

What Do We Talk About When We Talk About Dashboards?

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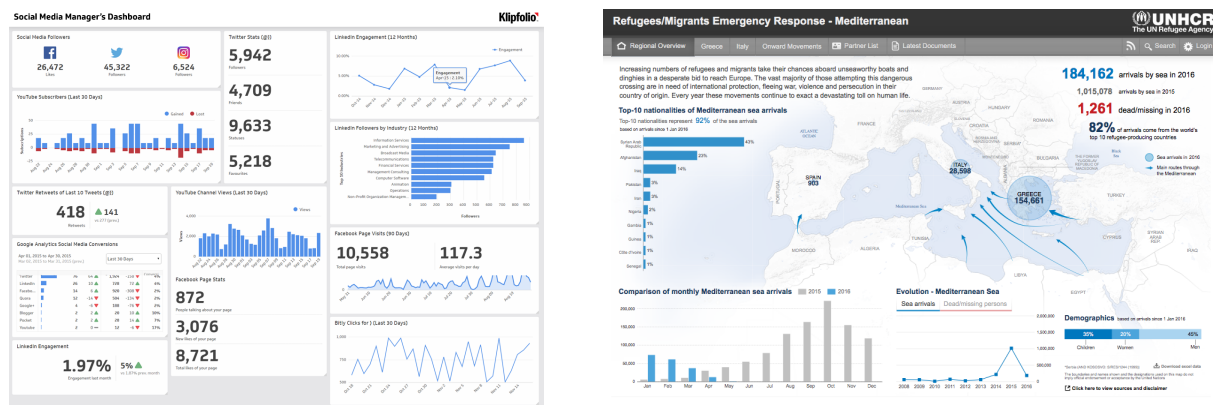


Fig. 1: Klipfolio's Social Media Manager Dashboard (DB065 from our example corpus, left) is a traditional dashboard, with large numbers representing key metrics, and tiled graphs of real-time data. The UNCHR Refugees/Migrants Emergency Response dashboard (DB117, right) also is a juxtaposition of key metrics and simple visualizations, but includes annotations and guided narrative elements. Are both dashboards? Do design principles meant for one transfer to the other?

Abstract—Dashboards are one of the most common use cases for data visualization, and their design and contexts of use are considerably different from exploratory visualization tools. In this paper, we look at the broad scope of how dashboards are used in practice through an analysis of dashboard examples and documentation about their use. We systematically review the literature surrounding dashboard use, construct a design space for dashboards, and identify major dashboard types. We characterize dashboards by their design goals, levels of interaction, and the practices around them. Our framework and literature review suggest a number of fruitful research directions to better support dashboard design, implementation, and use.

Index Terms—Dashboards, literature review, survey, design space, open coding

1 INTRODUCTION

Visualization dashboards are ubiquitous. They are built and employed by nearly every industry, non-profit, and service organization to support data-driven decision making. They are used by students to track learning, and by individuals to monitor energy consumption and personal health. Despite their prevalence, the visualization research community has rarely given dashboards their due consideration, with few exceptions [46]. Are dashboards simply an extension of known visualization design principles? Or is there more to their design and use?

We argue that dashboards are worthy of discussion and research in their own right. Their ubiquity alone makes them worthy of study, as the potential for impact is vast. But beyond that, they are *interesting*. Dashboards are diverse, appearing in many different contexts. They are shifting and democratizing and diversifying as their use proliferates; their contexts of use are expanding beyond simple monitoring and sin-

gle screen reports. Uniquely, compared to visualization modalities for presentation and exploration, **dashboards bring together challenges of at-a-glance reading, coordinated views, tracking data and both private and shared awareness**. Designers of dashboards must be mindful of literacy, contextually appropriate representations and visual language, and social framing. We identify dashboards as a distinct area of visualization that offers impactful directions for future research.

We took a two-pronged approach to understanding practices around dashboard design and use. We **conducted an exploratory survey of dashboards “in-the-wild” with the goal of discovering and identifying different types of dashboard design**. In parallel, **we conducted a multi-domain literature review in order to understand the practices surrounding dashboard use**. The domain review allowed us to build a characterization of uses and domains of dashboards and identify issues **that the literature sees as urgent**. These two complementary approaches mutually informed each other and allowed us to see the breadth of the ill-defined space of dashboards.

We contribute a design space for dashboards that goes beyond principles of visual encoding to include design dimensions such as functional design, purpose, audience, and data semantics. We identify diverse categories of dashboards with unique sets of characteristics across the dimensions. We also report issues and challenges surrounding dashboard use in practice, some of which emphasize the social context of dashboards as a primary interface to “big data.” Ultimately, we identify a set of interesting and critical research opportunities. We hope that our work will inspire and engage the community to embrace dashboards, study the challenges surrounding their use, and develop innovative dashboard technologies with broad-reaching impact.

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2 WHAT IS A DASHBOARD?

Even the definition of a dashboard is in flux. Few [19] describes dashboards narrowly: “a predominantly visual information display that people use to rapidly monitor current conditions that require a timely response to fulfill a specific role.” This definition entails single-paged, glanceable views of updating data. Wexler et al. [61] offer a broader definition: “a visual display of data used to monitor conditions and/or facilitate understanding,” which can include infographic elements or narrative visualizations (such as Figure 1 right). Through both the domain review and the dashboard design survey, it became clear that the term *dashboard* is widely used to refer to many different sorts of entities, challenging the dashboard stereotype familiar to the visualization community. Ubiquitous data, and visualization technologies available to the public, has broadened dashboard adoption to new domains. Consequently, the dashboard concept has evolved from single-view reporting screens to include interactive interfaces with multiple views and purposes, including communication, learning, and motivation, in addition to the classic notions of monitoring and decision support.

Broadly, then, we identify two different major design perspectives. We distinguish between the *visual genre* of dashboards (a visual data representation structured as a tiled layout of simple charts and/or large numbers as in Figure 1 left) and the *functional genre* (an interactive display that enables real-time monitoring of dynamically updating data). While many data displays use the familiar “dashboard” visual appearance, we found many tools that support the same functions but have very different visual designs, especially dashboards meant for mobile devices. We do not attempt to provide a single authoritative definition of dashboards. Instead, we acknowledge a tension between the visual and functional genres. For the purposes of this survey, we aim for inclusivity and consider a display a dashboard if it matches either the visual genre or the functional genre, or both. The next two sections explore our understanding of the dashboard space, derived through our design survey and domain review.

3 DASHBOARD DESIGN SURVEY

Using an exploratory methodology, we derived a design space consisting of 15 visual and functional aspects of dashboards.

3.1 Survey Methodology

Our design space is based on a chosen corpus of 83 dashboards. We qualitatively analyzed and coded this collection of dashboards to derive an initial design space. The corpus of images and sources is available in the supplemental material.

Each author collected his or her own set of visual displays that could qualify as dashboards, with the intent to capture breadth of both domains and visual design. The resulting broad sample was intentionally eclectic, to capture the current state of dashboards in the wild. We sourced example dashboards from (1) Tableau Public’s “Featured Dashboards,” (2) documentation from tools advertising “dashboarding” features, (3) displays advertised on Twitter and elsewhere as “dashboards,” (4) Google image search results for the terms “data dashboard” and “visual dashboard,” and (5) research papers in the domain review. (For example, we chose to display the Strava user interface after noting that Strava refers to their interface as a “dashboard.”) Our corpus of dashboard examples evolved throughout the analysis. During our analysis, we realized that our initial corpus lacked representation of typical “business” dashboards, likely because these are usually confidential. We therefore intentionally sought documented examples of business dashboards to add to our collection. Additionally, we realized that we needed specific dashboard examples; for tools and multi-dashboard collections, we chose a specific example, or removed them if no such example was available. Our final coding scheme focused on the visual design alone: we therefore excluded several kits or frameworks where no small set of representative images could be collected.

The dimensions in our design space were developed through an iterative process that involved collaboratively open coding and sorting the dashboards themselves, as well as reviewing the literature. In our open coding process, we generated terms and categories that could describe the variation within our corpus of dashboards, adding new

terms as we observed new design variations. We limited our codes to facets of the dashboard that could be revealed through superficial inspection of the representative images. This precluded analysis of other components of dashboard design, such as the types of computation or the internal architecture. While these components are important to dashboard design, we chose instead to focus on codes which would allow categorization of all samples (even those for which we had very little information) and which would highlight key design differences between visual and functional dashboard genres.

Towards the end of our open-coding process, two of the authors independently coded all of the dashboards using a preliminary set of design dimensions. They met over three sessions to review the evolving coding scheme and arrive at a mutual understanding with sufficient operationalization. They then completed coding the corpus of dashboard examples and checked how closely their coding matched. At this point, they computed inter-rater reliability using Cohen’s kappa ($\kappa = 0.64$; 86.5% agreement) in order to assess the reliability and repeatability of the coding schema. They then discussed all the mismatches until they came to an agreement, revising the categories, codes, and definitions as needed to reach 100% consensus.

After deriving the design space categories and codes, we used these factors to identify clusters in our corpus that highlight differences between the dashboards we encountered, as well as functional and visual commonalities. The resulting clusters that emerge from these results can be found in Table 1, and are marked by colored numbers (1–7). These diverse clusters reinforce the existence of ongoing shifts in how dashboards are conceptualized and designed, and point towards areas in need of additional research and guidance.

We organize the 15 distinguishing factors into categories: purpose, audience, visual & interactive features, and data semantics. We describe these aspects of dashboards in the following four sections.

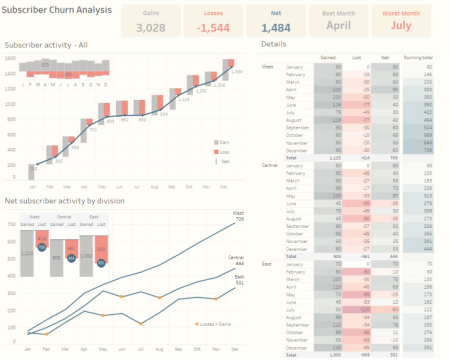
3.2 Purpose

The intended use of a dashboard drives the choices in its visual design and functional affordances. The factors presented here capture the roles of each dashboard in the process of analysis and communication. We find that the purpose of a dashboard has been substantially expanded from the colloquial “operational” dashboard to capture decision-making at higher levels, and may not even support decision-making at all.

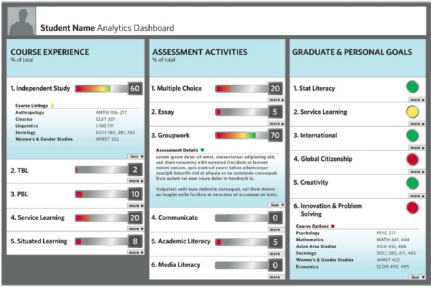
Decision Support (*Strategic, Tactical, Operational*): The decision support dimension reflects on the sorts of actionable decisions that dashboards are designed to support. Dashboards may be created to help an organization choose and evaluate a strategy (e.g., “we want users from around the world to be able to buy from our website”), refine their tactics (e.g., “our CDN helps us keep the website globally available”), or evaluate their operations (e.g., “users in Seattle are seeing slow network response”). We chose this coding based on existing literature [12, 18], and note that these levels of decision support are not exclusive. Three exemplar dashboard examples are shown in Figure 2.

Though we have described these terms by example (and they are defined within prior business literature, §5), we find it beneficial to think of the temporal lead and lag in the decision time. Operational dashboards describe the current and near past in terms of immediately quantifiable metrics that can be tied to their responsible entities. For example, if a management dashboard shows a gauge visual marking a warning value, immediate action can be taken to rectify the problem (see Figure 2c). Strategic dashboards take a longer view on actionability—combining many high-level metrics to drive decision-making over a longer temporal scale (see Figure 2a). We generally found that these categories were not mutually exclusive—in these situations, the dashboard tended to mimic an overview+detail design.

Communication and Learning: We encountered several examples of dashboards that did not solicit decision-making on any temporal scale. The communication and learning factor identifies dashboards that visually appear to be dashboards but may not function as a traditional dashboard. Rather than eliciting decisions on the part of the viewer or analyst, these dashboards exist to communicate or educate the reader, who may lack the context surrounding the presented data. These



(a) Strategic Dashboard (DB001)



(b) Tactical Dashboard (DB106)



(c) Operational Dashboard (DB102)



(d) Social Dashboard (DB028)

Fig. 2: Four dashboard exemplars demonstrating different attributes of dashboard design. A representative strategic dashboard (Fig. 2a) emphasizes the trends of paying subscribers along with monthly breakdowns for increases and decreases. Fig. 2b is a tactical dashboard that uses multiple metrics to summarize a student’s performance in a class. The operational dashboard (Fig. 2c) shows performance metrics that may be actionable, but with no collective summarization. The social dashboard (Fig. 2d) uses social and personal data to situate the context of the personal workout data. We demonstrate common factors of designs in the survey and highlight relevant challenges through our literature review.

dashboards echo an emerging trend of extending the functionality of dashboards and their contexts of use (§5.2.1).

3.3 Audience

The visual and functional aspects of a dashboard typically reflect the intended audience, their domain and visualization experience, and their agency relationship with the data.

Circulation (*Public, Social, Organizational, Individual*): To understand the interpersonal circulation of a dashboard, we quantize the generalizability of audience into four groups, each becoming more specific and requiring more context (where the necessary context might not be included in the dashboard itself). A *public* dashboard is intended for general consumption, and may describe societally-relevant data. Dashboards for *organizations* are broadly applicable for many different individuals within an organizational construct, such that these viewers share a common goal (say, supporting a business’ viability). *Social* circulation captures contexts in which an individual controls 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 doctor or financial planner). In coding, we considered the largest potential group supported by the dashboard, and the potential values are therefore mutually exclusive.

Some examples can be seen in Figure 4. The representative example for cluster 6 shows crime trends by state and type, presented for the general public. Cluster 1 demonstrates a dashboard exploring the customer relationship with the business, for use by individuals in an organization. An example of a social dashboard is shown in the example for cluster 7, presenting the value of different players for fantasy football. For an individual, the dashboard representing cluster

2 shows an individual’s home energy consumption. Another social dashboard is shown in Figure 2d, where social data is used to situate personal fitness information.

Required Visualization Literacy (*Low, Medium, High*): The complexity of visualizations on a dashboard can limit its comprehensibility. Instead of quantifying individual visual elements, we capture the visualization complexity through a quantized proxy of visualization literacy. For the purposes of operationalization, we consider *low* literacy to capture basic visualization types such as bar and line charts with typical faceting and aggregation (e.g. Figure 4, DB101). *Medium* literacy adds visualization features such as combined dual axes, scatterplots, cumulative measures, and heatmaps (e.g., DB005). We reserve the *high* literacy codes to capture those techniques known by a typical visualization student or practitioner: radar, treemap, and network visualizations, error bars or intervals, connected scatterplots, or other custom visualizations. For instance, DB052 contains an unfamiliar radial view.

Requires Advanced Domain Expertise: Many dashboards deal with business data or data general enough to be understood by a general audience, such as home electricity usage or personal finance. However, some dashboards require domain expertise to understand, such as the water metering metrics in Figure 4, DB034. This factor identifies cases in which additional domain or analysis context is needed in order to understand the dashboard and take action.

3.4 Visual Features & Interactivity

While interactivity is a familiar aspect of visualization, we found substantial differences between different dashboards. Interaction can happen at a number of different places in the dashboard lifecycle. We distinguish between three types of interactivity: tools may allow a user

to design (or customize) the dashboard; they may allow faceting of the data through data filters and slicers; and they may allow modifying the state of the data and world based on the data presented within the dashboard. These features speak to both the visual and functional affordances of dashboards.

Construction and Composition: Many dashboards allow consumers to modify the construction and composition of views. These dashboards provide flexibility for the viewer to customize the placement of views, modify the visual representations inside those views, or select the particular dimensions and measures to visualize. For example, the fitness dashboard in Figure 2d allows the user to choose which metrics to visualize. We considered a dashboard to have these capabilities if it contained a gear or \times icons within each view tile (indicating the functionality to remove or change properties of individual views), or if individual views had evidence of being flexible in their placement (e.g., draggable corners).

Multipage: While dashboards have traditionally been all-in-one view documents, some dashboards support tabbed layouts. These dashboards allow viewers to switch between pages, which may have visualizations that relate to a different component of decision-making or help to provide necessary context. With multipage dashboards, however, it can be difficult to consume the full breadth of information presented.

Interactive Interface: Many dashboards support multiple coordinated views. Interaction between views may involve faceting the data with slicers and filters, cross-highlighting by selecting data items within the views, and drilling up and down the levels of data hierarchy. These dashboards allow the consumer to focus their analysis on the data items that are relevant to them. We considered a dashboard to have interactive capabilities if we saw evidence of cross-highlighting (e.g., dimmed visual elements) or the presence of typical interactive components (e.g., drop-down menus, slicers).

Highlighting & Annotating: Several dashboards allow users to highlight and annotate particular views, thereby making persistent changes to the dashboard. These changes do not apply to the underlying data; rather, they allow users to annotate displays for future examination or for collaboration. For the purposes of operationalization, we consider any dashboard that highlights or otherwise distinguishes a subset of marks within any one view to support highlighting.

Modify Data or the World: Some dashboards have aspects of control panels: they have the ability to write back to the underlying database, or to control the external state of the world. Dashboards that support “what-if” analysis, modeling and data entry can be examples of writing back to the data source (or to a model). Other dashboards can interface to processes outside of the data source, such as a smart home dashboard that allows the viewer to turn off lights or adjust the thermostat.

3.5 Additional Data Semantics

Other than visual and functional features, dashboards can provide valuable semantics about the data and processes that they visualize. We capture these different type of semantics and the actions they elicit.

Alerting+Notification: A classic use of dashboards is to identify anomalies and highlight them for awareness and alerting purposes. These dashboards maintain real-time connections to data, and use user- or model-defined thresholds to raise an explicit alert to the viewer. These notifications indicate warning and critical scenarios, and prompt the viewer to take an immediate action to rectify the issue.

Benchmarks: Benchmarks add indications of breaking user- or model-defined thresholds, providing the viewer with additional data context. These benchmarks can take the form of gauges with ideal goals or warning thresholds (e.g., colors on gauges in Figure 2c), marks that show ideal directions (e.g., green up arrows and red down arrows), status “lights” that turn green, or goals explicitly marked as met, not met, or exceeded.

Updatable: Many dashboards are connected to datasets that are regularly updated, and the data within them automatically refreshes. An

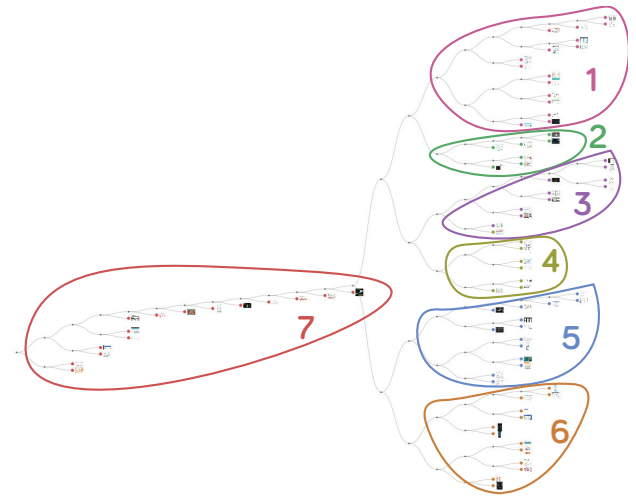


Fig. 3: Hierarchical clustering of the sample of 83 dashboards using a Hamming distance. We identified 7 clusters that exemplified different functional and visual characteristics of dashboard design. An interactive version of this figure is available in the supplemental material.

updatable dashboard accommodates changing data. While we anticipated many dashboards to fit this qualification, we identified in our early open-coding exercise several examples that were non-updatable: they described historical data or were highly customized to a singular point in time. One such non-updatable dashboard is “Word Usage in Sacred Texts” (DB010 in supplemental material).

3.6 Factors We Could Not Capture in the Survey

Our open-coding exercise also identified several other factors that we were unable to operationalize for the purposes of coding dashboards: analysis tasks, aspects of visual design, and context of use. However, we explore some of these issues in the domain review (section 5) and expand on potential avenues for future research in the discussion.

4 APPLYING OUR DESIGN SPACE

We encoded each dashboard in our collection as a string, with each encoded design dimension represented by a character. This allowed us to calculate a distance between dashboards as Hamming distance between strings. Figure 3 shows a minimized figure of hierarchical clustering of our collection. Using these clusters, we identified seven distinct clusters of dashboards, shown in Table 1. These seven clusters varied over the types of decisions they supported, along with the visual and functional features afforded by each design. For the purposes of analysis and discussion, we group them by similar characteristics. Figure 4 shows an exemplar dashboard for each identified cluster.

Dashboards for Decision-Making: We found two distinct clusters for decision-making (clusters 1 and 5). These dashboards tended to support either strategic (cluster 1) or operational decision-making (cluster 5). Many of these dashboards targeted audiences at the organizational level, and afforded functionality that allowed the consumers to interact with the views in order to focus on the data relevant for them. Over $\frac{3}{4}$ of these dashboards contained some sort of benchmarks, allowing viewers to identify areas of concern or improvement. Many of the examples in this cluster represent typical dashboards used daily in business contexts to understand sales and other metrics at a real-time level (operational) or over small/medium time periods (strategic).

Static Dashboards for Awareness: We identified two clusters of static dashboards (no interactivity, single page) for slightly different contexts of use (clusters 3 and 4). These dashboards tended to lack interactive elements commonly found in other dashboards, and tended to be designed for general awareness. Cluster 3 captures many dashboard examples to be used in an operational context, generally providing

Goal	Cluster	# Examples	Purpose				Audience			Visual Features				Data Semantics				
			Strategic	Tactical	Operational	Learning	Audience	Vis Literacy	Domain Expertise	Construction	Interactivity	Modify Data/World	Highlighting	Multipage	Alerting+Notification	Benchmarks	Updateable	
Decision-Making	1	Strategic Decision-Making	16	Y	Y	-	N	O	-	-	-	Y	N	N	Y	-	-	Y
	5	Operational Decision-Making	14	N	Y	Y	N	O	-	-	-	Y	N	N	Y	-	Y	Y
Awareness	3	Static Operational	10	N	N	Y	N	O	L	-	-	-	N	N	N	-	Y	Y
	4	Static Organizational	8	-	-	N	N	O	M	-	N	N	N	-	N	N	-	Y
Motivation and Learning	2	Quantified Self	7	N	N	Y	N	I	H	N	N	Y	N	-	Y	-	-	Y
	6	Communication	13	-	-	-	Y	P	M	N	N	-	N	-	-	N	N	Y
	7	Dashboards Evolved	15	-	-	-	-	P	H	-	-	-	-	-	-	-	-	Y

Table 1: The dominant characteristics observed for each cluster of coded dashboards. A factor is considered dominant if it occurs at least 50% over the prior probability, otherwise it is marked with a dash (-). **Y** indicates present or supported, **N** entails the opposite. **P** identifies the general public, **O** represents organizational audiences, while **I** indicates dashboards designed for individual consumption. **L**, **M**, and **H** indicate low, medium, and high visualization literacy required to understand the dashboard, respectively.

real-time data from sensors and metrics with low visualization literacy (line and bar charts) without much interactivity. However, we generally observed these dashboards to require advanced domain knowledge—additional context is needed to understand the semantic meaning of data trends and distributions.

Cluster 4 captures those dashboards geared toward an organizational audience with generally no interactivity. These clusters are comprised of dashboard examples that would be shown in a static setting and could be consumed at-a-glance, such as those e-mailed to executives and displayed on displays in a work environment. These two clusters seem to exemplify the design patterns of traditional dashboards.

Dashboards for Motivation and Learning: Outside of organizational contexts, we identified two clusters of dashboards concentrating on individuals and the general public (clusters 2 and 6, respectively). For dashboards tailored toward the individual, we observed primarily tactical and operation decision-making, with interactive interfaces and alerting. These examples tended to exemplify dashboards in personal matters, such as finance, exercise, and dieting. We could consider this cluster to be a result of the proliferation of personal visual analytics.

Dashboards designed to be used by the general public exhibited more ambiguous decision-making affordances. While about half exhibited strategic purposes, all seemed to be designed for the purposes of communication to and education of the consumer. In this cluster, dashboards tended not to have alerting or benchmarks, opting instead to present the data plainly to allow the viewer to come to an independent conclusion. We observed several examples of public health dashboards, dashboards of crime rates, and other types of civic data here.

Dashboards Evolved: The last cluster, 7, that we identified was a catch-all that did not fit into the other clusters. These examples tended to exemplify combinations of characteristics independent of the other clusters. Many of these examples visually appeared as dashboards, but may not fit the strictest definition of dashboard functionality. Figure 4 shows an example of a dashboard-style visualization of football players and their statistics for fantasy football.

5 LESSONS FROM THE FIELD: DASHBOARDS IN USE

In parallel with the dashboard survey, we conducted a multi-disciplinary review of dashboards in practice by examining literature reporting case studies, user studies, design exercises and deployment reports of dashboards used in Business Intelligence (BI), Education, Smart

Cities, Social Organizations, Health Management, and Personal Visual Analytics. We note that while we did not directly involve users in this research, many of the papers reported extensive user studies, often longitudinal investigations.

We examined literature primarily outside the fields of visualization and HCI, focusing on papers that described studies of real-world experiences of using dashboards in multiple sectors. Papers in our survey were sourced via Google Scholar and library searches with keywords including dashboard, visualization, analytics, and monitoring. Our primary goal with the domain review was to identify challenges related to dashboard technology and deployment. This review also informed our design space and coding terms by identifying factors that dashboard designers and users consider important in practice. These factors informed some of the coding terms. Most notably, “strategic”, “tactical”, and “operational” are common purposes of dashboards used for decision-making in the business literature [12, 18].

5.1 Domains and Uses

We commonly think of dashboards in business organizations, with goals such as optimizing decision making, enhancing operational efficiency, increasing data visibility, driving strategy and transparency, reducing costs, and facilitating communication [23, 36, 37, 65, 66]. Dashboards are commonly categorized by the type of decision-making they support: strategic, tactical or operational [36, 39]. Even within business intelligence there is considerable diversity in dashboard use. A BI dashboard is commonly now more than a single-view reporting screen: it is a portal to the information needed for some goal and may serve multiple analytical tasks [12, 36, 65]. Yet it is outside BI that dashboard purposes and needs become even more widely varied.

As an example, health organizations have been adapting dashboards at both large-scale (hospital management [60]) and patient-care levels [7, 17, 63], with a primary goal of supporting collaboration and awareness across diverse roles, time-frames and expertise. Urban informatics [9, 25, 34, 35, 40] and community organizations / non-profits [8, 27, 47, 48] all face challenges of integrating multiple disparate data sources, serving a large and diverse set of stakeholders, adapting to multiple platforms including mobile devices, and developing metrics and representations to represent intangible outcomes such as community awareness, engagement, and trust. Both learning analytics dashboards (e.g., [51, 57, 58, 64]) and personal behavior tracking dashboards (e.g., [21, 50]) may incorporate a social sharing and comparison

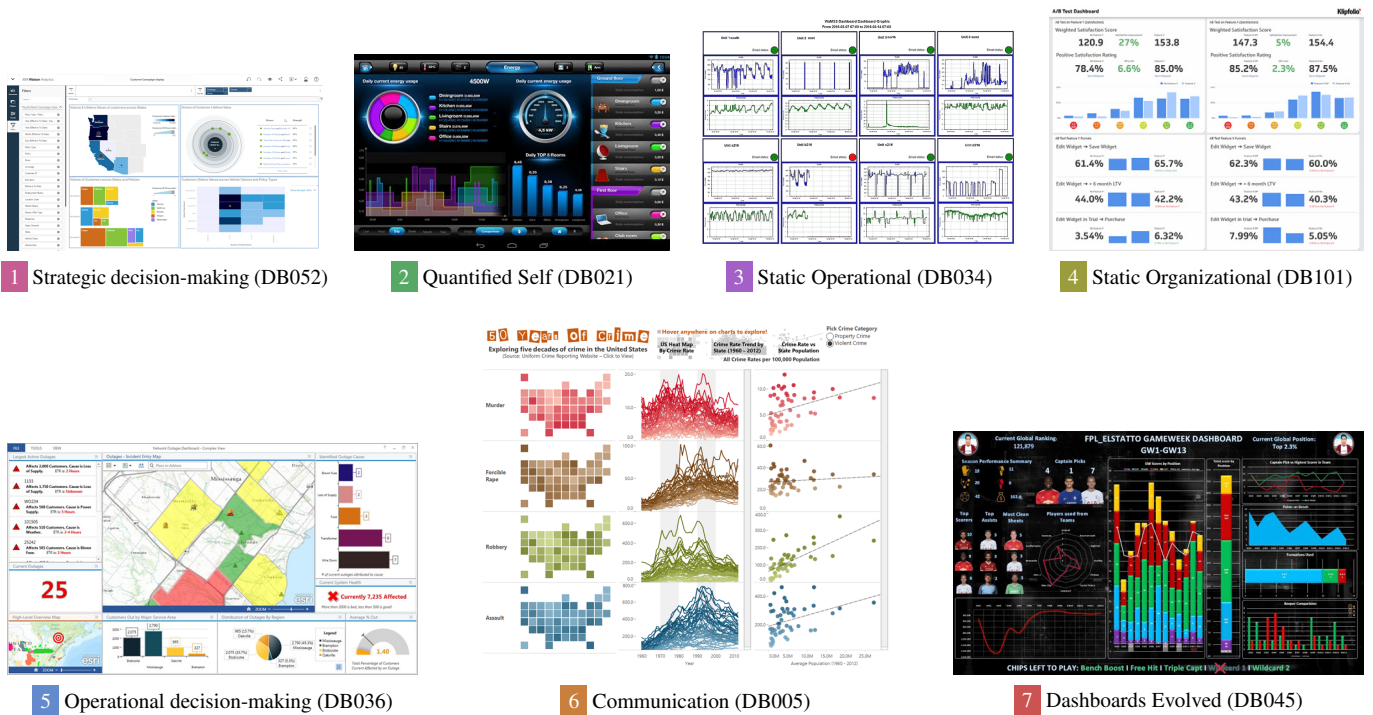


Fig. 4: Exemplar dashboards selected from our seven derived clusters. Clusters 1 and 5 demonstrate dashboards specifically targeting decision-making, while clusters 3 and 4 target awareness on behalf of the consumer. Cluster 2 targets the somewhat novel quantified self scenario (smart-home dashboard), while 6 represents dashboards tailored for general-purpose communication. Cluster 7 captures some novel extensions to traditional dashboards.

aspect, raising representational challenges and concerns about privacy. Across these diverse domains, dashboard limitations were reflected in a number of common themes. Some of these match current research questions in the visualization community, while others are novel. We discuss each in turn.

5.2 Familiar Challenges

Like many visualization tools, dashboards share issues that are familiar to visualization research; these are exacerbated in dashboards due to their diverse contexts of use and user populations. Major challenges related to the actual dashboard artefact are functional flexibility (including more control over authorship and configuration) and visual and analytic literacy.

5.2.1 End-User Flexibility

Numerous articles expressed a desire for greater flexibility in dashboards, including drill down options, level of detail adjustments, search, comparison support, and adaptability to different users, situations, and display devices or multi-display environments [6, 15, 21, 29, 36, 37, 39, 49, 51, 57, 61–63, 65]. While many interactive dashboarding tools provide support for basic functions like drill-down and search, automatic adaptation to different users and display environments is still an open research problem. Moreover, many dashboarding tools offer little opportunity for end users to reconfigure and customize views, a feature that was reported important in BI [29, 36, 65], health management [15, 63], learning analytics [51, 58], and personal applications [21, 50]. This includes the ability to integrate hybrid data sets [60] and add annotations to the data. In a recent project of dashboards for citizen engagement, users wanted to enter their own data, configure their own views, and redefine critical metrics to evaluate new proposals [30].

As the scope of dashboard use moves from merely reporting performance via proxy metrics to more in-depth problem solving [1, 11], users also want more analytical support in their tools, particularly “smart” features such as automated analytics (pattern identification, prediction) and

what-if simulations [37, 39, 44, 49, 61, 64, 65], or engagement features such as goal setting and gamification [58]. Automatic classification is one feature already showing benefits, such as automatically classifying a user’s location (e.g., home, work) from GPS data in personal monitoring dashboards [54].

An issue of communication is related to storytelling ability. Dashboards are increasingly used for decision making and communication across contexts: top-down, within departments, and across the organization [29, 36]. Dashboards that capture only the data and not the semantics of the data, or what was done in response to the data, can be insufficient for communication purposes. In BI, people often take screenshots of dashboards and put them into slide presentations in order to annotate them with contextual information [13, 14, 38], suggesting a need for more powerful storytelling features.

5.2.2 Visual, Analytic, and Data Literacy

A consistent theme in the literature was the challenge of supporting users with weak visual, analytic, or data literacy [12, 27, 33, 38, 49]. Galesic et al. [22] defined a metric of three levels of graph literacy: finding and extracting data (Level 1); integrating data and finding relations (Level 2); and analyzing implicit relationships, generating, and predicting (Level 3). Wakeling et al. [59] found that users were much more competent with Level 1 and 2 questions than Level 3, except with bar charts where they could answer Level 3 questions. A frequent example of analytic illiteracy was the confusion between correlation and causation. Visual literacy also included a lack of understanding of metrics and representation conventions across stakeholder groups [3].

Ease of dashboard use was repeatedly reported as a problem. There is a burden on authors to train end users, either through explicit instruction (e.g. tutorials) or guidance built into the dashboard itself [12, 13, 38]. While supporting non-expert users has been a theme in the visualization research literature for some time, the extent of the problem was beyond our expectations: even seemingly “simple” interactive features such as filters were often considered too complex for casual users [12].

Dashboard authors went to great lengths to support non-experts. They frequently described how they reduced interactive functionality or customizability to reduce complexity [2, 12, 38]. As stated by Malik [38], “...most users do not have the time or motivation to learn new software applications. The golden rule is to simplify, simplify, simplify!” Similarly [12], “If designed properly, tactical dashboards can meet the needs of both casual and power users. The key is to... support the information needs of power users and then turn off functionality as needed to avoid overwhelming casual users with too many bells and whistles or pathways to explore.” Another strategy is to establish cross-organization design principles, “The finance manager should be able to easily drive the credit or treasury dashboard because it looks and behaves similarly to the finance dashboard.” [38]

A similar learning curve faces dashboard authors themselves [13]. With the explosion of data democratization, dashboards are being built by people with a vast diversity of skills and knowledge, most of whom are not data analytics or visual design experts. Novice authors rely heavily on experts, templates, and learning resources to learn both dashboarding tools as well as visualization design principles and practices. Moreover, dashboard authors are often uncertain how to evaluate the effectiveness of the dashboards that they build [25, 58]. These observations emphasize the need for accessible templates, guidelines, and learning resources to help non-experts become proficient.

5.3 Dashboards Emphasize New Challenges

Some of the challenges regarding dashboards have a new twist, which indicate new opportunities for visualization research. These include choices of data and representation that are critical to dashboard contexts of use; and understanding the broader social impact of dashboards.

5.3.1 Data Design

Many issues related to data as they interface with dashboards emerged repeatedly over different data domains: confusion around the choice of metrics, impoverished vocabulary, the nature of adaptive views, and communicating metadata.

Metrics: Data choice and how they are presented affect both the scope and nature of decision-making [24, 29]. Metrics such as Key Performance Indicators (KPIs) communicate not only performance but also priorities and values. As an example, process KPIs matter for tracking compliance [43] (“Are we following all protocols?”) but are less appropriate for tracking performance relative to desired outcomes (“Is the client getting better?”) [7]. Performance dashboards often suffer from a poor taxonomy of strategic goals [29, 35, 65]; several studies suggest explicitly visualizing *strategy maps* that link KPIs specific to subgroups to the organization’s larger strategic objectives [36, 65]. Choosing the right metrics poses challenges for those less versed in analytics culture, particularly where trustworthy communication is the primary purpose such as in social organizations [8, 48] and public outreach. Most social organizations lack both organizational and data literacy to build up metrics and representations [8, 27, 48].

Impoverished data vocabulary: Our review also identified the need for more sophisticated metrics and representations to express the nuances of complex problem solving [3, 24, 31, 64, 65]. The California School Dashboard uses traffic-light colour coding designed to simplify data interpretation for parents. It caused concern among educators and parents around over-simplification of school “health” [55]. Such constrained “scorecard” views and quantitative models amenable to traditional data analytics can impose mechanistic, unsophisticated decision-making regimes [3, 24, 29, 35, 64] that are susceptible to misinterpretation.

Data choice re-frames problem definition and thus implicitly refocuses the values of possible solutions [3, 24, 29, 31, 45]. O’Connell et al. [45] reported a project to engage people in a dialogue around public safety using a community dashboard. Where urban social planners previously used an asset-based model of neighborhood health (social cohesion, resilience), the move to a data-driven representation refocused the conversation on a deficit-based model (crime, code violations).

Adaptivity: Different tasks require different levels of data: both richer access to data through drill-down or roll-up and task-appropriate data filtering [7, 16, 23, 29, 37, 63, 65]. Studies show that tasks with higher uncertainty require more disaggregated data but showing more detail all the time leads to information overload and decision inaccuracy [4]. For dashboards used in critical applications (e.g. healthcare), timely access to the “right data” is particularly important as decisions are made collaboratively across different situational and personnel contexts [17, 63]. For personal analytics applications, users tend to want control to select the data that matters for their personal goals [21, 62].

Data and metadata: Many cases we read discussed the need for the provision of metadata. A number of these issues relate to data quality: completeness [27, 47, 56], provenance [9], accountability [8, 31, 48, 64] and uncertainty [47]. These concerns were especially prevalent in the urban informatics and social organization domains, where quality of data, trust and accountability are critical [24, 48] but are often poorly elicited by current dashboards [31, 35]. Explicitly referencing where the data come from, and the degree of certainty in that data, are seen as important to enhancing public trust [9, 41, 47]. These issues are more complex when data are derived from automated algorithms and the reasoning is “invisible”. Researchers in policy note that providing information and explanation about the underlying data and the algorithmic and statistical techniques performed on it is important for both accountability and trust [9, 10, 64]. A different dimension of data and analytic “depth” emerged in reports of interactive dashboards with additional data views: indicating the level of analytic functionality [36, 37] or data detail [24] behind the view.

5.3.2 Social Impact

In our review, dashboards were often the primary interface to how people use “big data:” consequently, dashboard use is often a proxy for the social impacts of big data practices. Concerns raised included data-limited thinking, unintended reactions to data in the workplace, privacy, trust, and issues related to “data democratization:” who controls the data, who configures the view, and who gets to see what. These issues widen the discussion of dashboard design, introducing challenges of representation and framing relevant to both designers and researchers.

Data-driven thinking: Data views are not neutral although they convey the impression of objectivity and “truth” [24, 65]: how they are framed and visualized reflects the values and perspectives of the authors and determines their interpretation [28]. Rall et al. [48] allude to the danger of incorrectly designed visualizations in human rights advocacy: “visualized quantitative data lends human rights the stature of science.” Similarly, in a study of dashboards for school health, people interpreted the data as “trustworthy and definitive” [10] because the visual organization emphasized those associations as objective.

Dashboard use often restricts the scope of interpretation and decision making [3, 24, 31, 64]. Angrave calls dashboards the “visual expression of the KPI mindset” [3] and is one of many authors who caution that human behaviour can often not be simply quantified [23, 29, 32]. Education studies highlight challenges of lack of accountability in algorithmically generated prediction and concerns that these approaches are displacing the pedagogic expertise of educators [10, 42, 64]. Similarly, urban studies papers identified several visualization challenges: concepts like the flow of information in a society, contextual information associated with places, and the emergence of communities [9, 30, 34, 35, 40]. These questions of knowledge extraction are critical for both assessing community health [10, 40, 45] and for supporting citizen engagement [30, 34].

Social data as context: Data about peer performance or status are often used in dashboards to promote engagement and motivation (e.g., in personal dashboards [21, 26, 50], learning analytics [51] or employee/department comparisons [3]). How these data are framed and represented present challenges. Comparisons that emphasize competition can be highly motivational. For example, “the overriding element that helped to persuade some to remain engaged was the ability to share and compare energy consumption” [21]. Yet such competition can be de-motivating when the user feels the thresholds of performance are

out of reach [52]. Also, raw or simplistically aggregated data may not give the right picture (in one learning analytics study, students wanted “more equitable” representations of comparison with their peers rather than aggregate percentages [51]).

Sharing, security, and trust: Dashboards are increasingly used in a social context. Their use now crosses hierarchical and departmental boundaries, highlighting the need to integrate and align both key metrics and the representation and framing of them to support collaboration and communication [36]. When dashboards become portals to the information system, there are questions of access and agency. Who can see the data at all levels? Is access managed by role [29, 36]? Authoring models for data can be both unclear and insecure [30, 45], leading to issues of trust. A case study of a successful dashboard deployment in hospital management [60] identified two key aspects to promote shared understanding and employee acceptance: *shared context* (dashboards included details for the specific area and an overview of organizational strategic objectives / targets) and *transparency* (90 percent of dashboards could be seen by every employee).

Privacy: How individual data are presented impact both privacy and motivation. Studies show that students want control over what others can see and when, especially when they are viewing the data in public or mobile situations [51]. Beyond explicitly social data, many articles reported a dysfunctional impact of dashboards related to concerns of surveillance and anxiety about what data were being captured, who had access, and how they were interpreted [10, 17, 29, 51, 65].

6 DISCUSSION

Our exploration of dashboards took two complementary lenses: a perspective focused on the artefact design (the dashboards survey) and one focused on artefact practices (the domain review). They highlighted design issues and challenges that dashboard designers should consider, many of which pose interesting research questions for the visualization community. The clearest implication of our work is that we need to stop thinking of dashboards as a single entity and actually explore and experiment with design separately for different purposes, contexts of use, and data environments.

6.1 The Shifting Design Space of Dashboards

Our domain research and the clusters in the design space directly address the tension we identify between dashboards as a visual genre (e.g., a tiled layout of key metrics visualized in simple charts) and dashboards as a functional tool (e.g., affording real-time monitoring of operations). They confirm that the term “dashboard” does not pick out a unique method of organizing, presenting, and using data, but rather covers a diverse set of practices.

The fact that widely differing objects all situate themselves as dashboards complicates their design, as there is no guarantee that the design principles from one category of dashboard neatly transfer to another. For instance, layout decisions that are effective for the glance-ability of key metrics in operational decision-making dashboards (cluster 5) may not be effective for the narrative and anchoring needs of communication dashboards (cluster 6). A designer of such a communication dashboard (6) may wish to preserve the temporal or logical ordering of views in order to clearly communicate an idea, whereas a designer of an operational dashboard (5) may wish to order views such that the most critical information is the most prominent, no matter the temporal or semantic relationship between views. Designers of strategic decision-making dashboards (cluster 1) may need to consider issues of supporting interactive temporal aggregation, levels of detail, and re-analysis—concerns that would not arise in static, short-term, static operational dashboards (cluster 3). These differences reflect the growing needs for increased flexibility and extended functionality identified in the domain research.

We contend there are design principles that are shared across a broad category of artifacts in the visual genre of dashboards. Consistency among views [46], the signaling of dashboard affordances [61], and a general concern for managing complexity and comprehensibility [18],

are concerns that crosscut nearly every dashboard-like juxtaposition of multiple visualizations. Yet, the differing purposes across the sub-categories suggest that there are design principles that do not transfer. An author of a static dashboard for an organization (cluster 4) may wish to eschew customization, to ensure that the entire organization is making decisions based on a complete and universal picture of the data. However, the designer of a dashboard for personal informatics (cluster 2) would likely wish to afford customization by a user who would want to include the most relevant metrics for their lived experience.

As the functional use of dashboards is shifting and expanding, existing design considerations may too be expanding: in the case where dashboards are encroaching into information presentation territories previously considered to be the realm of infographics or narrative visualization, designers of dashboards must become mindful of storytelling, rhetoric, and persuasion, a point we explore further in Section 6.2. Our “Dashboards Evolved” cluster (7) captures an emerging space of dashboards that do not fit neatly into our prior conceptions of what dashboards look like or how they function. Just as other genres in areas like film and literature change over time as exemplars circulate and tastes and fashions evolve, dashboards too may undergo radical shifts in their conceptualization and visual signatures.

6.2 Where Do we Go From Here? Research Challenges

We observed major design challenges of functional flexibility, visual and data literacy expectations, data expressiveness and framing, and social impact. But what can dashboard designers and researchers do to address these questions?

We noted the importance of enhanced functional and visual design in our reviews. Our open-coding exercise identified several factors that we were unable to operationalize for the purposes of coding dashboards, notably the complex analysis tasks identified in our field survey. Visualization research commonly uses analysis task as an abstract proxy to compare the efficacy of different designs. More detailed usage analysis would expose the combination and composition of tasks (such as as used by Brehmer and Munzner [5] or Schulz et al. [53]). Identifying *how* dashboards help users analyze their content from a visualization perspective is important future work, particularly for non-experts.

We need better ways to assess and support visualization and analytic literacy with dashboard design. Enabling access to more data and providing more extensive analytical support can both extend the utility of a professional dashboard and can also scaffold and guide users who are less versed in data and visualization, enabling them to ask and answer their own questions. The challenge of designing for users with different levels of visual and analytic literacy cannot be addressed by assuming fixed designs for singular audiences. Dashboards are increasingly used for sharing information across roles, domain expertise and motivations both within and across organizations. They provide a common frame of reference with shared data and tailored representations for specific users. The current constructs we have for visual literacy [7, 63] fall short of capturing the diverse purposes and contexts of use that influence analytic success and may or may not facilitate proficiency gains. We need new methods to evaluate these complex comprehension tasks.

Future work could also extend our framework with dimensions visual design, which we left out for tractability. Aspects such as layout and arrangements can have significant impact on the efficacy of a dashboard, especially in relation to the analytic process of the consumer. In a context of a dashboard that has a potentially wide variety of uses, other aspects of design may become important to consider, such as affect [6] or memorability [5]. As dashboards venture into information presentation territories previously considered to be the realm of infographics or narrative visualization, designers of dashboards must become mindful of storytelling, rhetoric, and persuasion.

We suggest that the most compelling and difficult challenges for dashboard designers (and by extension, visualization designers) relate to our impoverished data and representational vocabulary. The popularity of infographic elements and styles notable in the clusters suggests an effort to capture elements of the dashboard purpose and background that are not easily reduced to data attribute-visual feature mappings. Beyond this, we see an expressed demand for visualization

that captures qualitative and more intangible concepts (e.g. organization health [34], social quality [13], and context [27, 44]). Mitigating the reductive impact of data-limited thinking models will require a richer and more expressive data and visual lexicon. This argues for a more comprehensive study of the affective and cognitive affordances of these new forms. This applies not only to the data themselves but also to the overall framing and contextual information of the dashboard. Provenance, relation to the larger context of shared goals, uncertainty, explanation of algorithmic conclusions [12, 40, 68] and appropriate social context (comparison, discussion) are examples of metadata and framing that may alleviate the tendency to over-simplify problem thinking and reduce concerns of accountability and trust. These in turn introduce challenges of representation and visual literacy.

6.3 Comparison to Existing Frameworks

One of our goals in this work was to gain a comprehensive understanding of the dashboard design space and to begin to develop a more coherent framework of design principles. Our research confirms that the term “dashboard” does not pick out a unique method of organizing, presenting, and using data, but rather covers a diverse set of practices. There is a lack of design frameworks that can accurately describe this emerging space: current models address limited aspects, but, we propose, fail to capture its extent and complexity. For example, Few has written extensively about dashboard design principles for strategic, tactical, and operational decision-making [18]. He also distinguished between what he calls “dashboards” (single screen, used only for monitoring) and “faceted analytical displays” (used for analysis) [20]. Our clusters go further than this in distinguishing the diversity of dashboard types, as defined by their purposes and characteristics. Our descriptive rather than prescriptive framework may fail to isolate *best* practices in dashboard design, but by widening our framework to *extant* practices, we can identify areas in need of further research attention.

There have also been several design frameworks proposed for traditional business intelligence dashboards that address both visual and functional scope [36, 39, 65]. Marx et al. [39] identified three dimensions to consider in BI dashboard design: a comprehensive information model (scoped relevant to both task and role), functional breadth (e.g., drill-down, simulations, alerts, and mobile access), and flexibility to accommodate different levels of visual and data literacy. Lea and Nah [36] extended Marx et al.’s framework to a multi-layered model of linked dashboards supporting the three types of organizational decision-making, based on data, display type, and analytical functions. These frameworks share some piecemeal elements with our own (e.g. purposes, functions, and visual literacy) but are much less comprehensive.

Most similar to our framework is one described by Yigitbasioglu et al. [65], who framed dashboard design as optimizing “fit” between 4 dimensions: purposes, users, design features (functional and visual) and outcomes. Purposes included planning, communication, monitoring and analysis. Functional features included analytical tools, drill-down/roll-up, view reconfiguration, and notifications, many of which are also present in our framework. *Functional fit* refers to how well a dashboard’s functions align with its purpose. Both functional and visual features enable *cognitive fit* with different types of users.

These frameworks explicitly acknowledge emerging characteristics of dashboard requirements in business applications: an increasing diversity in users (personality, task and role); dynamic flexibility in purpose and function (i.e., serving more than one type of decision-making), and more sophisticated interaction with data (level of detail adjustment, reconfiguring the displays, integrating analytical and what-if tools). However, they fail to encapsulate design dimensions relating to the myriad of ways in which dashboards are used, the ways they affect organizational practice and culture (*social fit*), and the challenges posed by the need for more flexible *data fit* (new metrics, richer representations). These issues are extremely relevant to the new generation of dashboards. Existing frameworks have also been explored solely in the business domain; our broader survey revealed new aspects such as dashboards for learning, interactivity that modifies the outside world, and dimensions related to data semantics.

7 LIMITATIONS

Our work is subject to some caveats. Most importantly, our methodology explored dashboards and their use indirectly through examples and literature. We did not directly consult dashboard users or designers and may therefore have missed some important design considerations, challenges, and potential mismatches between intended and actual system use. While the insights revealed by the literature do correspond to anecdotal reports we have heard about dashboard use, we consider systematic studies involving actual dashboard designers and consumers as an especially important avenue for future research.

In addition, the dashboards examined in our survey were intentionally diverse but are by no means a representative sample. It is encouraging that our resulting categories are semantically meaningful and can capture the commonalities within our diverse collection. Nonetheless, we fully anticipate that examining additional dashboards, use cases, and domains will reveal new insights and additional categories. Additionally, many of our design dimensions and observations may apply to other types of visual analytic systems; future work could explore these synergies and attempt to more clearly delineate the challenges unique to dashboards alone. Our design space should be taken as a first step rather than a complete characterization; we hope that this work will inspire others to further develop and refine it through alternative methodologies and complementary examples.

8 A CALL TO ACTION

Dashboards might seem, at first glance, comparatively simple: a handful of core chart types, placed in multiple coordinated views, might seem to pose few technical challenges. This surface simplicity can be deceiving: the whole of dashboards are far more than the sum of their parts.

Dashboards are both ubiquitous and critically important in a data-driven world. Uncountable numbers of businesses, non-profit organizations, and community groups depend on dashboards every day to get their work done. For many people in these organizations, dashboards may be their first (or only) encounter with data. Moreover, dashboard use has spilled out of organizational boundaries to individuals and the general public. Everybody is using dashboards, but are they well-prepared and supported?

The ubiquity of dashboards presents an opportunity. Visualization research that can facilitate dashboard design, development, and use has potential to change the lives of millions of people. Today, dashboard authors and consumers are *making do with what they’ve got*. It’s not enough. Dashboard designers struggle with one-size-fits-all dashboarding tools that fail to reflect the diversity of user needs and goals. They struggle with challenges of visual and analytic literacy, constrained data-driven thinking, and development of metrics that really reflect the things they care about. They are asking for greater flexibility, customization, adaptability, and deeper analytics.

Nearly every aspect of visualization and visual analytics research done in our community could be considered in the context of dashboards. How does visual perception change in dashboards? What does storytelling support look like for dashboards? How can automated analytical approaches be integrated? How can we support customizability and personalization for casual users? Can a dashboard itself teach literacy skills? The list of potentially impactful directions is immense. Are we up to the challenge?

As a research community, we can continue to see the dashboard industry grow in parallel to our own work. Or we can embrace dashboards as our own, engage with dashboard users in the wild, and tackle the interesting challenges they face. We invite the visualization community to systematically study dashboard design, create the dashboard of the future, and in doing so, impact the people who rely on visualization every day.

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REFERENCES

- [1] A. Abbasi, S. Sarker, and R. Chiang. Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems*, 17(2):i–xxxii, Feb. 2016.
- [2] C. Alonso-Fernandez, A. Calvo, M. Freire, I. Martinez-Ortiz, and B. Fernandez-Manjon. Systematizing game learning analytics for serious games. In *Global Engineering Education Conference (EDUCON)*, pp. 1111–1118. IEEE, 2017.
- [3] D. Angrave, A. Charwood, I. Kirkpatrick, M. Lawrence, and M. Stuart. HR and analytics: why HR is set to fail the big data challenge. *Human Resource Management Journal*, 26(1):1–11, Jan. 2016.
- [4] I. Benbasat and A. Dexter. Value and events approaches to accounting: an experimental evaluation. *Accounting Review*, 54(4):735–749, 1979.
- [5] M. Brehmer and T. Munzner. A Multi-Level Typology of Abstract Visualization Tasks. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2376–2385, 2013. doi: 10.1109/TVCG.2013.124
- [6] E. K. Choe, B. Lee, H. Zhu, N. H. Riche, and D. Baur. Understanding self-reflection: how people reflect on personal data through visual data exploration. pp. 173–182. ACM Press, 2017. doi: 10.1145/3154862.3154881
- [7] B. F. Chorpita, A. Bernstein, E. L. Daleiden, and The Research Network on Youth Mental Health. Driving with Roadmaps and Dashboards: Using Information Resources to Structure the Decision Models in Service Organizations. In *Administration and Policy in Mental Health and Mental Health Services Research*, pp. 114–123, Nov. 2007.
- [8] J. Coffman, T. Beer, P. Patrizi, and E. H. Thompson. Benchmarking Evaluation in Foundations: Do We Know What We Are Doing? *The Foundation Review*, 5(2):36–51, July 2013.
- [9] A. Crooks, D. Pfoser, A. Jenkins, A. Croitoru, A. Stefanidis, D. Smith, S. Karagiorgou, A. Efentakis, and G. Lamprianidis. Crowdsourcing urban form and function. *International Journal of Geographical Information Science*, 29(5):720–741, Jan. 2015.
- [10] R. Crooks. Representationalism at work: dashboards and data analytics in urban education. In *Educational Media International*, pp. 1–14. Routledge, Dec. 2017.
- [11] M. Djerdjouri and A. Mehailia. Adapting business analytics to leverage enterprise data assets. In R. Benlamri and M. Sparer, eds., *Leadership, Innovation and Entrepreneurship as Driving Forces of the Global Economy*. Nov. 2016.
- [12] W. W. Eckerson. *Performance dashboards: measuring, monitoring, and managing your business*. John Wiley & Sons, 2010.
- [13] M. Elias, M.-A. Aufaure, and A. Bezerianos. Storytelling in visual analytics tools for business intelligence. In *IFIP Conference on Human-Computer Interaction*, pp. 280–297. Springer, 2013.
- [14] M. Elias and A. Bezerianos. Annotating bi visualization dashboards: Needs & challenges. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1641–1650. ACM, 2012.
- [15] A. Faiola, P. Srinivas, and B. Doebbeling. A ubiquitous situation-aware data visualization dashboard to reduce ICU clinician cognitive load. In *17th International Conference on e-Health Networking, Applications and Services*, pp. 439–442. IEEE, Aug. 2015.
- [16] A. Faiola, P. Srinivas, and B. Doebbeling. A Ubiquitous Situation-Aware Data Visualization Dashboard to Reduce ICU Clinician Cognitive Load. In *17th International Conference on e-Health Networking, Applications and Services*, pp. 439–442. IEEE, Aug. 2015.
- [17] A. Faiola, P. Srinivas, and J. Duke. Supporting Clinical Cognition: A Human-Centered Approach to a Novel ICU Information Visualization Dashboard. In *AMIA Annual Symposium*, pp. 560–569. American Medical Informatics Association, Sept. 2015.
- [18] S. Few. *Information Dashboard Design: The Effective Visual Communication of Data*. O'Reilly, Cambridge, MA, 2006.
- [19] S. Few. Blog post: There's nothing more about semantics. <https://www.perceptualedge.com/blog/?p=2793>, 2017.
- [20] S. Few and P. Edge. Dashboard confusion revisited. https://www.perceptualedge.com/articles/visual_business_intelligence/dboard_confusion_revisited.pdf, 2007.
- [21] D. Filonik, R. Medland, M. Foth, and M. Rittenbruch. A Customisable Dashboard Display for Environmental Performance Visualisations. In *Persuasive Technology*, vol. 7822, pp. 51–62. Springer Berlin Heidelberg, 2013. doi: 10.1007/978-3-642-37157-8_8
- [22] M. Galesic and R. Garcia-Retamero. Graph literacy: A cross-cultural comparison. *Medical Decision Making*, 31(3):444–457, 2011.
- [23] J. Goldmeier and P. Duggirala. *Dashboards for Excel*. Sept. 2015.
- [24] J. Gray, L. Bounegru, S. Milan, and P. Ciuccarelli. Ways of Seeing Data: Toward a Critical Literacy for Data Visualizations as Research Objects and Research Devices. In *Innovative Methods in Media and Communication Research*, pp. 227–251. Springer International Publishing, Cham, Dec. 2016.
- [25] S. Gray, O. O'Brien, and S. Hügel. Collecting and Visualizing Real-Time Urban Data through City Dashboards. *Built Environment*, 42(3):498–509, Oct. 2016.
- [26] D. Huang, M. Tory, B. A. Aseniero, L. Bartram, S. Bateman, S. Carpendale, A. Tang, and R. Woodbury. Personal visualization and personal visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 21(3):420–433, 2015.
- [27] B. Kanter and K. Delahaye Paine. *Measuring the networked nonprofit using data to change the world*. Jossey-Bass, San Francisco, 2012.
- [28] H. Kennedy, R. L. Hill, G. Aiello, and W. Allen. The work that visualisation conventions do. *Information, Communication & Society*, 19(6):715–735, Mar. 2016.
- [29] H. Kerzner. *Project management metrics, KPIs, and dashboards*. Wiley, Nov. 2017.
- [30] Z. Khan, J. Dambruch, J. Peters-Anders, A. Sackl, A. Strasser, P. Frhlich, S. Templer, and K. Soomro. Developing Knowledge-Based Citizen Participation Platform to Support Smart City Decision Making: The Smarticipate Case Study. *Information*, 8(2):47, Apr. 2017. doi: 10.3390/info8020047
- [31] R. Kitchin. Making sense of smart cities: addressing present shortcomings. In *Cambridge Journal of Regions, Economy and Society*, pp. 131–136, Mar. 2015.
- [32] R. Kitchin. Urban data and city dashboards: Six key issues. *SocArXiv*, Sept. 2016. doi: 10.17605/OSF.IO/K2EPN
- [33] R. Kitchin, S. Maalsen, and G. McArdle. The praxis and politics of building urban dashboards. *Geoforum*, 77:93–101, Dec. 2016. doi: 10.1016/j.geoforum.2016.10.006
- [34] R. Kitchin and G. McArdle. Urban data and city dashboards: six key issues. In *Data and the City*, pp. 1–21. Sept. 2016.
- [35] K. Kourtit and P. Nijkamp. Big data dashboards as smart decision support tools for i-cities – An experiment on stockholm. In *Land Use Policy*, pp. 24–35. Elsevier, Feb. 2018.
- [36] B. R. Lea and F. H. N. Nah. Usability of Performance Dashboards, Usefulness of Operational and Tactical Support, and Quality of Strategic Support: A Research Framework. *HIMI HCII 2013, Part II, LNCS 8017*, pp. 116–123, June 2013.
- [37] H. Lempinen. Constructing a design framework for performance dashboards. In *Nordic Contributions in IS Research*, pp. 109–130. Springer Berlin Heidelberg, 2012.
- [38] S. Malik. *Enterprise dashboards: design and best practices for IT*. John Wiley & Sons, 2005.
- [39] F. Marx, J. H. Mayer, and R. Winter. Six principles for redesigning executive information systems—findings of a survey and evaluation of a prototype. *ACM Transactions on Management Information Systems*, 2(4):1–19, Dec. 2011.
- [40] S. Mattern. Mission Control: A history of the urban dashboard. *Places. The Journal of Public Scholarship on Architecture, Landscape and Urbanism*, pp. 1–20, Mar. 2015.
- [41] G. McArdle and R. Kitchin. The Dublin Dashboard: Design and development of a real-time analytical urban dashboard. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 4:19, 2016.
- [42] C. McCoy and H. Rosenbaum. Unintended and shadow practices of decision support system dashboards in higher education institutions. vol. 54, pp. 757–759. Washington, DC, Oct. 2017.
- [43] T. H. S. Morgan, D. Murphy, and B. Horwitz. Police Reform Through Data-Driven Management. In *Police Quarterly*, pp. 275–294, May 2017.
- [44] A. Mottus, S. Graf, N.-S. Chen, et al. Use of dashboards and visualization techniques to support teacher decision making. In *Ubiquitous Learning Environments and Technologies*, pp. 181–199. Springer, 2015.
- [45] K. O'Connell, Y. Lee, F. Peer, S. Staudaher, A. Godwin, M. Madden, and E. Zegura. Making public safety data accessible in the westside Atlanta data dashboard. In *Bloomberg Data for Good*, pp. 1–7. New York, Sept. 2016.
- [46] Z. Qu and J. Hullman. Keeping multiple views consistent: Constraints, validations, and exceptions in visualization authoring. *IEEE transactions on visualization and computer graphics*, 24(1):468–477, 2018.
- [47] L. Raftree. 13 tips on data dashboards for decision-making.

- <https://lindaraftree.com/2015/06/05/13-tips-on-data-dashboards-for-decision-making/>, 2018.
- [48] K. Rall, M. L. Satterthwaite, A. V. Pandey, J. Emerson, J. Boy, O. Nov, and E. Bertini. Data Visualization for Human Rights Advocacy. *Journal of Human Rights Practice*, 8(2):171–197, July 2016.
 - [49] R. M. Ratwani and A. Fong. connecting the dots: leveraging visual analytics to make sense of patient safety event reports. *Journal of the American Medical Informatics Association*, 22(2):312–317, 2014.
 - [50] M. Riphagen. Supporting reflective learning for daily activities using an interactive dashboard. In *ICERI2013 Proceedings*, pp. 3239–3249. IATED, 2013.
 - [51] L. D. Roberts, J. A. Howell, and K. Seaman. Give Me a Customizable Dashboard: Personalized Learning Analytics Dashboards in Higher Education. *Technology, Knowledge and Learning*, 22(3):317–333, June 2017.
 - [52] T. Rogers and A. Feller. Discouraged by peer excellence: Exposure to exemplary peer performance causes quitting. *Psychological Science*, 27(3):365–374, Mar. 2016.
 - [53] H. J. Schulz, T. Nocke, M. Heitzler, and H. Schumann. A design space of visualization tasks. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2366–2375, 2013. doi: 10.1109/TVCG.2013.120
 - [54] H. Tangmunarunkit, C.-K. Hsieh, B. Longstaff, S. Nolen, J. Jenkins, C. Ketcham, J. Selsky, F. Alquaddoomi, D. George, J. Kang, et al. Ohmage: A general and extensible end-to-end participatory sensing platform. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 6(3):38, 2015.
 - [55] J. Tucker. How is your school doing? online dashboard gives parents new tool. <https://www.sfgate.com/education/article/How-is-your-school-doing-California-School-11001927.php>.
 - [56] O. Velcu-Laitinen and O. M. Yigitbasioglu. The Use of Dashboards in Performance Management: Evidence from Sales Managers. *The International Journal of Digital Accounting Research*, 12:36–58, 2012.
 - [57] K. Verbert, E. Duval, J. Klerkx, S. Govaerts, and J. L. Santos. Learning Analytics Dashboard Applications. In *American Behavioral Scientist*, pp. 1500–1509, Sept. 2013.
 - [58] K. Verbert, S. Govaerts, E. Duval, J. L. Santos, F. V. Assche, G. Parra, and J. Klerkx. Learning dashboards: an overview and future research opportunities. *Personal and Ubiquitous Computing*, 18(6):1499–1514, Aug. 2014. doi: 10.1007/s00779-013-0751-2
 - [59] S. Wakeling, P. Clough, J. Wyper, and A. Balmain. Graph literacy and business intelligence: Investigating user understanding of dashboard data visualizations. *Business Intelligence Journal*, 20(4):8–19, 2015.
 - [60] J. Weiner, V. Balijepally, and M. Tanniru. Integrating Strategic and Operational Decision Making Using Data-Driven Dashboards: The Case of St. Joseph Mercy Oakland Hospital. *Journal of Healthcare Management*, 60(5):319.
 - [61] S. Wexler, J. Shaffer, and A. Cotgreave. *The Big Book of Dashboards: Visualizing Your Data Using Real-World Business Scenarios*. John Wiley & Sons, 2017.
 - [62] M. Whooley, B. Ploderer, and K. Gray. On the Integration of Self-tracking Data amongst Quantified Self Members. pp. 151–160, Sept. 2014. doi: 10.14236/ewic/hci2014.16
 - [63] B. A. Wilbanks and P. A. Langford. A Review of Dashboards for Data Analytics in Nursing. In *CIN: Computers, Informatics, Nursing*, pp. 545–549, Nov. 2014.
 - [64] B. Williamson. Digital education governance: data visualization, predictive analytics, and ‘real-time’ policy instruments. In *Journal of Education Policy*, pp. 1–19. Routledge, Jan. 2016.
 - [65] O. M. Yigitbasioglu and O. Velcu. A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems*, 13(1):41–59, Mar. 2012.
 - [66] J. Zeng and K. W. Glaister. Value creation from big data: Looking inside the black box. *Strategic Organization*, 36(4):147612701769751–36, Nov. 2017.