Towards a Deeper Understanding of Data and Materiality

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ABSTRACT

Data physicalization enables people to represent and interact with data physically rather than digitally. Physical representations afford visual analysis in comparable ways to traditional, desktop-based visualization by introducing new capabilities, such as facilitating tactile manipulation, accessible interactions, and immersion, that are beyond traditional 2D visualizations. However, physicalization has historically been a niche aspect of visualization research due to its unique challenges. In this paper, I discuss the current challenges of data physicalization and address three areas where data physicalization can aid other research thrusts: broadening participation, supporting analytics, and promoting creative expression. This paper exemplifies each approach through the lens of my work.

CCS CONCEPTS

• **Human-centered computing → Visualization theory, concepts and paradigms**.

KEYWORDS

data physicalization, design space

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1 INTRODUCTION

Data is now woven into the fabrics of our everyday life: science, business, medicine, social media, and everyday human activity. Data has been traditionally visualized through the desktop model, but current and anticipated advancements in material science and digital fabrication are radically changing how we can possibly represent and interact with data.

Data physicalization—the practice of mapping data to physical form—is an emerging research field that sits at the crossroads of various domains, including data visualization, tangible user interaction, and design [17]. Through my doctoral research, I focus not only on creating physical artifacts that can aid in analytical insight but also on how we can use data as a material to design for the myriad of life (e.g., the clothes we wear, the objects we use, the environments we inhabit). This focus is demonstrated in three research thrusts: broadening participation, supporting analytics, and promoting creative expression.

2 BACKGROUND

Data plays a critical role in problem-solving and decision-making in various domain applications [5, 13, 22]. For example, operators use sensor readouts to supervise multi-robot systems for space exploration [6, 27]; doctors use CT and MRI scans for presurgical planning and intraoperative procedures [23, 29]. All of these scenarios rely on users interacting with data to gather additional information, such as zooming into critical details, filtering for important information, or panning around models to view otherwise hidden surfaces. However, many analytical tasks can no longer be completed using static images alone [8, 18].

Many data-driven systems use a WIMP (Windows, Icons, Menus, and a Pointer) paradigm and rely on the graphical user interface (GUI). These constraints introduce challenges when users (1) work with multi-dimensional data with an inherent structure and would benefit from physical models (e.g., high-fidelity, material-realistic surgical models) compared to 2D graphical renditions or (2) work in contexts where the traditional GUI is infeasible (e.g., robotic operators supervising in an outdoor field test, doctors operating during surgeries). While past work has explored ways of interacting with data beyond WIMP (e.g., direct manipulation [24], instrumental model [3, 4], reality-based [16]), these techniques are still digital. We lack a concrete means of evaluating and creating interaction techniques when data is *physicalized*.

Knowing *how* and *what* physicalization will add to the visualization toolkit requires a deep understanding of how physicality fits within existing visualization tools. Analogous to the microwaves in the 50's, "[physicality] is useful for some things, but they [will not] replace the rest of your kitchen" [10]. This understanding calls for careful considerations that are beyond conventional data visualizations. For example, while all visualizations must consider the expressivity of their designs (e.g., data encoding and data interactions), physicalization designers must also be mindful of structural considerations and the context where the physicalization exists [2]. These considerations reflect how data physicalization sits at the crossroads of various domains but currently lacks a cohesive lens. As a consequence, designers and researchers may be unaware of the knowledge and practices emerging in other communities. For example, *data visualization* (i.e., how to effectively encode data), *tangible user interface* (TUI) (i.e., how to amplify the capabilities of the human body and physical world for interaction design), or *design* (i.e., how to identify and leverage a material's potential).

To provide a cohesive lens of each intellectual community, I conducted a literature survey on data physicalization and proposed a

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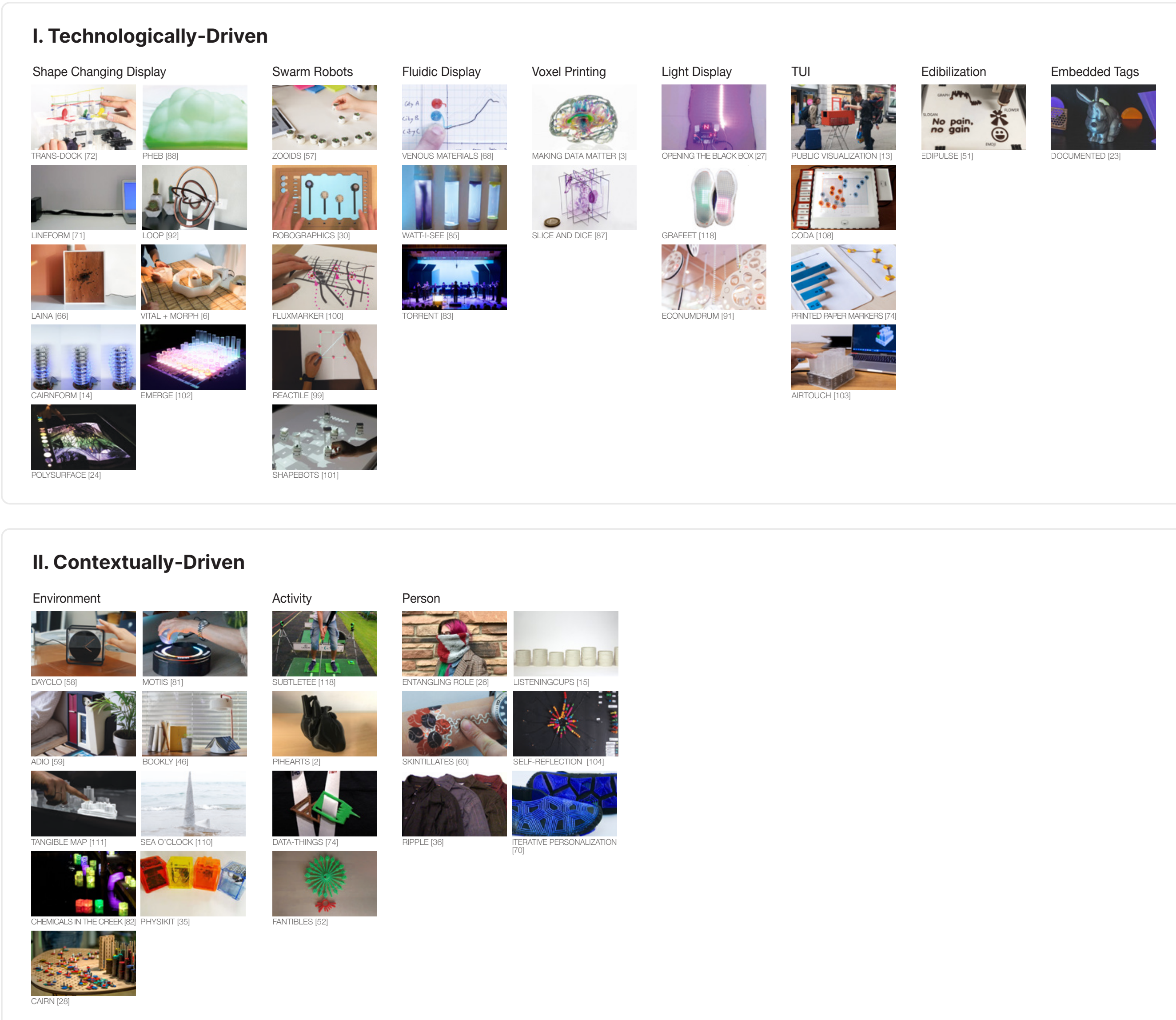

Figure 1: Eleven examples of physicalization's embodiment [2]. The physical embodiment is categorized as either technologically- or contextually driven. All images are copyright to their respective owners.

design space that considers the interdisciplinary design consideration organized by three facets: context, structure, interaction [2]. This project presents a systematic review and meta-analysis of 47 data physicalizations. The project contributes a quantitative congregation of the findings by offering high-level design considerations into creating physicalizations and bridge languages and practice across the visualization, design, and TUI communities (Figure 1), while suggesting future directions and identifying challenges in the field.

2.1 Challenges of Physicalization

After conducting the literature review, I identified three challenges.

C1: Fabrication: Constructing data physicalizations involves a large design space [2], which includes but is not limited to: material choice, scale [19], interactions, and data encoding. This introduces combinatorial possibilities that a user has to consider when designing physicalizations. In addition, despite material and fabrication advancements, visualization lacks fundamental guidance on how to employ these techniques to efficiently represent and interact with data and how to leverage the analytical affordances of physical representations. This also highlights a technical challenge in understanding how to accurately map data to the given material. Users will need to consider the tradeoffs between material properties (e.g., fluid-based systems [20] and smart materials over electromechanical and magnetic actuators [25]).

C2: Interpretation: Currently, there is no formal design language (analogous to Grammar of Graphics [31]) that helps users interpret data physicalizations. Many data physicalizations either use conventional 2D data visualization representations or are idiosyncratic where each encoding is unique to the creator. This starkly contrasts with the field of information visualization where there is an existing design language to help communicate data findings.

C3: Application of data physicalization: Due to its infancy, data physicalization, as a field, still lacks a concrete role for analytical purposes. Researchers have hinted towards using physicalizations for analytical purposes [17], but we have yet to see the full potential of data physicalization for analytical purposes as outlined by Jansen et al. By looking at other disciplines, we see possibilities in how physicalization may aid in pre-surgical planning [14] and star formation [15].

But beyond analytical purposes, data physicalization also carries the potential of introducing casual information visualization [21]. With the internet of things (IoT), data is ubiquitous where data literacy is now a crucial life skill. Physicalization has the potential to help introduce and engage laymen with data visualizations. Various researchers have explored the potential of using data physicalization for educational or reflective purposes.

3 RESEARCH GOALS & METHODS

My doctoral research on data physicalization specifically looks at the relationship between physicality and data—how do tangible interactions enable people to better understand and engage with data? How should data be represented physically? How can data physicalizations incorporate data interactions (e.g., zooming into critical details, filtering for important information) to better support accurate analysis? The proposed research seeks to make contributions across three thrust areas while keeping in mind of the research challenges (Section 2.1). Thrust 1 will focus on understanding how physical representations can enable broader participation when working with data. Thrust 2 will focus on how to employ fabrication techniques to efficiently represent and interact with data and how to leverage the analytical affordances of physical representations. Thrust 3 will explore how data acts as a material to create new designs.

Figure 2: Toolkit made from everyday materials to foster children's data visualization literacy.

Thrust 1: Broadening Participation. Thrust 1 explores how physicality can broaden participation when interacting with data. Exclusively digital solutions present challenges and limitations to certain populations (e.g., people with low-vision or visual impairements [11, 26], children). These challenges present the need to further investigate how to expand the ways we can interact with data and visualizations.

As one form of exploration, I created a toolkit made out of everyday materials (e.g., paper, cardboard) that explores how constructionist practices can help introduce children to data visualizations concepts, and in turn, cultivate their data visualization literacy (DVL) [1] (Fig. 2). Past work on children's DVL has often relied on exclusively digital solutions, where they may come off as "black boxes" to young children and limit their embodied experiences. Physical representations enable children to engage in embodied learning that would not be possible with a 2D screen. Our workshops with children showed that the toolkit helped children creatively engage and interact with visualizations. Children with prior knowledge of data visualization reported the toolkit serving as more of an authoring tool that they envision using in their daily lives, while children with little to no experience with visualizations found the toolkit as an engaging introduction to data visualization concepts. The novelty of physicalizing data offers an unprecedented method for children to engage with and better understand data in their respective contexts.

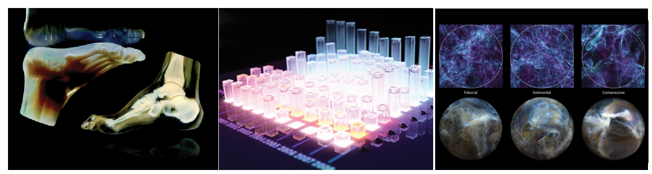

Figure 3: Physical artifacts intended for analytical insight: multimaterial 3D print [14], EMERGE [28], Touching the Stars [15].

Thrust 2: Supporting Analytics. Thrust 2 explores how physicalizations add to the visualization toolkit from an analytical lens. As mentioned in Section 2, the field currently lacks a deeper understanding of when interacting with data physically versus digitally. I contend the act of physicalizing data, especially through an analytical lens, should be intentional and meaningful. For example, this requires understanding which datasets would be the most meaningful to analyze (Fig. 3) and knowing how to analyze them physically.

Visualization shows the importance of dynamic interactions, where analysts engage in a series of interactions when exploring a dataset [5]. This reflects findings from my literature review where the number of data interactions a system can support affects the richness of the data exploration [2]. I plan to investigate other datasets from other fields (e.g., medicine, biology) to understand how physicalization utilizing state-of-the-art fabrication techniques can support analytics and decision-making processes.

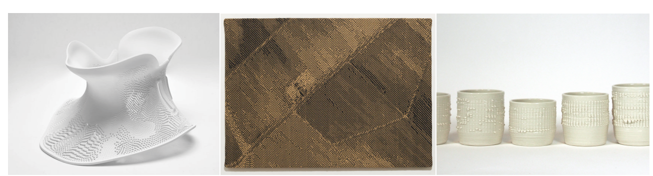

Figure 4: Physical artifacts that use data as a material source: biomimetic neck collar [12], guilded tapestry [30], personal ceramic cups [7].

Thrust 3: Providing Creative Expression. Thrust 3 explores how data acts as a material to create new designs (Fig. 4).

Rooted in visualization, Jansen et al. [17] have formally defined physicalization as a research field that focuses on "how computer-supported, physical representations of data (i.e., physicalizations) can support cognition, communication, learning, problem solving, and decision making". There are examples of physical artifacts encoded with data within my conducted survey but do not meet what Jansen et al. have defined. Collectively, these are examples where data is used as a material source when making.

Engineers, scientists, and artists are also building physical artifacts guided by data [7, 9]. Like a craftsman working with their surrounding materials, data is now another material source and is part of the artisanal spirit when making. As data continues to be embedded in our world, in future work, I aim to collaborate with different researchers from different practices (e.g., biology, textiles) to explore the new and unexpected meetings of the digital and materials worlds.

4 EXPECTED CONTRIBUTIONS AND POTENTIAL IMPACT

Data is ubiquitous where it is now woven into the fabrics of our everyday life. However, we are currently limited in how we interact with data. This work makes fundamental contributions to bridge disciplines spanning data visualization, human-computer interactions, and digital fabrication. In doing so, this paper contributes:

(1) **A cohesive lens of data physicalization design space**: context, structure, interactions
(2) **Challenges of data physicalization**: fabrication, interpretation, application
(3) **A preliminary exploration of the design space**: broadening participation, supporting analytics, and promoting creative expressions

For future work, I will continue to explore the physicality of data with respect to the three thrusts, complete the current work-in-progress projects, and discuss the benefits and limitations of each project to identify future research opportunities.

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