

# On Being Actionable: Mythologies of Business Intelligence and Disconnects in Drill Downs

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## ABSTRACT

We present results from a case study of the use of business intelligence systems in a human services organization. We characterize four mythologies of business intelligence that informants experience as shared organizational values and are core to their trajectory towards a “culture of data”: data-driven, predictive and proactive, shared accountability, and inquisitive. Yet, for each mythology, we also discuss the ways in which being actionable is impeded by a disconnect between the aggregate views of data that allows them to identify areas of focus for decision making and the desired “drill down” views of data that would allow them to understand how to act in a data-driven context. These findings contribute initial empirical evidence for the impact of business intelligence’s epistemological biases on organizations and suggest implications for the design of technologies to better support data-driven decision making.

## CCS Concepts

**Information Interfaces and Presentation** → **Group and Organization Interfaces** → **Computer-Supported Cooperative Work**.

## Keywords

Big Data; Business Intelligence; Data Analytics; Mythology

## 1. INTRODUCTION

Systems commonly referred to as ‘business intelligence’ (BI) are being adopted by organizations across sectors of society. Studies have found that the use of these systems can lead to the optimization of production and manufacturing work, reductions in customer attrition, increased profitability, better decision support and the creation of competitive advantage [26][35][52]. BI systems are the most prominent user-facing manifestation of ‘big data’ and its related computational turn in thinking within organizations<sup>1</sup>. As Gary King, director of Harvard’s Institute for Quantitative Social Sciences asserts:

*The march of quantification, made possible by enormous new sources of data, will sweep through academia, business and government. There is no area that is going to be untouched. (quoted in [29])*

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GROUP '16, November 13–16, 2016, Sanibel Island, FL, USA

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ACM 978-1-4503-4276-6/16/11...\$15.00

DOI: <http://dx.doi.org/10.1145/2957276.2957283>

Yet the sort of epistemological shift towards quantitative data and computational thinking that is embodied by BI systems isn’t without its critics. boyd and Crawford, for example, argue that the shift towards quantitative data changes assumptions about the meaning of knowledge and about how people “should” engage with information [8]. They contend that there is an increasingly pervasive “mythology” of big data:

*...the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy. [8]*

This mythology, they argue, must become more transparent in research about big data and, we argue, related technologies. Despite the extensive market share of BI tools and their prominence in organizations, there is surprisingly little research about BI tools in human–computer interaction or its related disciplines. We address this gap in the research literature—studying the human experience of technologies that manifest the computational turn in thinking in organizations. In doing so, we also strive to give the HCI community a voice in the discourse and design for big data. We focus, in particular, on understanding the mythologies that informants in one human services organization experience as shared organizational values and ascribe to their organization’s investment in business intelligence, which multiple informants referred to as a trajectory toward a “culture of data.”

The mythologies of business intelligence are pervasive in the marketing of these systems, which claim to enable better-informed decision making, faster and more agile decision making, aggregation of all key data, end-user empowerment, etc.:

*With Domo, it's easy to see the information you care about in one place and use it to make faster, better-informed decisions.<sup>2</sup>*

*Imagine what your business could achieve if everyone had the information they need when they need it. You could enable more agile, fact-based decision-making throughout your organization.<sup>3</sup>*

*Empower your people with 24/7, user-friendly access to the business intelligence and Big Data mining tools they need to make faster, more informed decisions.<sup>4</sup>*

<sup>1</sup> Global revenue from BI and analytics tools is projected to reach \$16.9 billion in 2016, a 5.2% annual increase [17].

<sup>2</sup> <http://www.domo.com/>

<sup>3</sup> <http://go.sap.com/solution/platform-technology/business-intelligence.html>

<sup>4</sup> <http://sisense.com/>

However, our findings suggest that as individuals use these systems to translate data into action, they experience disconnects between the drill downs provided in business intelligence systems and the kinds of data that individuals are looking for in order to make actionable, data-driven decisions.

*When a student enrolls, they bring with them all kinds of characteristics—their age, their gender, their race—so their demographic information, right? But they also carry with them... their family situation: Are they... with parents? Are they on their own? Are they married? Are they, do they have kids? What ages are they? So they carry all those. (I8)*

The data collected by this organization and aggregated into visualization widgets on the dashboards of its middle- and upper-level management does not represent anonymous masses. It represents the clients they serve and the employees who carry out the mission of the organization. In the drill downs of the business intelligence tools that they use, these informants imagine the human who underlies the analytics—each individual who metaphorically stands beneath and *carries* his or her data (I8). Yet the human context they imagine is largely or entirely missing from the business intelligence systems they use, creating a crucial disconnect in their data-driven decision making.

In this paper, we characterize four values—each of which aligns with one of the mythologies of BI systems—that these informants describe as being core to their trajectory towards a “culture of data” in their organization. Yet, for each mythology, we also discuss the ways in which being actionable is impeded by a disconnect between the aggregate views of data that allow them to identify areas of focus for being actionable and the imagined “drill down” data that would allow them to understand how to act in ways that show care and concern for their clients and employees. These findings contribute initial empirical evidence for the impact of business intelligence’s epistemological biases on organizations and suggest implications for the design of technologies to better support data-driven decision making.

## 2. RELATED WORK

This research draws from three strands of related work including research in business intelligence; data, mythology, and values; and data and information management in the nonprofit sector.

### 2.1 Business Intelligence

Business intelligence includes the “techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions” [10]. Although definitions vary, we use ‘business intelligence’ to refer to this holistic understanding of these multifaceted, sociotechnical practices situated within the ecology of tools used for data-driven decision making.

BI is characterized as having two interdependent components: ‘*getting data in*’ and ‘*getting data out*’ [52]. ‘Getting data in,’ more commonly known as data warehousing, includes extracting data from heterogeneous source systems as well as cleaning, transforming, consolidating and loading data into databases to enable organizations to have a “single version of the truth.” Watson and Wixom suggest that data warehousing is the most challenging part of BI since it incurs more than 50 percent of the unexpected costs and requires 80 percent of the time and effort; the challenges of data warehousing arise from “poor data quality in the source systems, politics around data ownership, and legacy technology” [52].

‘Getting data out’ is also commonly referred to as business intelligence or, sometimes, analytics. Organizations normally pay more attention to getting data out as “only when users and applications access the data and use it to make decisions does the organization realize the full value from its data warehouse” [52]. We refer to business analytics as a set of individual and collaborative sociotechnical practices related to the appropriation of data through visualization, exploration, and analysis.

Previous research has identified various benefits of using business intelligence, including the optimization of production and manufacturing work, reductions in customer attrition, reductions in data redundancy, facilitation of new genres of questions by end users, increased profitability, better decision support, and the creation of competitive advantage [26][35][52]. Factors correlated with the successful adoption of BI systems include committed management support, a clear vision and well-established business case, a highly skilled team, sustainable data quality and integrity, and user-oriented management [23][45][55]. As business users move from reactive to predictive analysis, the level of benefits become more global in scope and difficult to quantify [52]; there is still, however, a need to better understand *how* businesses reap these benefits [18].

Researchers have also identified numerous technical and social challenges in the adoption and use of business intelligence. There are substantial challenges that exist in the data warehousing process that forms the back end of many business intelligence systems, with relevant data found across diverse and distributed data sources; these challenges are exacerbated by information management issues such as redundant data entry, lack of data quality, legacy systems, and politics of data ownership [55]. Organizational issues like the absence of support from leadership, intraorganizational politics and a lack of available expertise also add to these challenges [7][11][23][45]. Other challenges include employees’ resistance to change, preferences for qualitative and/or quantitative data, and difficulty acting on data [14][38].

Researchers recommend both technical and social efforts to help organizations overcome barriers to adoption, including improving the efficiency of infrastructures, aligning organizational policies and workflows with business intelligence needs and values, and providing committed leadership and expertise [1][44][55][56].

### 2.2 Data, Mythology and Values

boyd and Crawford argue that ‘big data’ is an interplay of three elements: technology that gathers, links, and analyses large data sets; analysis for economic, social, technical and legal patterns; and mythology that data can offer a higher form of intelligence and knowledge [8]. Similarly, Morgan’s seminal scholarship on the metaphors through which we understand organizations highlights quantitative data as one of the mythologies shaping organizational life, lending decision making a semblance of rationality [33]. Although definitions of big data vary, researchers increasingly acknowledge that big data is less about the *size* of the data and more about gleaning knowledge from of the data [8][6][6]. Big data represents a social and cultural shift in how we create and use knowledge:

*Big Data reframes key questions about the constitution of knowledge, the processes of research, how we should engage with information, and the nature and categorization of reality. [8]*

Because big data is a sociotechnical phenomenon, it entails all the biases that come from “human design” [13]. There is, however, a dearth of empirical evidence of the nature of these biases and how

they play out in practice. Multiple researchers have raised concerns about the potential misuse of data, whether due to its decontextualized nature or due to the epistemological biases that big data—and, we argue business intelligence systems—embody [8][9][13][48].

Previous research has also raised concerns about the biases of big data leading to new digital divides between data haves and have nots and between individuals and organizations that do and do not have computational literacies [8][14][25]. Manovich suggests that in this era of big data, there are three types of people: those who create data (both consciously and by leaving digital footprints), those who have the means to collect it, and those who have expertise to analyze it [31].

No data is truly ‘raw’; the identification of what data are to be measured and how data are categorized are political acts, motivated implicitly or explicitly by different values [36][39][47]. As data are aggregated in business intelligence systems, values are embodied by the design of the system [15][32]. Values are also enacted in practice, through the use of the technology [28][50]. And researchers have advocated for understanding values tensions in contexts where the same values may be shared by both technology design and end users but where the logics behind how those values are enacted are different [50].

## 2.3 Data and Information Management in Nonprofit Sector

The nonprofit sector serves many critical functions and offers services that are underprovided by the government and the for-profit sector [19][34][42][43][49]. Nonprofit organizations are under increasing pressure to demonstrate their performance and impact to funding agencies [21]. So while data collection is a substantial part of the work that most nonprofits do, there is increasing evidence of the costs: “Nonprofits are often collecting heaps of dubious data, at great cost to themselves and ultimately to the people they serve” [46]. Research about performance and accountability in nonprofit organizations suggests that as data collection becomes the focus, this focus can diminish the quality of service to clients [2][3][4][5]. Kong also notes that it is not helpful to apply management strategies that work in the for-profit organization to organizations in the nonprofit sector because those strategies typically fail to address the social dimension of mission-driven organizations [27].

More generally, nonprofits often operate under significant constraints in technical resources and expertise that can make collecting, managing, and using data a challenging endeavor [41][51].

## 3. METHODS

We conducted a case study of the use of business intelligence in one human services organization. Case studies are a powerful method for deriving in-depth insights in an organizational context [57]. Existing case studies of BI in the private sector have focused on characterizing challenges of and success factors for BI adoption [20][22][53]. Here, our focus is on the mythologies of BI use and the ways in which the design of BI systems supports or thwarts these mythologies.

### 3.1 Research Context

Helping Hand<sup>5</sup> is one of a relatively small number of nonprofit organizations using BI tools, and the particular data needs and

pressures in the nonprofit context highlight challenges to carrying out data-driven work. Helping Hand is a large, local affiliate of a national human services organization that assists low-income populations through a range of programs and services:

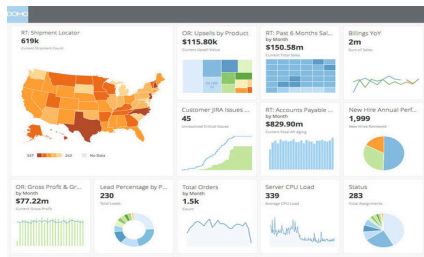
- **Business Services.** Helping Hand’s business services department operates small businesses with employees who are often clients of the organization. The information management needs of this department include employee scheduling, production, inventory, and revenue.
- **Education Services.** The education services department at Helping Hand manages charter schools for low-income, at-risk youth. Their information needs include demographic information about their student population, class scheduling, records of student attendance and achievement, job placement, and salary of placement.
- **Mission Services.** Although all departments operate within the same, overarching mission, the mission services department offers a variety of programs to support the resiliency of their clients. This department relies on information management to understand the *impact* that the organization has on clients. Significant information challenges center around questions about how to assess the impact of its programs and what information should be collected to do so.

In early 2013, Helping Hand was awarded a small grant to fund the purchase of 50 licenses for the business intelligence system Domo, as well as salary support for a business intelligence staff position. Informants attributed the grant proposal’s origin to the confluence of three events: a senior manager joining the staff with a corporate background and experience using business intelligence tools in that context, senior managers attending a data analytics conference during which they identified Domo as the right BI tool for their organization, and a serendipitous conversation with the soon-to-be-hired BI manager. The primary motivation for the adoption of Domo was to promote a “culture of data” within the organization, to support their actions “using sound evidence” (I12). To this end, the BI Manager held numerous individual meetings and focus groups with various organizational stakeholders to identify and prioritize key metrics, start to wrangle data from across a breadth of sources into their data warehouse, and coordinate end-user training. Based on usage log data at the time of the interviews in the fall of 2014, Helping Hand estimated that of the 50 licenses that were purchased, Domo had 15 daily or weekly users; 15 monthly users (accessed primarily for monthly reporting activities), 5 users who had not logged in since their initial training; and 15 users who were still waiting for their data to be added to or configured in the backend data warehouse. There are also 7 additional potential users who have requested licenses.

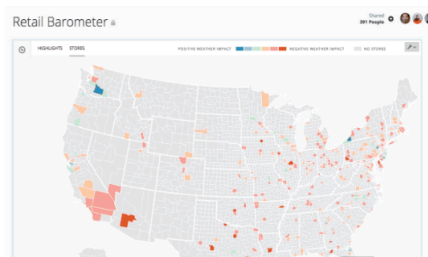
Each Domo user accesses data via a dashboard, initially setup by the manager of BI (e.g., Figure 1a). The dashboard is tiled with ‘cards’ that represent the results of a query performed on the data. Clicking on a card reveals an aggregate-level view of the data resulting from a given filter or query, offering high-level trends and pattern analysis (e.g., Figure 1b). Clicking further on the aggregate-level view accesses the drill down, which provides more granularity to the quantitative data (e.g., Figure 1c).

Domo is currently used at the highest levels of Helping Hand management and across the leadership of all departments. Other BI software is used—with varying degrees of success and varying degrees of redundancy—across different subsets of departments.

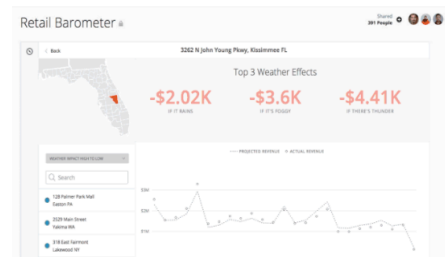
<sup>5</sup> The name of the organization and all of its internal departments have been anonymized.



**Figure 1a. Dashboards in Domo are customizable to provide snapshots of aggregated views of data.**



**Figure 1b. Aggregate views in Domo provide high-level visualizations of data (e.g., national retail data).**



**Figure 1c. From the aggregate view, users can drill down into quantitative data with more granularity (e.g., retail data from a specific state).**

Education services, for example, also uses Tableau<sup>6</sup>. As suggested by previous research, informants in all departments used their BI system(s) as one small part of a broader ecology of information management tools—using various Excel spreadsheets, Outlook Address books, and paper-based systems to accommodate the needs and individual styles of their knowledge work [24][51].

### 3.2 Informants and Data Collection

We conducted semi-structured interviews (76 minutes, on average) with 17 individuals (5 female) who have end-user licenses to use Domo and sometimes other BI tools for their work at Helping Hand. 13 informants held positions in middle- and upper-level management across several departments of Helping Hand; 4 informants worked in the IT and BI departments and were responsible for the backend data warehousing and the front end data analytics.

We conducted semi-structured interviews with each informant using a protocol focused on the following areas of inquiry:

- The nature of the participants’ work, their roles in the organization, and how the participants understood their work to fit into the mission of the organization;
- The different data sources they use in their work; how they collect, extract, analyze and explore that data; and the ways they make decisions with or without that data;
- The ways that the data they use relates to the mission of the organization—whether it supports or complicates the mission; and
- Their experiences of the constraints and benefits of business intelligence.

The interviews were transcribed on a rolling basis to facilitate ongoing analysis.

### 3.3 Data Analysis

We analyzed data iteratively and inductively using grounded theory [12]. Our initial open coding foregrounded what a culture of data meant to our informants, resulting in 33 values-related coding categories. Through iterative affinity diagramming and axial coding, we identified four core values: *data-driven*, *predictive and proactive*, *shared accountability*, and *inquisitiveness*. We returned to the data related to these core values, conducting another round of coding focused specifically on understanding the role of technology as it supports or thwarts these values, noting that these values also aligned with the mythologies ascribed to big data and BI tools. Through this

analysis, we identified a series of disconnects between aggregate and drill down views of data that fundamentally shape and are shaped by understandings of what data are “actionable.”

## 4. RESULTS

In the following sections, we introduce four core mythologies of business intelligence: *data-driven*, *predictive and proactive*, *shared accountability*, and *inquisitiveness*. Informants most frequently experienced these mythologies in terms of organizational values, both instrumental and terminal [40]. These mythologies align with the common marketing of big data and business intelligence. Yet, through our discussion of each mythology, we highlight the ways in which the enactment of each is problematized by recurring disconnects between aggregate views of data and its drill-down in business intelligence systems. These disconnects relate to informants’ understandings of what it means for data to be actionable and valid for data-driven decision making.

Note that the informants frequently used the phrase ‘drill down’ both in a literal sense—to use the drill down feature in the BI tool to get finer granularity quantitative data—and also, more commonly, in a metaphorical sense—to get more information that does not actually exist in their BI system. We use the term ‘drill-down’ in the same multi-faceted fashion.

### 4.1 Data-Driven

The middle- and upper-level management informants at Helping Hand all speak positively and optimistically about the organization’s ability to use data moving forward to improve program strategies, personnel evaluations, and workflow to serve their overarching mission better than before. Yet, informants have differing and sometimes conflicting perspectives about what kinds of data should be considered legitimate for substantiating the organization’s impact and/or actionable for decision making.

Most informants conveyed a significant inclination towards using quantitative data to “prove” the effectiveness of their individual performance or the impact of the organization’s work. For these informants, quantitative data is seen as the only acceptable indicator or “picture” of performance for many stakeholders:

*It’s really a prove-it-to-me type of mentality and I think it’s data that’s going to help us do that. (I13)*

*So that’s what we are going to try—to use the data to really drive us, and you can’t quantify everything, that’s just the reality, we are aware of that... but it does paint a pretty nice picture. (I3)*

From the informants’ perspectives, quantitative data “proves” impact whereas qualitative data helps people “connect

<sup>6</sup> <http://www.tableausoftware.com>

emotionally” to the mission of the organization: “We want them to... connect emotionally to what we are doing. So... we tell specific stories” (I17).

Most informants do not explicitly point to qualitative data as a legitimate basis for data-driven decision making. For these individuals, qualitative data-driven decision making isn’t authoritatively substantiated, it is “just based on... anecdote” (I12).

Only one informant articulated a view of qualitative data as being a “somewhat” legitimate form of empirical data for serving as the basis of data-driven decision making. He describes qualitative data as “observational” and “unstructured”:

*There is data input to every decision but some of it like I say is not in digital form, it’s just observation, observational data... So that’s somewhat data driven but [it’s] unstructured data. And so that generates another conversation or decision point. (I6)*

Here, though, the strongest hedge in the informant’s language isn’t related to the qualitative nature of the data but the fact that the data is not in digital form. He describes the use of observational, unstructured data as actionable because it enables him to take action, for example to have a follow-up conversation. Other informants questioned whether data had been appropriately vetted and whether they were a reasonable basis for communication and decision making if they were not digitized and included in Domo.

Although most informants did not explicitly identify qualitative data as being a legitimate basis for being data-driven, nearly all informants recounted experiences of data-driven decision making that centered around the use of qualitative data. I11, for example, reflected on an instance in which he wanted to troubleshoot production issues and expressed frustration that the data available to him in the BI system lacked the qualitative, “human element” that he wanted:

*I can see if, you know, you’re missing [production] because you don’t have enough people producing or the people you do have producing are producing at half. And then when I am, you know, coaching... there is also that human element: “Well there was a death in that family, you know. I lost two people; I haven’t been able to replace them yet. I’m working on that.” That, you know, [there are] usually good reasons behind it and they’re addressing it and they get right back up but, you know, if I could drill a little bit deeper. (I11)*

This informant explains how quantitative data is used for keeping track of their production, but he wishes he could drill down “deeper,” beyond the quantitative data in the system to qualitative data that could explain the context behind the numbers. In order to drill down to the depth that he needs, this informant has to speak to the site leaders to incorporate the “human element” into his understanding. The drill down data that he seeks is not actually captured in the BI tool—nor could it easily be given the quantitative emphasis of existing BI tools. Here, the BI system seems to exacerbate the uncertainty that the informants experience in considering whether qualitative data are a legitimate basis for data-driven decision making.

Among the informants at Helping Hand, Domo is held up as an embodiment of the promise of the data-driven organization, particularly as it represents the aggregation of their activity: “At the core of our approach, one of our central tenets is measuring outcomes with data and with this system, Domo, that aggregates

everything we do...” (I5). Yet, the aggregation of data in Domo supports only part of what is desired for acting on that data. This same informant continues to emphasize the complementary need to “drill down” to the context surrounding the individual clients who are being served. And, he emphasizes that the aggregate views of quantitative data are most valuable when they are used in service of the “drill down” views of data that, ideally, enable them to understand why an individual has been successful or not:

*Our ability to measure outcomes dramatically affects how we can serve an individual. So knowing across the board where we are successful generally speaking and being able to drill down and look at on an individual basis how that success came about and we can do that. And that supports our mission in everything from the heart to the wallet. (I5)*

For these informants, the relationship between being data driven and being actionable manifests through the conflicted interplay between quantitative and qualitative data. The language that the informants are almost uniformly using to characterize the relationship is a metaphor borrowed from the business intelligence tool they use—a relationship between the aggregate and the drill down. Yet, intriguingly, while the informants speak of the drill down as ideally providing qualitative, actionable evidence of the human context surrounding the quantitative data, Domo (as with nearly all analytics tools) only provides quantitative “drill down” data, the individual-level quantitative data that is the basis for the aggregate-level quantitative data.

While the performance and legitimacy of the organization is supported by aggregate views of quantitative data, being actionable is supported by individual-level, qualitative “drill down” data that is important for responding to the unique circumstances of individuals. The informants use both qualitative and quantitative data but are unsure whether qualitative data is considered legitimate since this qualitative data doesn’t actually exist in the business intelligence system. And it is frequently not even found in digital form. As such, its legitimacy is—at best—contested; at worst, the validity of this data as an actionable basis for decision making is threatened.

## 4.2 Predictive & Proactive

As informants work towards achieving a “culture of data” within their organization, they envision that a predictive use of data will also enable them to be more proactive. As they ramp up their business intelligence efforts, one informant characterizes the trajectory towards being proactive as the “real value” of these systems:

*I think we are on the cusp... of shifting from a reactive look at data to a predictive data.... The real value comes... when we can actually start to predict things that are going to happen and then intervene before they do. (I8)*

According to this informant, the “real value” of business intelligence doesn’t come just from the ability to aggregate historical data, but from being able to predict what is going to happen so he can act on it. This predictive capability, he continues, comes from being able to compare the drill-down “characteristics” of individuals with aggregate views of data, asking questions like: “What are the common characteristics of people who have graduated? Who have dropped out?” (I8). Yet, to act on these aggregate views of data on behalf of individuals means walking a fine line between capitalizing on the predictive capabilities of the BI system and respecting the lived experiences of their clients:

*If we say that if you are an African American male, that's 23 or under, who has two kids, you know, who comes to us with fewer than 10 credits, you are highly unlikely to graduate. Right? It doesn't mean that the next African American male that shares these characteristics is not going to graduate but what we can do is start to surround him with additional support early to raise his chances, right? So it's... it is profiling... but it's what we hope is profiling in a really, really positive manner. (I8)*

The informant recognizes the disconnect between the quantitative, aggregated data and the individuals with real relationships and struggles that stand to be singled out but also surrounded with additional support as a result of predictive analytics. Despite the recognition of this uncomfortable disconnect, and without clear answers about the right path forward or the right language to use to describe the proactive work that is likely to happen at the drill-down, individual level, informants are still keen about the proactive use of predictive analytics to guide their actions as they serve their clients.

### 4.3 Shared Accountability

For the informants at Helping Hand, a “culture of data” should foster shared accountability among individuals across the organization as well as with external funders and community members. Since the mission of all their departments is to assist low-income populations, one informant points out how important it is to keep all the programs accountable to the shared organizational mission:

*My job is to use all of these programs plus all the resources that exist in [Helping Hand]... using sound evidence-based programming.... It is all these contributing. We have to work together or it doesn't work. (I12)*

The value of shared accountability is manifested in many of the informants' work practices, but most significantly in data reviews:

*Data reviews we started because—it's actually fundamental to, I think, the model. We want everybody to be accountable for their own data and to understand their own data (I12).*

Most informants view data reviews as an opportunity to address their performance and any issues associated with it in a transparent manner with other members of the organization, providing some additional context to the quantitative data. While the shared visibility of data and the open discussion in data reviews may enable valuable forms of professional facework, it may also foster competitiveness within some subcultures internal to the organization:

*They are hyper competitive... and they're like one of the most data crazy groups that you ever see... so like data hungry. [They] will go through and say, “Well, I had this percentage of my students earn credit this past term year and you only had 10% lower than I did...” And I'll sit in meetings and they'll just totally call each other out... It's crazy! (I4)*

From a management perspective, access to aggregate views of data also enables the leadership to identify outliers in the productivity of their workforce and coordinate mentors and other resources to help address whatever productivity gap might exist:

*If we see an issue at one school and success at another, we can say to them, the school leader that's struggling, “Hey, you need to go talk to the school leader who is knocking it*

*out of the park with that; and let's do some coaching there.” (I8)*

Although the focus here is on the employee rather than the client, there is the same emphasis on understanding and supporting the individual who underlies the data. Here, aggregate views of data are helpful in comparing employee productivity, but the drill down views of quantitative data are more deeply understood and acted on in conjunction with extensive qualitative data provided through the mentoring process, outside the BI tool.

As with the multiple tenors of data use that emerge from shared accountability in data review meetings, there are also multiple tenors of data use resulting from the shared accountability of data with management. The middle- and upper-level management informants raise questions about how data should relate to employees' incentives and evaluation. Here, “performance” is used to reflect the more qualitative or subjective perceptions about employees' work whereas “outcomes” are reflections of work that have been metricized for the business intelligence system:

*I read a quote the other day.... It basically said something to the effect of... you cannot connect pay with performance because performance is circumstantial. But I think you can connect pay and data and incentives to outcomes... right? So performance and outcomes, I think, are different... Our perceived performance of something... our perception of somebody's performance could be totally different... but the outcomes could still be great. Or my perception is that the performance is great but the outcome is horrible.... And so that's what we'd like to do, is really make sure however you decide to achieve your goal... we can really start to tailor some things. (I3)*

This informant is still wrestling with the sometimes-conflicting forms of data that he receives about employees' work and acknowledges that observational data might not align with the quantitative data in the system. But he is still optimistic about finding some evidence-based means to evaluate employees against their goals.

Here, aggregate views of data enable the identification of employees whose productivity levels are outliers. The mythology or value of shared accountability, then, raises questions about how different individuals with access to data treat the individuals who are identified in the data.

### 4.4 Inquisitiveness

As more data are integrated into the data warehouse and as more users have access through Domo to the data that they want to use for data-driven decision making, the informants hope that the system will enable them to be more inquisitive about the data. A few informants reported already having conducted hypothesis-driven mini experiments by studying aggregated, longitudinal data for certain trends. In one instance, the informant created a card in Domo to “prove” the effect of missing quota on production levels:

*I have a rolling twelve-month card that runs production along with the sales... and the reason why we did that was because our production... was super low and we weren't making quota. And we were trying to prove to the regional managers, well if you make quota, the next week immediately your sales are up. (I1)*

The readiness-at-hand of the data, in this case, empowered this user to ask questions of the data that he was curious about. Another informant discusses a similar hypothesis-driven study of data to answer his question about whether more communication

about the mission of the organization makes their customers want to donate by rounding up their payment at the stores:

*One thing I'm curious about is that the stores that have that increased communication... are people rounding up any more frequently at those stores because they're theoretically learning more about the mission than they would at stores where we don't have those communication efforts? The reason why I'm interested in that is because there could be a couple of different hypothesis on that... This data can help us to... prove that one way or another. (I13)*

The ability to act on a value of inquisitiveness, however, relies on a certain level of technical and information literacy. Approximately 75% of all cards seen by all but one user were created by the IT or BI staff, who identify data sources, select a visualization widget, and configure the scope of the visualization. Both of the mini-studies described earlier rely on data presented in cards that had already been pre-configured in ways that were suitable for the questions they wanted to ask. Individuals who create their own cards have done so only after requesting and receiving multiple hours of one-on-one training from the IT or BI staff.

Creating a new card requires some degree of scripting skills. At the time of the study, only one user had created his own cards by modifying the scripting from existing cards; the BI staff is unsure whether his cards have been configured correctly. If inquisitiveness persists as being an organizational value, it is one that likely will privilege users who learn new skills to support the dynamic creation of new cards to answer new kinds of questions.

Users who do not yet have these skills or who prefer to explore their data in other ways—the majority of our informants—use Excel spreadsheets for their data analysis, either by collecting data redundantly in their own spreadsheets or by exporting data from the BI tool or other source systems. They feel it enables a richer and more accessible set of features for sensemaking than the drill down that is the sole analytic feature possible given a pre-defined set of cards:

*I can't look at this [card] formatting. For me, I find it too hard. I think this is my problem, not the system's problem.... If I am not in control of the columns... it's too hard to look at, so I reformat everything. (I17)*

Most of the informants noted that their BI tools, including Domo, do not provide sufficient or sufficiently accessible control and flexibility for exploring and understanding their data. Even with a general understanding of the affordances of business intelligence tools, there is still a perceived disconnect between the resources and expertise required to make use of the pre-defined aggregate views of data and the dynamically explorable data, ideally something beyond the drill down. In order to be inquisitive and ask questions of their data beyond the visualization widgets currently set up in their dashboards, the BI tools assume both scripting and data literacy skills beyond the current expertise of these users. Fostering inquisitiveness and supporting sensemaking through different drill downs is beyond the scope of accessible features for the majority of informants at Helping Hand.

## 5. ON BEING ACTIONABLE

### 5.1 Mythologies of Business Intelligence and the Space for Action

Morgan refers to quantitative data as one of the mythologies shaping organizational life by lending a semblance of rationality

to decision making [33]. He claims that quantitative data in formal organizations plays the same role as magic in primitive societies, enabling clear-cut decisions to be made in situations that might otherwise be open ended. Even though these techniques don't reduce risks, the mythology of rationality as supported by quantitative analysis provides credibility to organizational actions. Similarly, the mythology of big data is believed to provide higher levels of intelligence with an aura of objectivity, truth, and accuracy [8]. These mythologies compel us to question the values and biases that are embedded in organizational data and to critically examine the data that becomes legitimized through organizational action—what data is collected, what data is digitized, what data is aggregated and visualized in business intelligence systems [36][47]. It also compels us to question what kinds of action it may support or thwart.

If users consider the data in business intelligence systems to be the only valid representations of organizational ground truth for publically admissible data-driven decision making, as data reflecting informants' uncertainty about qualitative and unstructured data suggests, these biases stand to propagate through their actions. Just as the interplay of inclusion and exclusion of data in measurements can create a space for possible action [36], the space for action within an organization can be constrained by the data and visualizations contained in the business intelligence system. Especially for a human services organization serving at-risk individuals, it is important to question what data is included and excluded from measurement to understand how the values embodied by data shape rational action and organizational culture.

### 5.2 Disconnects Between Aggregate and Drill-Down Views

Informants in this study were optimistic about the organization's ability to foster data-driven decision making—action grounded in evidence. Yet, there is a disconnect between the kind of data these informants had available to them in the drill down of the business intelligence system and the kind of data they were looking for to provide context for their actions. For the informants in this study, quantitative data alone was not sufficient to make actionable decisions for each client's or employee's unique circumstances; they sought out qualitative data to provide more context.

Sociological scholarship predating both BI systems and the sociotechnical turn towards big data has highlighted the importance of conducting interpretive work around aggregated, quantitative data [16] (see also [30]). Even so, existing BI tools have an exclusive or nearly exclusive focus on supporting quantitative interpretive work. Our research in this new context echoes existing scholarship about the importance of interpretive work around quantitative data and highlights how essential it is that *the ecology of organizational information management systems supporting big data be redesigned to support qualitative data*. But further, our research suggests that *by not fully supporting the interpretive work of the users, the BI system further exacerbates the uncertainty that our informants expressed in considering whether qualitative data should be considered legitimate*. Despite the uncertainty, informants continue to use qualitative data collected outside the BI system—a form of shadow data—because it supports their work and enables them to take action.

Aggregate views of data have enabled these informants to present consistent data about the organization's impact to external stakeholders:

*It's saying, "Look. Here is the impact the [programs] are having. Here is the investment you are making." We'd like to grow the investment and we will give more impact. (I8)*

Aggregate views of data in the BI system are actionable, then, for the advocacy, education, and fundraising work that the organization is constantly doing. Aggregate views of data have also been found to be useful by some informants for validating or refuting certain hypotheses through the accumulation of their activity. For example, as the BI team at Helping Hand was able to import production and sales data into Domo, the management was able to "prove" to the site leaders that as they meet their daily production quota, their sales increases. By verifying such hypotheses with aggregate views of data, individuals can focus their efforts in more strategic ways. Aggregate views of data have also enabled these informants to see similarities and disparities among data, enabling them to identify outliers, both positive and negative. While aggregate views of data in BI systems stand as a valuable precursor to acting on data, the aggregated quantitative data alone is typically insufficient.

When these informants talk about drilling down to see individual-level data, what they are looking for is much more experiential and qualitative than the drill down provided by the BI system. This idealized "drill down" serves to enable action with clients and employees (who have been identified through aggregate views of data). Here, for data to be actionable, it has to provide enough of the "human element" to identify the right trajectory of action for each unique individual's circumstances—whether that is through mentorship, counseling, programming or otherwise.

At Helping Hand, informants are struggling to balance both quantitative, aggregate-level data and qualitative, individual-level data in their data-driven decision making and action. Their instantiation of Domo, however, only provides quantitative data—in both the drill down and aggregate. As such, this system reifies an epistemological bias about the kinds of data that are appropriately "rational" and "legitimate" for making grounded decisions in organizations [33]—an epistemological bias that these informants at Helping Hand are pushing back against, albeit uncertainly.

### 5.3 Design Implications and Future Work

For the design of business intelligence and data analytics systems, it is critical to find ways to more *robustly and accessibly* support the collection, aggregation and exploration of *combinations* of qualitative and quantitative data. Future research should explore the potentially varied relationships among quantitative and qualitative data in data-driven decision making and the actionable use of data across a variety of different organizations to provide a more comprehensive understanding of the design space. Our empirical work suggests value in linking aggregate views of quantitative data to finer-granularity, unstructured case notes, for example.

More significantly, this research is also a call to reconsider design for qualitative data—structured and unstructured—across the entire ecosystem of information systems used for data-driven decision making. This research challenge has implications for the user interface down to the underlying infrastructure, as well as for the interoperability of these systems. There need to be accessible ways of collecting—thus, validating—qualitative data so that they stand a chance of making it into aggregations of data in the first place, as well as accessible ways of aggregating qualitative data across multiple systems, which in nonprofit organizations may be quite niche or even custom-built. The design implications of this

research extend beyond the BI tools, then, and implicate the entire pipeline of information management tools that constitute the ecology of systems being adopted by data-driven organizations.

Addressing the entire ecology of systems becomes even more critical as we reflect on the ways that BI system use differed between middle- and upper-level management informants. The upper-level management informants in this study found much more value in having data aggregated into a single BI tool. The middle-level management informants juggled many more tools in their work, using the BI tool to report up and other information management systems—sometimes data sources for the BI tool, but more often siloed systems—to manage down. So while the adoption of the BI system was intended by the upper-level management to unify the organizations' data into a singular platform that would represent organizational ground truth, this value did not extend far down the organizational chart. More often, informants were working to enact a "culture of data" from within a messy ecology of tools, some of which contained data that became less valued because it wasn't validated by being included in the data warehouse backing the BI tool.

Organizations don't exist in a vacuum; they exist among an ecology of organizational technologies, practices and expectations [37]. Any attempts to legitimize qualitative data, then, must be addressed more broadly across this ecology. If the field of human-computer interaction does not help to design better ecologies of systems, then we become complicit in propagating the epistemological biases of big data.

Especially for human services organizations, there is an increased pressure to produce evidence of impact and outcomes for key stakeholders and funders [46]. However, researchers have argued that it is imperative to account for the human, social element of mission-driven organizations, since human services organizations, in particular, invest in people rather than profit [27]. While unpacking the biases that are embedded in business intelligence systems may be particularly important in the organizational context of this case study, the kinds of epistemological biases highlighted in this research could be of relevance to other organizations across sectors of society.

## 6. CONCLUSION

For the informants at Helping Hand, the mythologies of business intelligence are experienced as powerful commitments to a set of organizational values. But as they attempt to enact these values through the use of BI tools, the full complement of data that they need to translate data into action are not supported by their information systems. And when data are not in the systems, there is clear uncertainty about whether data "counts" as a legitimate basis for data-driven decision making. Just as workflow systems were found to overconstrain work practices in organizations [47] (in response to [54]), we find that this class of system (BI) also overconstrains work practices *and* ways of thinking about the work. The mythologies of business intelligence scope data in and out of the system, scope understandings about legitimacy, and scope the actions that are made based on data.

In this research, we have made the following contributions:

- Identified four core mythologies that characterize an organizational culture of data: data-driven, predictive and proactive, shared accountability and inquisitiveness;
- Identified breakdowns in data-driven decision making that stem from disconnects between the aggregate and drill-down views of data in business intelligence systems;



- Provided empirical evidence of the epistemological biases of business intelligence systems propagating into confusion about what data is and should be considered legitimate for data-driven decision making; and
- Offered the first case study of the use of business intelligence and data analytics in a nonprofit organization, highlighting tensions in BI use that arise from the human services context.

Our empirical evidence suggests that the enactment of mythologies surrounding a data-driven culture require more comprehensive support for diverse types and combinations of data than are currently supported by this organization's ecosystem of information management tools. For the informants at Helping Hand, when they "drill down," they want to understand the "human element" represented by the data and they rely on that human element to help them know how to translate data into action. Given the recognition that there is a human being who underlies data, the question of how to act becomes a fundamentally moral one. And the design challenge we face is to re-envision the ecology of information management systems in ways that enable organizations to legitimize data that is most meaningful for being actionable, where what it means to be actionable may very well hinge on the moral treatment of the individuals who underlie data.

## 7. ACKNOWLEDGEMENTS

We are indebted to the informants at Helping Hand for sharing their time and experiences with us.

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