to function as foundations (see Figure 3). This progres-

sion echoes engagement patterns noted by other museum researchers [2, 6, 12] wherein visitors generally progress through both physical and conceptual engagement. We reported details of our task elicitations in [3].

These findings reveal that guiding an open-ended learning situation requires a facilitator to simultaneously perform different types of tasks, which can be very overwhelming, and as a result might lead to an oversight of higher level tasks, i.e., tasks that support visitor conceptual engagement with the exhibit. Hence, a key realization is that the design of dashboard should supply information in a way that supports “real-time task management” for the facilitators. In other words, the dashboard tool should not leave extra burden on facilitators to decide on information and action at any given time. Based on these insights, we are considering a “pragmatic sequencing” in our design. Similar to a “learning progression” [26] but with less of a pure content focus, we define a “pragmatic sequencing” as one which predicates certain facilitative tasks on prior tasks or events, and which (when possible) divides learning activities into loose phases (like “introduction to exhibit elements and rules,” “first engagement with exhibit,” etc., see Figure 4). Within this structure, the dashboard system should afford: (1) reminding the facilitator to accomplish the foundational tasks for each phase, and (2) selectively suggesting possible facilitative tasks in each phase by using contextually-aware alert systems and checklist elements.

Introducing a phase structure is a design direction that can reduce the scope of the problem, but due to the nature of open-ended activities, task competition is still an issue within one phase; the facilitator has to concurrently attend to several events and changes in the state of the exhibit at a given time. Next, we discuss using “layered visualizations” as a viable approach that can help mitigate this challenge.



Figure 5: Materials used in the prototyping session: raw data cards (top) and sample visualizations (bottom).

Layered Visualizations

In the third participatory design session, we engaged facilitators with creating scenarios that illustrate them using available data to inform their ongoing practices. The goal was to learn how the tool can help them engage meaningfully with available data, data transformations, and different ways of visualizing data. In this process, we provided a set of variable cards showing available “raw” data that can be used to design data-supported tasks (see Figure 5). We structured each scenario to be centered around presenting one primary data, such as “the number of living plants in a biome”, and made it optional to add supplementary data. Interestingly, in most cases, the facilitators showed interest in working with multiple concepts that are connected to each other. For example, setting the primary concept to observe “the number of living plants in a biome”, and adding a comparison with “the amount of water consumed in that biome” while tracking “the number of users in front of a biome”. Moreover, the facilitators suggested that a core challenge for them is to connect the local changes (i.e., in one biome) with global changes (i.e., in the whole world).

However, working with multiple visualizations can be demanding of one’s attention. We guided the facilitators to discuss how they like to work with multiple visualizations, and we found using a “layered” structure could be a viable approach. There were three cases of this layered structure that emerged from the design sessions: (1) using a schematic of the exhibit that shows the global view and adding zoomed in layers that focus on a local biome; (2) using a multi-layer design where multiple concepts are represented on one visualization and the facilitators can choose which layer to work with; and (3) adding filters on one visualization to focus on a subset of data. Research shows that multi-layer designs can also enable users of complex systems to get started easily and progress at their own pace

and according to their needs [28].

Designing for Integrated Attention

While we encouraged the facilitators to design for tasks that could be accomplished throughout exhibit use, most of the scenarios they chose to develop were for times when they can pause the visitor physical interaction with the exhibit, for example during a reflection phase. Even then, the facilitators only considered using the tablet for having access to “quick” formative information or visualizations that serve as “conversation starters.” Prior work showed that facilitators were concerned with how much attention would be needed to operate a dashboard (e.g., selecting from menus) [13], but we didn’t anticipate that the facilitators would consider the data visualizations themselves as diversions of their attention. Probing the facilitators revealed that their preference for simple representations was as much about data literacy as about attention management: worries that they could not explain the representations to visitors, or even a lack of confidence in their own ability to interpret richer data visualizations while in the thick of managing the exhibit.

To address this design challenge, we are considering forms of information that can be rapidly accessed, for example, automatic alerts to help facilitators monitor visitors and decide when to intervene (during an engagement phase), or representations that can easily be perceived. In the following, we introduce another design consideration that can address this issue by using “literal representations.”

Literal Representations

As part of the design process, in the third participatory design session, we introduced more than 90 sample data visualizations to the facilitators (Figure 5) taken from the Data Viz Project’s visual list [10]. Our goal was to learn which data representations the facilitators are more comfortable working with. We found that, in general, the facil-

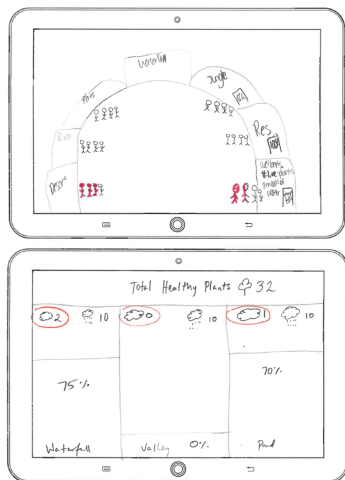


Figure 6: Examples of design sketches created by facilitators, which use visual references to the exhibit (i.e., literal representations): tracking the number of users in front of each biome using pictorial fraction charts (top) and comparing the number of living plants with the amount of water in each water source using icon counts and a waffle chart (bottom).

itators tended to choose representations that are pictorial or iconic, in other words, representations that form a “literal” connection with the exhibit itself, which is in keeping with how novices prefer information to be visualized [18]. For example, if the goal is to compare “the number of living plants in different biomes,” a literal representation would be to show an icon of a tree where its size represents the number of plants in a given biome, rather than a more abstract data representation like a bar chart. See Figure 6 for more examples.

This highlights an important design insight for us: when designing a data-driven dashboard, we have to be careful with visualizations that are perhaps unfamiliar, at least at first, and it is important to support a meaningful transition into and out of the tool. In other words, to promote effective uses of visual information, we need to be very thoughtful in supporting transitions between the dashboard and the physical space. We suspect lessons can be taken from the literature on multiple-linked representations to guide this aspect of design [16, 4].

Conclusion and Future Work

In this study, we explored the design of a data-driven learning dashboard to support educational facilitators manage visitor learning in an open-ended museum exhibit. Our findings outline a number of design ideas that we will implement and test *in situ* with facilitators over the next year. We argue that our task-centric strategy for understanding the problem space is a viable approach when designing to support facilitation in any open-ended educational situation. Any setting that is highly fluid and requires educational facilitators to be engaged in a multitude of different tasks at any moment, from teachers managing an inquiry-driven curriculum (e.g., [22]), to clinical training for nurses (e.g., [9]), can take this approach. We believe that designing a real-time

dashboard is more than just developing a new technological artifact, but rather a new socio-technical system.

Our preliminary findings highlight a key realization when designing for an open-ended learning environment: it is critical for dashboard designers to shift from pure content acquisition perspective to a more pragmatic perspective that pays extra attention to the “tasks” that the educators need to perform in the work space, whether in a classroom setting or in an informal learning situation. We thus provide a specific method for addressing the recent calls for researchers to attend to designing dashboards in context [1, 21].

One major advantage of a task-centric approach is that it opens the door to supporting the professional development of facilitators. Not all facilitators are equally practiced with all types of facilitative tasks, and codifying their work in terms of discrete tasks allows us to gather information on which tasks they execute and in which sequences, so that we can build a picture of what best practices might look like, and how facilitators deepen their practices over time. Moving forward and building on our task-centric design approach, we will extend our contextual analysis to examine the role of facilitators’ expertise in the ways that they perform tasks and see themselves using a dashboard tool. Our goal is to create a tool that promotes universal usability and supports facilitative tasks for both novice and expert educators, and supports novices as they build their expertise.

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