



HAL
open science

ClayPhys: Towards Toolkits that Support Making Expressive Data Physicalization

Bahare Bakhtiari, Yichun Zhao, Jiayue Wong, Aurélien Tabard, Sowmya Somanath, Charles Perin

► To cite this version:

Bahare Bakhtiari, Yichun Zhao, Jiayue Wong, Aurélien Tabard, Sowmya Somanath, et al.. ClayPhys: Towards Toolkits that Support Making Expressive Data Physicalization. In proceedings of the 2026 CHI Conference on Human Factors in Computing Systems, ACM, Apr 2026, Barcelona, Spain. <10.1145/3772318.3790871>. <hal-05546329>

HAL Id: hal-05546329

<https://hal.science/hal-05546329v1>

Submitted on 10 Mar 2026

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY 4.0 - Attribution - International License

ClayPhys: Towards Toolkits that Support Making Expressive Data Physicalization

BAHARE BAKHTIARI, University of Victoria, Canada

YICHUN ZHAO, University of Victoria, Canada

JIAYUE WONG, University of Victoria, Canada

AURÉLIEN TABARD, Lyon 1 Université, CNRS, INSA Lyon, Centrale Lyon, Univ Lyon 2, LIRIS, UMR5205, F-69622, Villeurbanne, France

SOWMYA SOMANATH, University of Victoria, Canada

CHARLES PERIN, University of Victoria, Canada



Fig. 1. Participants creating data physicalizations using our toolkit *ClayPhys*.

Existing toolkits for data physicalization prioritize ease of use and adoption by novices. This is often achieved by limiting the affordances of the materials used and constraining design possibilities. The result is limited opportunities for creating expressive physicalizations. To address this limitation and to better understand how to support the creation process of expressive physicalizations, we created *ClayPhys*, a low-fidelity data physicalization toolkit designed to encourage making expressive data physicalizations. Our toolkit consists of clay, clay work tools, instruction and documentation handbooks, and warm-up activities that scaffold the design process. We studied the use of *ClayPhys* in a one-day workshop with nine expert participants. From our analysis of participants' created data physicalizations, we observed that using *ClayPhys*, participants could map data to different visual and physical variables, and that their designs incorporated various data interaction styles. Informed by our findings, we discuss implications for designing higher-fidelity expressive data physicalization toolkits.

Additional Key Words and Phrases: Data physicalization toolkit, visualization, expressive

ACM Reference Format:

Bahare Bakhtiari, Yichun Zhao, Jiayue Wong, Aurélien Tabard, Sowmya Somanath, and Charles Perin. 2026. *ClayPhys: Towards Toolkits that Support Making Expressive Data Physicalization*. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26)*, April 13–17, 2026, Barcelona, Spain. ACM, New York, NY, USA, 33 pages. <https://doi.org/10.1145/3772318.3790871>

Please use nonacm option or ACM Engage class to enable CC licenses



This work is licensed under a Creative Commons Attribution 4.0 International License.

© 2026 Copyright held by the owner/author(s).

Manuscript submitted to ACM

1 INTRODUCTION

Representing data in a tangible manner is a growing topic of interest in the visualization community (e.g., [4, 40, 41, 45, 47, 52]). The process of representing data using physical materials is called ‘*data physicalization*’ and it is defined as a process of encoding data into the geometries and properties of physical materials [52]. Researchers have proposed different approaches for designing, building, and studying such physicalizations. One such approach is the constructive approach, which is understood as “*the act of constructing a visualization by assembling blocks that have previously been assigned a data unit through a mapping*” [50]. To make the constructive approach usable and accessible to data physicalization makers, researchers have designed and studied constructive physicalization toolkits [25, 39, 51, 85, 106, 115]. Here, a toolkit refers to a platform that facilitates the creative exploration of design spaces and the creation of new interactive artifacts [67]. Existing constructive data physicalization toolkits support goals such as enabling self-tracking personal data [39, 116], performing data analytics and sense making [39, 51, 85], and encouraging self-reflection [25, 106]. However, they have not explicitly focused on supporting the creation of expressive data physicalizations [51, 116].

Many existing constructive data physicalization toolkits rely on pre-made tokens [18, 26, 39, 85, 87, 113, 116], which limit the types of representation end-users can create using these toolkits. Indeed, the use of pre-made tokens **limits personalization opportunities**: because the tokens are pre-made, end-users have limited opportunities for data mapping. For example, DataChest provides different emojis to represent emotions and stars to represent goal attainment [116]. Such mapping limits people from representing their emotions and goal attainments in alternative ways that could be more personal or unique to them. In addition, the use of pre-made tokens **limits the types of physical variables** (such as texture and friction) that can be used for creating data physicalizations [47]. Current toolkits primarily promote the creation of 2D visualization idioms in a 3D environment (e.g., a 3D bar chart made by stacking wooden blocks). For instance, ProtoBricks enables representing data using position, 1D size, and color variables, and limits the use of other physical variables like texture. Finally, the choice of tokens influences the types of interaction users can have with the data physicalization [50]. Because most current data physicalization toolkits use wooden or plastic tiles [51, 116], or Lego blocks as tokens [18, 39], they **limit interactions** to methods such as stacking and unstacking.

Although the choice to use simple tokens can help novices use toolkits easily and learn about data physicalization [50–52], it also makes it difficult to support other goals people have, such as creating more personalized representations and expressing themselves through such physicalizations [51]. Similar considerations exist in the domain of digital data visualization: while traditional visualization aims to support data analysis and sense-making [123, 124], visualization sub-domains such as personal [48] and casual [88] visualization, and approaches such as data humanism [77] focus more on promoting personalization and expressiveness [62, 68, 69, 83, 103]. These approaches are particularly relevant for data physicalization because an increasing number of data physicalizations involve collecting, representing, and reflecting on personal data [4, 57, 95, 106].

We investigate the design of toolkits to support the creation of expressive and personalized data physicalizations. We picked clay as material for our investigation as it is malleable and easy to manipulate. To this end, we designed a low-fidelity toolkit, *ClayPhys*, enabling users to prototype data physicalizations composed of clay, clay work tools, wire, and a set of handbooks for instruction, documentation, and guidance. We conducted a full-day workshop with 9 participants, in which we asked each participant to create three tangible data representations using *ClayPhys*. We then conducted one-on-one semi-structured interviews to gain a deeper understanding of participants’ processes and challenges in creating data physicalizations using *ClayPhys*, and of how they could envision a higher-fidelity

version with technology integration that could help overcome those challenges. From our workshop, we gathered video recordings of the interviews, pictures of the physicalizations participants created, and documentation handbooks that participants filled out throughout the workshop. We qualitatively analyzed the participants' data physicalizations and documentations to understand their process of data physicalization.

From our analysis, we found that *ClayPhys* enabled prototyping expressive physicalizations. Participants created 27 unique data physicalizations leveraging four physical marks (point, line, area, and volume) and 13 different physical variables. Furthermore, *ClayPhys* enabled the design of diverse interactions by considering nine physical actions (e.g., linear motion, rotation) to achieve 19 data actions (e.g., comparison, filtering).

Informed by our results, we discuss implications for designing future technology-supported toolkits that enable going beyond prototyping and creating final expressive data physicalizations. We discuss four implications for technology integration that can further our low-fidelity toolkit: 1) supporting personalized physical vocabulary, 2) defining assembly models for interactive physicalizations, 3) supporting low threshold entry points and high ceiling explorations for novices and experts and 4) supporting data representation within computational fabrication workflows.

In this paper, we present *ClayPhys*, a low-fidelity toolkit-based artifact contribution [118], that sheds light on opportunities for designing hybrid tools for facilitating the creation of expressive data-physicalization prototypes. *ClayPhys* supports new possibilities for representing data through physical actions, data actions, and iterative material manipulations. Informed by the evaluation of *ClayPhys*, we discuss a set of implications that can inform the design of future, higher-fidelity data-physicalization toolkits. We further discuss how these implications extend to the broader domain of HCI—including tangible user interfaces and digital fabrication—pointing toward hybrid toolkits that integrate data interaction and material manipulation with computational workflows.

2 BACKGROUND AND RELATED WORK

Our research lies at the intersection of topics related to data physicalization and toolkits in HCI. In this section, we first discuss research related to toolkit design and evaluation. Next, we discuss what expressivity means in data visualization and how it has been supported in data visualization. Finally, we discuss the limitations of existing data physicalization toolkits and how we aim to address these limitations.

2.1 Toolkit Design and Evaluation in HCI

A toolkit is a generative platform that helps people explore different ideas [67]. Within HCI, Ledo et al. explain that toolkits can have three types of goals: 1) creating interactive software and hardware artifacts and interfaces, 2) providing access to complex algorithms, and 3) enabling creative exploration of a design space [67]. Our work is concerned with the third type of goal: we explore how to design a flexible toolkit that supports expressive data physicalizations.

Several toolkits in HCI have explored supporting expressivity in a variety of application areas, such as haptics (e.g., [122]), materiality (e.g., [22]), crafts (e.g., [54]), personal informatics (e.g., [70]), and visualization (e.g., [68]). Recent data visualization studies have focused on how systems can support expressive visualization (e.g., [68, 119, 120]). Such system designs are based on previous research on sketching as a low-fidelity freeform approach for creating more advanced and expressive data visualizations [93, 112]. Likewise, in this work we leverage a freeform approach, but in the data physicalization domain, by proposing a low-fidelity data physicalization toolkit based on clay. By evaluating our toolkit, we aim to understand how to design data physicalization toolkits that support the creation of personalized and expressive data physicalizations.

2.2 Expressive Data Representation

Bruns et al. describe expressivity as the “*human ability to express themselves in terms of movement, actions, intent, and emotions when interacting with a system*” [20]. In visualization research, expressivity has been assessed in terms of diversity of data representations [62], of flexibility in layout design [83], and of capacity for creativity in design [119].

Creating visualizations and physicalizations that are expressive has been a much-discussed goal in the visualization community, often positioned in contrast with the more traditional use case of creating effective and legible data visualizations for domain experts to perform analytic tasks and make informed decisions. While traditional data visualization focuses on efficiency, readability, and analytics [21, 124], expressive data representation emphasizes qualitative and implicit aspects of data (the ones usually hard to quantify [62, 70, 111]), focuses on aesthetic and artistic values of the representation [68, 83], and values creativity and uniqueness of data representations as well as expression of authors’ style [68, 83]. Visualization researchers have also reported the benefits and need for expressivity in contexts, such as personal informatics (to enable sense making and reflection on personal data [106]), artistic and casual representations of data (to foster discussion and communication [66, 78, 89]), and democratization of data tools (to make data accessible to novices and to the public [50, 83]).

One of the most researched techniques for supporting the creation of expressive visualizations is creating freeform visualizations by sketching [103]. It is a low-barrier practice that enables the creation of personalized data visualizations (e.g., [68, 69, 83, 103]). Sketching in data visualization, also known as freeform visualization, is known to improve expressiveness in representing data [63, 83, 103, 119], to foster the creation of customized visualizations [62, 63, 68], to enable fast and fluid idea generation with a low learning curve [19, 68, 69, 119], to improve engagement [68], and to facilitate data collection on the go [17].

Data physicalization does not have a straightforward equivalent to sketching for creating freeform physicalizations. Freeform data physicalization remains challenging because it requires working with three-dimensional physical materials, and therefore also presents new opportunities for exploring how to support expressivity. For example, toolkits that enable creating freeform data physicalizations can explore how physical variables can be used to encode data, and how sensory affordances can be utilized to enable experiencing data in different ways such as touching, hearing, and tasting [33, 45, 65].

The few studies that have investigated freeform physicalization highlighted that simply providing participants with easy to manipulate materials does not necessarily lead to more expressive physicalizations. For example, Thudt et al [106] in their study provided participants with materials like beads and plasticine, and found that three out of their nine participants used easy to manipulate materials like plasticine, but only one created something unique with that material, while the other two focused on the colors of plasticine for categorization in their physicalization. Similarly, in another study in which participants created physicalizations with candy [65]—a relatively flexible material—the participants primarily relied on a limited set of variables such as the amount of candies, their type, shape, and color. Willett et al. [117] explored the use of clay, tiles, and Lego blocks as materials for conducting a constructive data physicalization activity in a classroom to teach information visualization. They found that although clay was more difficult and time-consuming to work with than tiles and Lego blocks, participants using clay proposed some of the most creative designs. In sum, while giving end-users easy to manipulate materials like clay can sometimes help them make creative physicalization designs, there is a need to also explore how to introduce such materials to participants so they can think about different ways to make expressive data physicalizations. We aim to address this gap by designing a toolkit that not only uses easy to manipulate building materials like clay, but also provides participants with additional

supports like clay working tools, and guidance materials for learning to use such tools and clay for creating expressive data physicalizations.

2.3 Data Physicalization Toolkits

Data physicalization toolkits have been presented by visualization researchers as aids to help end-users create data physicalizations. Recent work includes the design and evaluation of constructive physicalization toolkits for self-tracking [26, 116], awareness and reflection [25, 106, 113], rapid prototyping [39], forming a mental model and comprehension of data in a given domain [85, 87], and teaching information visualization concepts and improving data literacy [18, 49, 51].

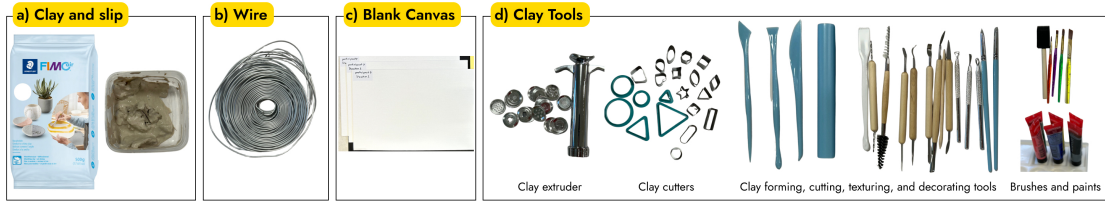
We identified two challenges with the existing toolkits for creating expressive data physicalizations. The first challenge is that, when existing toolkits have been used in studies, participants have tended to create similar outputs, using *similar physical marks and similar physical variables*. This challenge can be attributed to the limitation of the types of materials these toolkits offer, e.g., Lego blocks [18, 39], pre-made 2D tokens and tiles created by 3D printing [85, 87, 116] and/or laser cutting [26, 49, 51, 113], and sets of craft material including beads, plasticines, tape, thread, and labels [25, 106]. These different materials each afford data representation through certain physical marks and physical variables. Pre-made 2D tokens, tiles, Lego blocks, and beads typically lead to people representing data with color, size, and shape [18, 39, 87, 116]. For example, stacked Lego blocks or wooden tiles afford representing data with 1D size. More flexible materials, such as plasticine, can afford creating more diverse freeform shapes. However, when provided in previous studies, plasticine was used by participants mainly to categorize by color [106] or nearly not used at all [25]—perhaps because data mappings are less straightforward than with more structured material.

The second challenge is that previous toolkits support *limited interaction types*. The toolkit designers are usually the ones who define the possible physical actions (e.g., horizontal assembly [116], vertical assembly [87], and stacking and unstacking [39]). However, physical actions are opportunities for physicalization authors to define how to interact with their data physicalization and what data insights to gain from those physical actions. To understand how to support diverse interactions in data physicalization toolkits, in this work, we intentionally asked workshop participants to think about and design for interactions, so it could inform how toolkits should be designed to enable a variety of interaction types.

3 CLAYPHYS TOOLKIT DESIGN

Our goal with *ClayPhys* is to provide an expressive medium for data physicalizations that enables the creation of personalized physicalizations and leverages the variety of data mappings and interactions that freeform materials afford. Below we describe the different components of *ClayPhys*: clay as the core building material, wire and clay tools for constructing data physicalizations, data mapping and making instructions for encouraging users to think about how material and data mapping design space could help them to be more expressive in data representation, documentation sheets for sketching and reflection, and guidance handbook consisting of clay object catalogue [44, 79, 105] as a source of inspiration, and the definition of variables as a guidance for data mapping (Figure 2).

Clay and Slip. : Clay has been widely used in HCI studies as a material to generate artifacts with tactile qualities (e.g., [9, 10, 14, 42, 43]), and researchers have started to use clay for data physicalization [8, 33, 34, 84]. Clay is a flexible material that supports creating various shapes [114], and has been used both as input and output materials in HCI [86, 114]. Additionally, clay has been widely used in prior work on hybrid fabrication workflows because users can



e) Data Mapping Instructions

Physical Activity Dataset
 This dataset includes physical activity details over 7 days. Dataset includes 8 attributes including activity, total exercise time, burned calories, average heart rate, distance, number of steps, mood data, and perceived fatigue in each day.

Ordinal/Quantitative	Nominal	Quantitative	Quantitative	Quantitative	Quantitative	Quantitative	Nominal	Ordinal
Date	Activity	Total exercise time (hr)	Burned Calories	Average Heart Rate (b/min)	Distance (km)	Steps	Mood	Perceived Fatigue
Feb 19	Outdoor Walk	1.8	433	111	10.29	11884	😊	Moderate
	Outdoor Run	0.15	39	131	0.56	-	😊	-
Feb 20	Outdoor Walk	1.2	306	108	6.40	8487	😊	Low
	Outdoor Cycle	1.7	361	121	15.7	-	😊	-
Feb 21	Outdoor Walk	0.8	198	95	3.99	5599	😊	Low
	Dance	0.65	179	124	-	-	😊	-
Feb 22	Outdoor Walk	1.1	282	103	7.74	10403	😊	Moderate
Feb 23	-	0	0	-	0.1	22	😞	High
Feb 24	Outdoor Walk	2.7	584	107	14.86	19378	😊	Moderate
Feb 25	Dance	1.2	330	138	-	-	😊	Low

Strategy Try to use Clay's potential for data physicalization. For example try to create physicalization that is not easily achievable using pen and paper or using digital visualization.

Step 1: Variable selection
 In this iteration you should select at least two variables among the list of variables below to encode data. Variables should be of different categories. (e.g. you cannot select only blue variables or only red variables in one iteration). In total you can select as many variables as you want. Draw a circle around selected variables. You can decide to change or add variables in the middle of physicalization, but your decision.

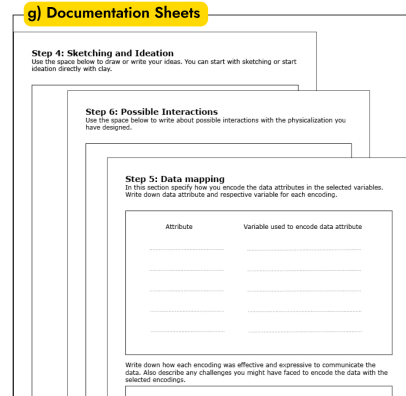
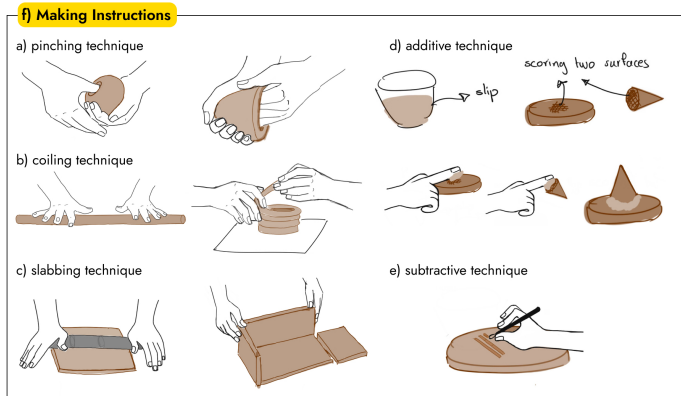
Step 2: Visualization approach selection
 In this step you should select one approach among constructive data physicalization and sculptural data physicalization approach.

Constructive Approach
 The necessary components of constructive approach are: A set of basic units or tokens, which can be mapped to data, a token grammar, which declares how the attributes of the tokens can signify data, an environment in which the tokens can be placed, an assembly model, which describes the constraints and freedom with which the tokens can be assembled (Huron et al. 2014).

Sculptural Approach
 A data sculpture is a data-based physical artifact, possessing both artistic and functional qualities, that aims to augment a nearby audience's understanding of data insights and any socially relevant issues that underlie it (Zhao et al. 2008).

Strategy Next iterations: Select new variables of two visual and haptic categories, or add new variables to the variables used in previous iterations.

Strategy Iteration 1: Select a physicalization approach (constructive or sculptural). Iteration 2: Select remaining physicalization approach. Iteration 3: No limitation for physicalization approach.



h) Guidance Handbook

Physicalization Visual Variables Definition/Description (Hornecker et al. 2023)
 Examples:
Size: In DataVis size concerns the amount of space taken up by a mark on the canvas and can be length, width, area, repetition of a mark, and volume. In data physicalization it can be expanded to include depth, thickness, or height (Hornecker et al. 2023).
Color: In DataVis color refers to three distinct variables including hue, value (bright-ness or luminance) and saturation. In physicalization it has expanded to include opacity, glossiness, or transparency (Hornecker et al. 2023).

Physicalization Haptic Variables Definition/Description (Tactile) (Hornecker et al.)
 Examples:
3D-form/Contour: 3D-form/Contour as a tactile variable refers to felt form or con-tact-contour of a physicalization (Hornecker et al. 2023).
Surface Texture: The surface texture of a physicalization concerns texture properties and pattern directly representing data, such as roughness, pattern, and graininess (Hornecker et al. 2023).

Physicalization Haptic Variables Definition/Description (Kinesthetic) (Hornecker et al.)
 Examples:
Inertia: Refers to the resistance of physical object to changes in velocity and includes changes to the object's speed or direction of motion (Hornecker et al. 2023).
Weight: This variable refers to the perceived weight of a physicalization or its elements. It is a kinesthetic variable because it is perceived through our muscles that counteract the weight (Hornecker et al. 2023).

Fig. 2. The ClayPhys toolkit's eight components, labeled a-h in the figure.

manipulate it during and after fabrication [12, 13, 114]. Given the established role of clay in hybrid fabrication research and its support for creativity and idea generation, it is well-suited to our workshop’s goal of informing high-fidelity toolkits.

Building on this body of work, we use clay as the primary material for physicalizing data. Clay is easy to start working with, even with minimal prior experience, and it enables the creation of a wide range of 2D and 3D forms. We used air-dry clay as the core material in *ClayPhys* because it is an inexpensive and safe material to work with by hand and to use indoors without special ventilation. We also included *slip*, made by combining clay and water, which acts as glue when attaching pieces of clay (see Figure 2a).

Wire. We included Aluminum alloy wire (0.055 inch in diameter) because it is widely used in claywork to create armatures or skeleton structures. These armatures act as internal support to hold the shape of structures made with clay. In our toolkit we included wires so participants could create different layouts, such as networks and hierarchies, as well as create different structures of tall, thin, and branching objects (see Figure 2b).

Blank Canvas. We provided a blank canvas for each physicalization. Canvas has multiple roles, such as a base for designing the layout, for providing annotation, labels, and legends, and for carrying the data physicalization (see Figure 2c).

Clay Tools. We included many clay tools including forming tools (clay extruder, modeling tools, and ribs), cutting tools (clay cutters, knives, needle tools, and loop tools), texturing tools (wire brushes, ribbon tools), and decorating tools (brushes and cutters for surface patterns). These tools have different affordances and thus allow representing data through different visual and physical variables. For example, texturing tools afford creating a variety of textures with different roughness. Similarly, a clay extruder enables the extrusion of clay coils with a uniform cross-section while controlling the length of extrusion, which is a challenging task without any tools. Additionally, these tools help with speed, accuracy, and consistency in making (e.g., using clay cutters). We also included paint and brushes so participants could represent data through the color visual variable (see Figure 2d).

Data Mapping Instructions. We introduced concepts relevant to data physicalization using the data mapping instructions document. This included a data set, a list of variables to select from for making a physicalization, and explanation of different visualization approaches to encourage users to go beyond common data visualization idioms (e.g., bar charts). These instructions were not intended to be prescriptive but to help participants explore different data mapping options. We included three sections in the data mapping instructions:

i) Sample dataset—we included a dataset that contained a mix of qualitative, ordinal, and quantitative data attributes. While many traditional visualizations are focused on quantitative data [59, 111], prior work shows the importance of qualitative data for reflection [106] and meaning making [76]. Therefore, we included both quantitative and qualitative data in our sample dataset. We chose to include a dataset about physical activity as that is a topic most participants could understand and interpret as personal data or as a dataset gathered from someone else. We also included data attributes with diverse ranges and scales of values (e.g., total exercise time ranges from 0 to 2.7 hrs while steps data ranges from 22 to 19578); we included cases of missing data points and zeros; and we used different text and emoji formats for qualitative data in the dataset.

ii) Variable selection sheet—this sheet included a list of visual and haptic variables that have been discussed previously in the literature [47]. Current data physicalization toolkits support a limited set of variables, such as position, size, color, and shape [39, 116]. In contrast, haptic variables such as roughness, friction, inertia, and weight are rarely supported [47].

We included the more encompassing list, so participants could more easily consider variables that they may not have otherwise thought about.

iii) Visualization approach sheet— Researchers have proposed different approaches for designing and building data physicalizations like the constructive approach [50], and data sculptures [121]. Previous research has shown that both the constructive and sculptural approaches are expressive, allowing people to create and control representations of data for functional and artistic purposes [50, 121]. However, these two approaches result in very different types of data physicalizations; the constructive approach leans toward the assembly of discrete units, while the sculptural approach leans toward generally shaping materials and representing data in a physical form. By introducing these approaches in *ClayPhys*, we intended to encourage participants to think about different types of data physicalizations they could create (see Figure 2e).

Making Instructions. In *ClayPhys*, we included instructions that explained fundamental hand-building clay forming techniques (pinching, coiling, slabbing [55]), additive techniques (e.g., slip and score), and subtractive techniques (e.g., carving and cutting). We provided these instructions to lower the skill barrier required from participants to implement data mapping ideas (see Figure 2f).

Documentation Sheets. To facilitate data physicalization making and to understand participants' process, we gave participants a set of documentation sheets where they could sketch and plan different ideas for the data physicalizations they wanted to make. These sheets were meant to help encourage active thinking about the design process and reflecting on the different design considerations the participants were making throughout the study (see Figure 2g).

Guidance Handbook. In the guidance handbook, we included three sections:

i) We provided a three-page catalogue of clay objects to inspire participants to think about diverse form factors. Prior research shows that designers use examples as a source of inspiration for designing data visualizations [7]. Such examples can either be related to data or have no direct relation to data, like art exhibitions [5]. To avoid fixation on the visualization idioms [7], we provided a diverse range of clay objects instead of data representation examples only. Our examples came from different sources such as websites, articles, and books for creating the clay object [38, 44, 55, 56, 58, 72, 79, 81, 90, 94, 99, 105]

ii) We defined the variables introduced in the data mapping instruction section. We made this decision based on our pilot studies, where participants did not understand the meaning of many variables.

iii) We included a brief description of the clay tools (see Figure 2) to facilitate documentation if participants wanted to refer to them.

Strategies to help users go beyond their comfort zone. Inspired by the principles introduced by Roberts et al. for creative visualization learning activities [92], we developed two considerations to scaffold the use of the toolkit and enable participants to step outside their comfort zone. First, by explicitly asking them to think about data representations that are not easy to create using pen and paper, we tried to encourage participants to think about the benefits of using physical materials that can be molded into three-dimensional shapes. Second, we wanted to ensure that participants use a range of variables, both typical and non-typical. To this end, we ask users to select in each iteration at least two variables from the visual and haptic list of variables. We further asked that they select at least two new variables from the visual and haptic lists in the subsequent iterations. We implemented this constraint because we expected that different variables would lead to different types of interactions, and using a variety of variables could also result in more creative and expressive physicalizations with clay. In our study, we asked participants to select an approach

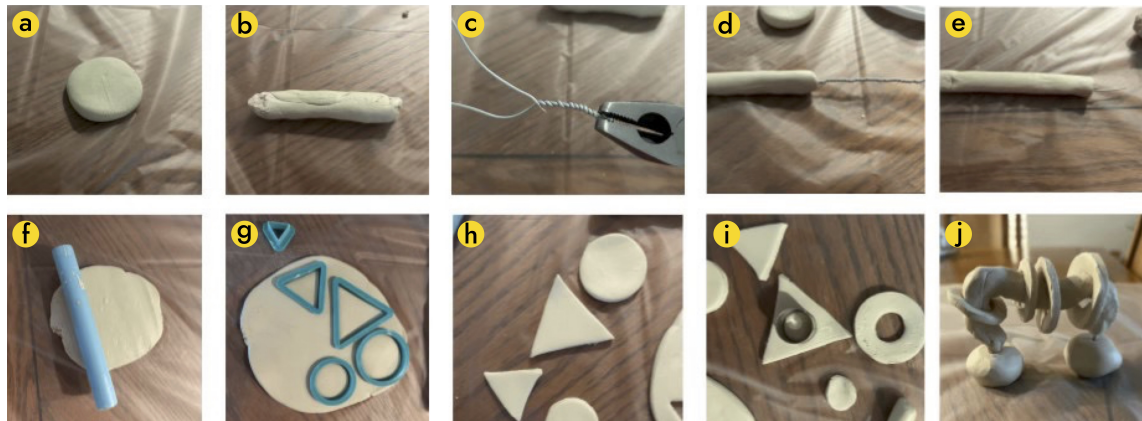


Fig. 3. Guided warm-up activity: a) making base for the structure, b) coiling clay, c) twisting wire for strengthening the structure, d) passing the wire structure through the coil, e) extracting the wire from the other end of the coil, f) rolling clay to make a slab, g) using clay cutters with different sizes and shapes to make tokens out of the slab, h, i) cutting a hole in the tokens, j) assembling the tokens and the coil

(either constructive or sculptural) in the first iteration. Then they were asked to use the other approach in the second iteration. In the last iteration, they could use any approach they wanted, including a combination of constructive and sculptural, or an entirely new approach not introduced in our visualization approach sheet. We used this strategy to make users think beyond simple tiles or blocks as tokens, help them think about form factors and properties of each token without prompting them to explore specific data encodings.

Warm-up Activities. To help participants get started with clay, we included two warm-up activities. In the first activity, we guided them through step-by-step instructions to build an abstract object. Figure 3 shows this activity. We designed this activity so participants could practice making tokens and working with toolkit materials and tools—for example, making a wire armature, assembling pieces, and using a roller or a cutter. The second activity was an open-ended activity in which participants were asked to try out forming, additive, and subtractive techniques that we introduced in the making instructions.

4 STUDY METHODOLOGY

To better understand how physicalization toolkits can support the creation of expressive and personalized data physicalizations, we conducted a full-day workshop [6] in which participants were asked to create physicalizations using *ClayPhys* materials and handbooks. We then conducted semi-structured interviews to gain a deeper understanding of participants' processes and challenges in developing data physicalizations using *ClayPhys*, and how they imagined a more advanced toolkit could assist them in their creation process. Our study was approved by our University ethics board.

4.1 Workshop Procedure

Participants who provided consent to take part in the study were invited to join the workshop, and were asked to complete a demographics questionnaire which included questions related to their background, and expertise in data visualization, physicalization, and clay work. The workshop took place over seven hours, and started with an

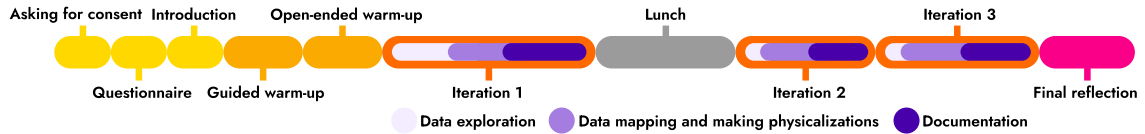


Fig. 4. Workshop study procedure, from left to right.



Fig. 5. Study setup: left: arrangement of tables, cameras, and presentation screens in the room; right: photo studio for capturing images of the physicalizations for each iteration.

introduction presentation in which the research team introduced the workshop structure and timeline. These initial activities, consent, questionnaire, and introduction, took one hour in total. Next, participants completed a guided and an open-ended warm-up activity. After the warm-up activities, participants engaged in three iterations of making data physicalizations, each involving data exploration, data mapping, making, and documentation. In all iterations, participants used the same dataset but created a new physicalization each time. The workshop concluded with a thirty-minute group discussion and reflection about opportunities and challenges they faced. Figure 4 shows an overview of the workshop timeline.

4.2 Workshop and Documentation Setup

The hands-on workshop took place in a room where participants were sitting around a table, and cameras were placed in the center to capture the workshop interactions (see Figure 5). With this layout, the participants could interact and talk to each other. The room was also equipped with displays for presentation.

Each participant was provided with a work surface that consisted of i) a black surface for clay work. The choice of the black surface was to create enough contrast to take high-quality pictures; ii) three canvases for transferring the three physicalizations that participants were asked to create; and iii) sketching tools and the main toolkit (See Figure 5). We prepared a photo studio with three cameras (two fixed and one free), and a rotating stand to take pictures from different angles of the final physicalizations on canvases (see Figure 5). Participants received one guidance handbook, one handbook consisting of data instruction, making instruction, and documentation sheets per iteration (three handbooks in total).

Table 1. Summary of participants' demographics information (for Background, CS: Computer Science, FA: Fine Arts, D: Design).

	Age	Gender	Background	Years in visualization	Expertise in visualization	Times created visualization	Times created clay objects
P1	27	Male	CS, FA	Prefer not to answer	Little expertise	1-5	1-5
P2	25	Female	D	1 year	Little expertise	once	1-5
P3	26	Female	D	1 year	Little expertise	More than 5	once
P4	45	Female	CS	20 years	Expert	1-5	More than 5
P5	30	Male	CS	3 years	Knowledgeable	once	once
P6	27	Male	CS, D	6 years	Knowledgeable	once	1-5
P7	32	Female	CS	5 years	Expert	1-5	Never
P8	22	Female	D	1 year	Little expertise	1-5	More than 5
P9	41	Prefer not to answer	CS, D	15 years	Knowledgeable	More than 5	1-5

4.3 Post-workshop Semi-Structured Interview

We conducted one-on-one semi-structured post-workshop interviews with all participants. The goal was to better understand participants' processes, challenges, and experiences with the data physicalizations they created. We asked participants questions about their process for selecting data attributes, selecting variables, and constructing the physicalization. Additionally, we asked about their challenges in each stage and what solutions they could envision to help address those challenges.

4.4 Participants

We aimed to recruit participants with some experience in data visualization, so that we could maximize workshop time spent on the data physicalization process rather than on teaching basic data and visualization literacy, and exploring and understanding the dataset [28]. Additionally, to avoid some form of novice block, we recruited participants who created data physicalization at least once. Given that few people have experience in data physicalization, and that the participants had to be physically co-located for the workshop, we recruited nine participants through our professional connections (convenience sampling). Participants information is summarized in Table 1.

Our participants had backgrounds in computer science ($n=4$), design ($n=3$), or both ($n=2$). Three participants identified as male, five as female, and one preferred not to answer this question. They were aged 25 to 45. All had created a data physicalization at least once before, with a range of techniques and materials including 3D printing, laser cutting, paper, soap, wire, wood sticks, magnets, food, and Lego blocks. They self-reported as having different levels of visualization expertise, including little expertise ($n=4$), knowledgeable ($n=3$), and expert ($n=2$). Eight of the nine participants had created clay objects at least once before.

4.5 Data Collection and Analysis

We video-recorded the interviews, collected participants' completed documentation handbooks, and photographed the final physicalizations in each iteration.

We transcribed all interviews and one coder (R1) performed preliminary inductive coding [27] of all interview transcripts. A second coder (R3) then independently coded one interview, after which R1 and R3 met to discuss the

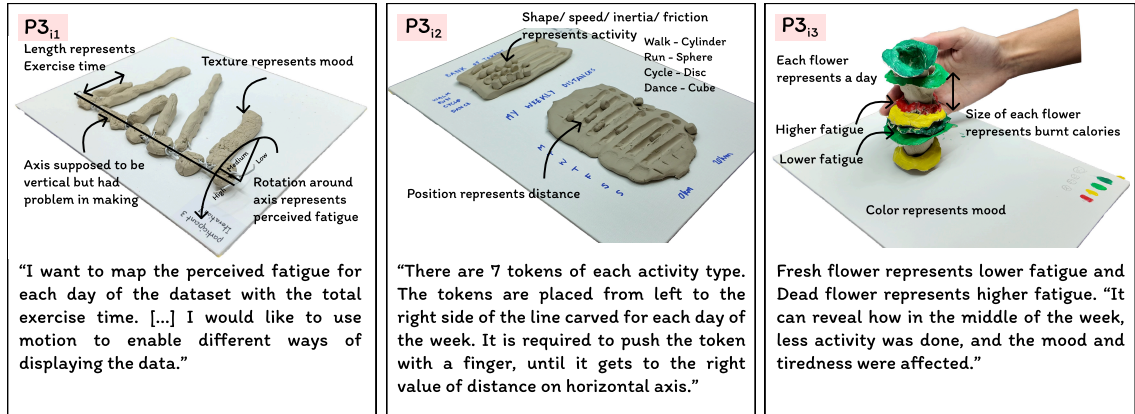


Fig. 6. Data physicalizations created by P3, in all three iterations, and the description of each physicalization.

codes one-by-one to discuss disagreements. The entire research team then met and discussed the codes and refined the codebook in successive meetings. R1 and R3 then applied the refined codebook to an additional transcript and again discussed the codes and revised the codebook. R1 then used the revised codebook to open code [102] the remaining interview transcripts. Similarly, for the documentation sheets, one coder (R1) inductively coded the entire set. Then a second coder (R2) independently applied inductive coding to all three documentation sheets of one participant. Then R1 and R2 met to discuss the codes one by one to reach an agreement. Then they applied the same process to a second documentation sheet and refined the codebook. R1 then used the refined codebook to update the coding for the full set of documentation sheets. In choosing the transcripts and documentation sheets for doing the iterative refinement among the research team, we chose the ones providing more diverse and rich insights based on the preliminary inductive coding.

In total, 82 codes were generated from open coding handbooks and interview transcripts. The codes included concepts such as interaction, metaphor, physicalization approaches, affordances of clay, challenges due to expertise with clay, inherent challenges of clay, and envisioned solutions to those challenges.

To analyze the photographs of the final physicalizations, R1 and R2 applied open coding. R1 then used Miro to categorize the physicalizations based on the codes, and iteratively discussed the categorizations with the rest of the research team. After the discussions, nine categories emerged based on the physical actions that physicalizations afford.

Finally, R1, R2, and R4 conducted a thematic analysis [27] of the codes by performing iterative axial coding. From axial coding, we formed four themes related to how *ClayPhys* supported expressive data physicalizations: 1) the general experience of participants with clay as a freeform medium for data physicalization; 2) Data mapping: consisting of data types, physical marks, and variables; 3) Interactions: consisting of physical actions and data actions; 4) Metaphors used to express data.

5 RESULTS

5.1 General experience with the toolkit

Overall, all participants were able to create three unique physicalizations—one for each of the three iterations. In this section, we discuss participants’ experiences with using *ClayPhys*. We use n_{ph} to refer to the number of physicalizations,

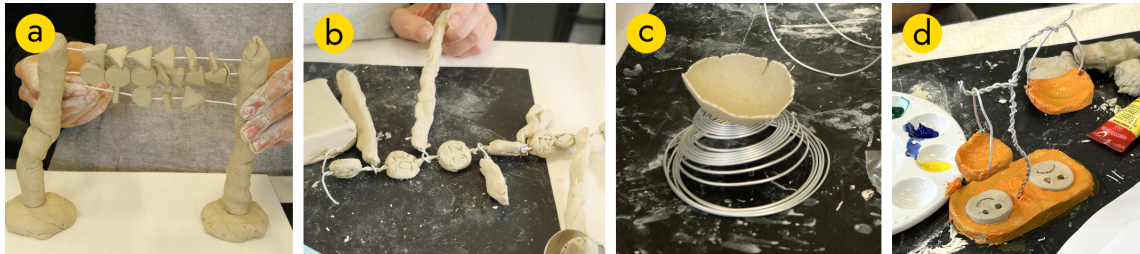


Fig. 7. Use of wire armature in data physicalization as a) a guide to move tokens along it, b) an axis to rotate tokens around it, c) a spring-like structure for physically encoding weight, and d) a support structure for clay physicalization.

n_{pa} to refer to the number of participants, and Px_{iy} to refer to iteration number y for participant x . Figures 12, 13, and 14 in Appendix show the 27 (9×3) physicalizations grouped by participant (see Figure 6 as an example).

Positive experience. Overall, participants enjoyed the process of making data physicalizations, and perceived the manual making as a reflective and meditative part of data physicalization ($P1, P2, P3, P4, P5, P7$). They described their experience as “fun” ($P1$ and $P4$), “relaxing” ($P1$), “exploratory” ($P4$), and “fast and crafty” ($P1$).

Low Learning Curve. $P7$ reflected “[...] clay is a very forgiving material. If you want to redo something, it’s pretty easy to do, or if you want to add something.” Some participants ideated using clay directly and did not use sketching as a starting point ($P2_{i1}, P2_{i3}, P3_{i2}, P4_{i3}, P6_{i3}, P7_{i1}, P8_{i3}$). Others used sketching in combination with working with clay to ideate.

Sources of Inspiration. Participants expressed at different points during the workshop that different components of *ClayPhys* inspired them to generate ideas. For example, $P8$ spoke about the list of variables and said, “I think constraints can be inspiring for me [...] especially this table because [...] I think [I’ll] be lost in the [data] table.” Additionally, participants found having a catalogue of ideas useful for inspiration ($P3, P7, P8$). However, participants suggested adding instructions for creating each artefact in the catalogue ($P6$), and suggested that the ability to filter the examples based on the possible data mappings ($P4$) would improve the use of a catalogue as a toolkit component.

Usability. Participants successfully utilized *ClayPhys* materials and tools to physicalize data. For example, in eight physicalizations ($n_{pa} = 7$) participants used wire in very different and expressive ways: as a guide to move tokens along it ($P4_{i1}, P6_{i1}$), as a guide to rotate tokens around it ($P3_{i1}$), as a springlike structure for representing balance ($P9_{i1}$), and as a support structure for the clay ($P2_{i2}, P4_{i2}, P5_{i2}, P8_{i3}$) (See Figure 7). Participants highlighted the value of *ClayPhys* in facilitating prototyping and exploration ($P1, P5, P6, P7, P9$), examining different possibilities ($P3, P5, P7$), exploring different variables ($P2, P3, P6, P9$), getting inspiration for ideation ($P1, P2, P3, P7, P8$), and thinking about possible metaphors ($P6$).

Participants created physicalizations with different layouts using different combinations of blank canvas, wire, and clay objects. Eight physicalizations ($n_{pa} = 5$) used position on the canvas to represent data, one physicalization used the canvas to create a tabular structure to represent data, and four physicalizations ($n_{pa} = 3$) scattered objects across the canvas to represent different data points. Blank canvas was also used for providing legend (11 physicalizations $n_{pa} = 6$) and labels (seven physicalizations $n_{pa} = 4$).

Hands-on Thinking Facilitator. All participants expressed that hands-on manipulation of material was a way of thinking and experimenting. When they started interacting with clay (P2, P3, P8), participants found that it helped them gain awareness of the properties of the material, it inspired them to explore new mappings and interactions (P1, P5, P7), and made the process of designing happen spontaneously (P4, P8).

Expressivity. We found that *ClayPhys* encouraged participants to use diverse data mappings, interactions, and metaphors to express both qualitative and quantitative data, which in turn resulted in the creation of unique data physicalizations. In the following sections, we discuss each of these aspects in detail.

5.2 Data Mappings

Data mapping refers to assigning data values to marks (physical marks in our case) through variables of those marks [23, 24]. *ClayPhys* enabled participants to try out different data mappings to create their data physicalizations (see Figure 8). We briefly describe the data physicalizations they created in terms of the three components of data mapping: data, physical marks, and physical variables.

5.2.1 Data. Some participants found that *ClayPhys* supports representing qualitative data well. Participants P1, P8, P2, and P3 found qualitative attributes such as mood and fatigue more inspiring than quantitative attributes when using *ClayPhys*. They stated that clay affords making “expressive” and “organic” shapes and forms that can capture nuances of the meaning behind data and make someone feel a certain way. For example, P1 explained about their first physicalization: “I tried to picture a form, a shape that would make me feel either good or very bad”, and they figured that “fire” and “shit” communicate good and bad feelings. Similarly, P8 elaborated that qualitative data like “activity” provided mental “image” and “illustration” for them, while numbers provided “a more abstract way of thinking”; they added that they preferred to work with qualitative data because numbers make them think of 2D visualizations.

For representing quantitative data, the constructive approach was useful for creating distinct tokens to represent data points, for example, to map quantitative data to “the size or the amount of clay” (P1). However, some participants found it challenging to be precise when mapping quantitative data to clay material (P3, P4, P6, and P7). For example, P3 said “I really liked the pinching technique, but it was also quite hard to get a precise shape with this technique”. P4 in their handbook noted “I find it very difficult to be accurate with quantitative data with clay, so I wanted to go for something where I didn’t feel like it needed to be exact [and consequently chose] more categorical data”. Eight out of nine participants imagined that technology or manual guides to facilitate precise encoding when mapping data to quantitative data could be useful to include in toolkits like *ClayPhys*.

While all participants widely used *ClayPhys* to represent qualitative data (see Figure 8), they faced some challenges because of their limited ability to make more complex shapes (e.g., fire (P1)). For example, P1 said “[...] I need to acquire more skills at clay modeling before I can really convey emotions with it.”

5.2.2 Physical marks. Physical marks for data physicalization are the equivalent of visual marks (point, line, and area) used in data visualization [11]. Marks are units whose properties (e.g., color, shape, texture) can be changed to encode data.

We found that using *ClayPhys*, participants used many different physical marks using a combination of different clay work techniques and tools provided in the toolkit. They used points (in 13 physicalizations), lines (in 10 physicalizations), areas (in 5 physicalizations), and volumes (in 9 physicalizations) (see Figure 8). In terms of clay work techniques and tools, in eight physicalizations ($n_{pa} = 5$), participants used a combination of slabbing and a form of subtraction (e.g.,

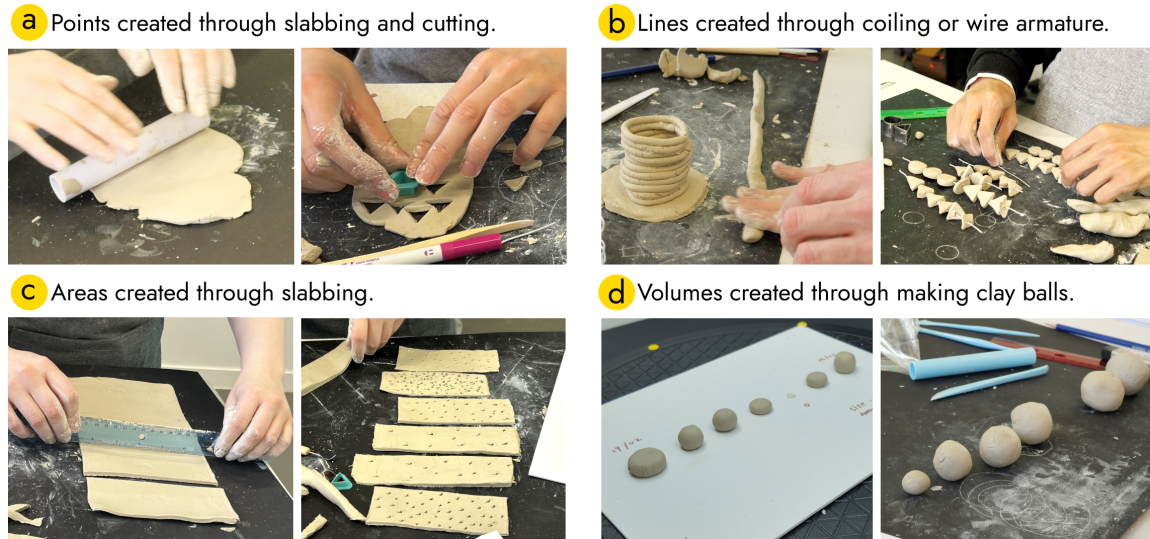


Fig. 9. Physical marks created using different clay techniques: a) slabbing and cutting to create points, b) coiling or using wire to create lines, c) slabbing to create areas, and d) making clay balls to create volumes.

using clay cutters) to create points (see Figure 9a). In three physicalizations ($n_{pa} = 3$), participants used wire to create lines. In three other physicalizations ($n_{pa} = 3$), participants used coiling to create lines (see Figure 9b). In three physicalizations ($n_{pa} = 3$), participants used slabbing to create areas (see Figure 9c). In seven physicalizations ($n_{pa} = 6$), participants created balls of clay with certain amounts of clay to create volumes (see Figure 9d).

The freeform characteristics of clay, along with the different tools and techniques provided, encouraged participants to explore a variety of tactile and kinesthetic variables by changing the properties of physical marks to convey both qualitative and quantitative data. These variables included texture ($P2, P5, P6, P7$), shape (all participants), force ($P4, P6$), friction and speed ($P2, P3, P4, P5$), viscosity ($P2$), balance ($P8, P9$), and light ($P2, P7$) (see Figure 8).

5.3 Interactions

Participants envisioned different ways to interact with their physicalizations to gain insights about the data represented. By open coding participants' final creations and their documentations, we identified two main components in interaction: **Physical Action**, and **Data Action** (see Figure 10). Physical actions [51] refer to the ways in which a user can manipulate a data physicalization by physically engaging with it. Data actions are data-related insights and tasks that are facilitated by those physical actions [36].

5.3.1 Data Actions. The main goal of a data representation is usually to gain data-related insights by performing low-level analytical actions such as comparing and filtering, or higher-level actions such as reflection and decision making. As a result, to support expressivity in data physicalization, it is important to enable personalizing data actions.

According to Brehmer and Munzner's taxonomy [15], low-level actions are about how a task is performed, and high-level actions are about why a task is performed. Following this framing, Dimara and Perin's taxonomy [36] defines data actions (low-level actions to process and input data) and perceptualization data actions (high-level actions to

		Data Actions		Examples of interactions
		Low-level processing and input data actions	High-level representation and perceptualization data actions	
Passive	Touching 	<ul style="list-style-type: none"> Comparing (P1₂ - P2₂) Identifying trend (P6₂ - P6₃) Identifying correlations (P2₁) Finding relations (P6₃) Transforming (P6₃) Input data (P6₁₃ - P2₁) 	<ul style="list-style-type: none"> Reflection (P2₃) Telling a narrative (P1₃) Encrypting data (P1₂ - P4₃) Using relatable metaphor (P1₃ - P2₁ - P4₂ - P4₃ - P6₂ - P6₃ - P7₃) 	P2 ₁ :  Touching the mix of clay and water
	Grabbing 	<ul style="list-style-type: none"> Comparing (P2₃) Identifying correlations (P1₁) Finding relations (P7₂) 	<ul style="list-style-type: none"> Associating a nominal data to a shape (P1₁) Using relatable metaphor (P1₁ - P7₂) 	P1 ₁ :  Grabbing objects
Active	Planar Motion 	<ul style="list-style-type: none"> Comparing (P2₃) 	<ul style="list-style-type: none"> Using relatable metaphor (P2₃) 	P2 ₃ :  Rolling tokens on a surface
	Linear Motion  	<ul style="list-style-type: none"> Finding relations (P3₂ - P5₂) Input data (P3₁₂) 	<ul style="list-style-type: none"> Getting an overview (P3₂) Playfulness (P5₂) Using relatable metaphor (P3₂) 	P5 ₂ :  Changing the length of the track  Sliding the token on the track
		<ul style="list-style-type: none"> Comparing (P6₁) Filtering (P6₁) Seeing distribution (P6₁) Identifying correlation (P4₁) Finding relations (P6₁) 	<ul style="list-style-type: none"> Getting an overview (P4₁) Playfulness (P4₁) Using relatable metaphor (P4₁) 	P6 ₁ :  Moving tokens along the axis 
	Rotation  	<ul style="list-style-type: none"> Comparing (P3₁) Filtering (P3₁) Finding relations (P3₁) 		P3 ₁ :  Rotating the bars around the central axis
		<ul style="list-style-type: none"> Comparing (P8₃) Finding relations (P8₃) 	<ul style="list-style-type: none"> Seeing consequences of actions (P8₃) Reflection (P8₃) Decision making (P8₃) Designing a journey for the data (P9₁) Using relatable metaphor (P8₃) 	P8 ₃ :  Central axis The bowls are supposed to rotate around the central axis
	Collection  	<ul style="list-style-type: none"> Comparing (P8₃) Aggregating (P5₃ - P7₁ - P8₁ - P8₂ - P8₃ - P9₁) Finding relations (P8₁ - P8₂ - P8₃) Rearranging (P7₁) Input data (P7₁ - P9₁) 	<ul style="list-style-type: none"> Getting an overview (P7₁) Decision making (P8₁ - P8₃) Seeing consequences of actions (P8₁ - P8₂ - P8₃) Reflection (P8₁ - P8₂) Designing a journey for the data (P9₁) 	P8 ₂ :  Stacking tokens in associated containers
<ul style="list-style-type: none"> Identifying trend (P3₃) Identifying correlations (P5₁) Finding relations (P3₃ - P5₁ - P9₂) Transforming (P9₂)* Rearranging (P9₃) Sorting (P9₃) Input data (P9₁₂ - P5₁₃) 		<ul style="list-style-type: none"> Reflection (P3₃) Associating a nominal data to a shape (P3₃) Using a relatable metaphor (P3₃ - P5₁) 	P9 ₂ :  Stacking objects on top of each other	

Fig. 10. Identified physical actions with the physicalizations, what data actions they support, and examples of interactions

represent and perceptualize data for self and others). We use Dimara and Perin’s taxonomy [36] to present the 19 unique data actions we identified in the data physicalizations created by the participants.

We found that participants could perform the following low-level data actions: identify correlations and relations (in 15 physicalizations created by $n_{pa} = 9$ participants), compare (in 6 physicalizations created by $n_{pa} = 5$ participants), aggregate (in 6 physicalizations created by $n_{pa} = 4$ participants), rearrange (in 4 physicalizations created by $n_{pa} = 4$ participants), get an overview (in 3 physicalizations created by $n_{pa} = 3$ participants), find trends (in 3 physicalizations created by $n_{pa} = 2$ participants), filter (in 2 physicalizations created by $n_{pa} = 2$), see distributions (in 1 physicalization), and sort (in 1 physicalization). Participants envisioned inputting data as an action in 7 physicalizations (created by $n_{pa} = 6$ participants).

In terms of higher-level actions, participants employed representation actions when they associated qualitative data with a shape (in 2 physicalizations created by $n_{pa} = 2$ participants) and when they initially mapped data to one variable that could later be perceived or interpreted through another variable (in 2 physicalizations created by $n_{pa} = 2$ participants). They employed perceptualization actions for self and others when they created a relatable metaphor (in 15 physicalizations created by $n_{pa} = 8$ participants), reflected (in 6 physicalizations created by $n_{pa} = 3$ participants), encrypted data (in 2 physicalizations created by $n_{pa} = 2$ participants), created a playful experience (in 2 physicalizations created by $n_{pa} = 2$ participants), made decisions (in 2 physicalizations created by $n_{pa} = 1$ participant), told a narrative (in 1 physicalization), and observed consequences of actions (in 1 physicalization). This wide spectrum of data actions demonstrates that participants were leveraging *ClayPhys* to create expressive physicalizations from a data actions perspective.

5.3.2 Physical Actions. One of the main ways to engage with the data in physicalizations is through physical actions. Physical actions result in perceiving data through different sensory modalities. Diverse physical actions facilitate different data actions, which in turn, result in a wide range of interactions. As per the definition of Bruns et al., expressivity relies on human expression through movement and actions [20]. To this end, it is important to facilitate creating diverse physical actions for creating expressive data physicalizations. We identified six different physical actions that facilitated the data actions we described previously (see Figure 10). These physical actions can be categorized into two main groups: **Passive actions**, which include touching (e.g., $P2_{i1}$, $P6_{i3}$) and grabbing (e.g., $P1_{i1}$, $P7_{i2}$); and **Active actions**, which include planar motion ($P2_{i3}$), linear motion ($P3_{i2}$, $P4_{i1}$), rotation (e.g., $P4_{i1}$, $P6_{i1}$), and collection (e.g., $P8_{i3}$, $P9_{i2}$). In this section, we discuss each physical action and provide examples of how each supports corresponding processing and input data actions.

Passive actions consisted of touching and grabbing. Touching and grabbing were common actions with most data physicalizations.

► **Touching** was, in some cases, the only physical action used to interact with the data physicalization. For example, in $P2_{i1}$ (see Figure 10-first row), the only way to interact with the stains of mixed clay and water is to touch each physical mark to feel the viscosity that encodes mood. In $P5_{i3}$, the length of extruded clay tubes represents distance, but due to the delicate nature of the representation, it would be difficult to apply other physical interactions beyond touching to gain insights about the data.

► **Grabbing** was used to perceive and **compare** data values that were mapped to weight ($P2_{i3}$ and $P1_{i1}$) and texture ($P2_{i3}$ and $P7_{i2}$).

Active actions were of four types. :

► *Planar motion* refers to using motion on a single plane. In $P2_{i3}$, this action corresponded to moving and rolling one or more objects on a surface to perceive fatigue. $P2$ explained “*The shape allows the object to move at a more or less fast speed, and more or less easily [as a result] the more fatigue, the less speed [and] motion*”.

► *Linear motion* refers to motion of an object that is constrained to a straight or curved path. The constraint can be physical, by only allowing linear movement ($P4_{i1}$ and $P6_{i1}$), or conceptual, by making linear movement meaningful ($P3_{i2}$ and $P5_{i2}$). In $P3_{i2}$, $P3$ explained: “*The tokens are placed from [the] left to the right side of the line carved for each day of the week. It is required to push the token with a finger, until it gets to the right value of distance on [the] horizontal axis.*”

► *Rotation* refers to cases where a physical structure allows a physical mark or aggregations of physical marks to rotate around an axis. This action enables **rearranging** data and looking at it from different points of view. In $P3_{i1}$, bar-like units that represent days have the freedom to rotate around a central axis (structure). The length of each bar represents exercise time that day, its texture represents mood, and its radial position represents the perceived fatigue for the day. The sketch in the handbook shown in Figure 11) shows an example from the workshop depicting how a viewer can interact with this physicalization by rotating the bars. By aligning all the bars and viewing the physicalization from the front view, the user can see the change in exercise time over days. By rotating the bars to their correct radial position in terms of perceived fatigue and viewing the physicalization from the top view, the user can compare the perceived fatigue. The rotation action in $P3_{i1}$ also enables **filtering** data, as shown in Figure 11: the user can filter in days with bad mood and then compare exercise times only for those days.

Rotation enabled **comparison** in $P8_{i3}$. Here, each bowl represents either a happy or an unhappy mood. By collecting activity tokens on the two sides of the structures, the user aggregates the activities that contribute to a good or a bad mood. $P8$ explained “*If the unhappy side is too full, the bowl is supposed to break or fall. At this time, the user should change his sport routine*”.

► *Collection* refers to cases where viewers can **input data** by collecting a set of tokens in a container or stacking tokens on top of each other to see **aggregation** over time. Collection was used as a way to create input physicalizations [17]—physicalizations focused on collecting and modifying new data points [17]—to make decision ($P8_{i1}$ and $P8_{i3}$), and to see the consequences of actions ($P8_{i3}$).

Two physicalizations relied on bars as containers. A bar in $P7_{i1}$ represents a day, and its height represents the number of steps that day. Each bar is used to stack lower-level units representing activity types with different shapes, as $P7$ described: “*you could use the bars to collect the activities [...]*” In $P8_{i1}$, each bar represents an activity, and is used to stack lower-level units whose patterns represent the mood for the day when this activity took place.

Three physicalizations relied on bowls as containers ($P8_{i2}$, $P8_{i3}$, and $P9_{i1}$). For example, a bowl in $P8_{i2}$ represents an activity in a day. $P8$ annotated their sketch of bowls in their handbook: “*Having bowls where you can put the number of calories.*”

5.4 Diverse Metaphors to Express Qualitative Data

Results show that *ClayPhys* encouraged participants to explore the use of metaphors to represent, as well as interact with data. A metaphor is a way of understanding a concept by using another concept [64, 111]. In our workshop, participants created metaphors by communicating abstract concepts through physicalizations that embodied a familiar object or form [74, 115].

They created metaphors in two ways: 1) by associating a variable with a colloquial way of describing a phenomenon (e.g., rough texture associated with rough mood); and 2) by associating user actions with human experiences (e.g., friction felt when moving an object was associated with representing tiredness).

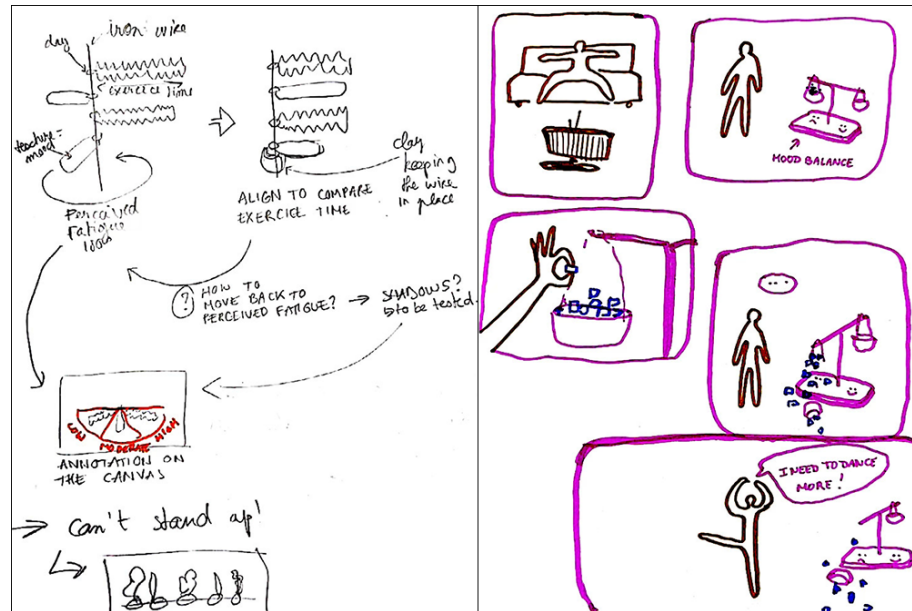


Fig. 11. Rotation enabled different data actions. Left: filtering data by rotating the bars around the central axis and aligning them. Right: comparing the weight of the two sides through rotating around the central axis

To bring metaphors to life, participants leveraged *ClayPhys* to use a range of physical variables, including:

- **3D form/contour:** Participants used clay to create various geometrical and organic shapes. They created objects including flower ($P3_{i3}$), snake ($P1_{i3}$, $P8_{i1}$), smiley curve ($P6_{i2}$), curved path ($P5_{i2}$), poop ($P1_{i1}$), fire ($P1_{i1}$), and shoes ($P4_{i1}$)
- **Texture:** $P7$ used texture to represent mood data and explained the mapping as “texture represents the mood, the worse it is, the spikier”. Similarly, $P5$, $P6$, and $P7$ used the metaphor of rougher textures to indicate increased fatigue.
- **Force:** $P4$ drew inspiration from the German expression “*Ich bin platt*”, [meaning] *I am flat or I am exhausted*” and created tokens with different levels of flatness to represent perceived fatigue. Similarly, $P6$ associated the amount of force and pressure applied to clay with perceived fatigue.
- **Viscosity:** $P2$ added water to clay and explained: “no water added [means] excellent mood, a lot of water [added] [means] bad mood.”
- **Light:** $P7$ used light as a metaphor to represent mood data and explained “I wanted to make an object that you could put a candle in - so that the light you can see reflects the mood. [...] I wanted to make holes in different shapes for each activity, and the higher the mood, the more holes.”

Participants reflected on their process of making metaphorical data representations in different instances. For example, $P3$ documented their process as— “[...] trying the pinching technique to evoke tiredness through the metaphor of a flower (fresh [and] open or a dead flower).” $P5$ had sketched two distinct representations of paths for a slide and had termed the straight path a “Good mood track”, and a winding path as the “Bad mood track”. $P1$ reflected on their creative process: “I figured that rolling [...] already make[s] something comfortable to play with, and then I figured “oh right, let’s do a snake””

in their handbook. They also described the metaphor further: *“The snake is resting because it is tired. It is shedding more or less according to its past days’ fatigue.”*

Participants also designed metaphors by supporting different physical actions:

- **Touching and Grabbing** were used to bring a common sensation to the viewer. For example, touching rough texture was associated with feelings of low mood or high fatigue ($P1_{i3}$, $P2_{i3}$, $P3_{i1}$, $P7_{i2}$).
- **Moving** a token and perceiving its reaction was used to associate the reaction of the object with the actual reaction of a human to a phenomenon. For example, slow movement ($P2_{i3}$) and friction ($P4_{i1}$) were associated to fatigue. $P3$ represented running with the token that moves faster in their physicalization (sphere) and walking with a token that moves slower (cylinder).
- **Collecting and aggregating** tokens was used to associate structure collapse to very low mood and burnout over time in a user in $P8_{i3}$. In this physicalization, when the aggregation of tokens is over a certain threshold, this creates an imbalance in the structure, and the structure collapses the same way a human would.
- **Collecting and stacking** tokens was used to associate the rhythm of evolution of the data physicalization over time to the rhythm of the phenomena. For example, ($P3_{i3}$) was described as representing *“evolution of mood and tiredness throughout a week”* through the rhythm created by *“superposition of flowers”* and the metaphor of *“openness”* and *“freshness”*.

Unlike most existing data physicalization toolkits that mainly focus on quantitative data and provide limited types of mapping to represent qualitative data such as a set of emoticons or using a set of colors [26, 51, 87, 116], our findings show that *ClayPhys* supported expressing both quantitative and qualitative aspects of data in diverse and unique ways, be it in terms of representation or in terms of interaction.

5.5 Challenges with *ClayPhys*

While participants were positive about their experience using *ClayPhys* and wanted to maintain hands-on experimentation with material, they identified areas for improvement. **Consistency** and **accuracy** in mapping data points to physical variables and to the creation of multiple tokens to accurately represent data. For example, $P1$, $P2$, $P4$, $P5$, and $P9$ found that creating a texture that reflects the data consistently and accurately was tedious.

Some participants struggled with **constructing structures to support interaction**. $P8$ found it difficult to implement their idea in their third iteration because the structure was too rigid and did not break or fall as they had envisioned it would. Similarly, $P3$ faced the laws of physics, explaining *“The weight was excessive, it couldn’t stand, so I had to remove the mood variable, and lay down my physicalization.”*

Some participants had challenges with **constructing layouts** with wire. For example, $P4_{i2}$ consists of half-hearts that each represent data, laid out in a circular layout. It is only upon assembling the units that they realized that the weights of the units were excessive and the structure was unstable. $P6$ expressed challenges in making *“non-data driven parts”* to compose *“data-driven parts”*. They explained, for their second iteration: *“I intend to make a vase with seven flowers, but due to my limited skills on clay I can only end up with the current version.”*

6 DISCUSSION AND IMPLICATIONS FOR DESIGN

Results from the study show that participants used *ClayPhys* to create expressive data physicalizations, while also revealing the limitations of a purely manual approach. In this section, we discuss a set of implications for design for

developing hybrid higher-fidelity toolkits for expressive data physicalization informed by our study results and the literature in data physicalization, tangible user interfaces (TUI), and digital fabrication.

6.1 Implication 1: Supporting Personalized Physical Vocabulary

Participants found working with *ClayPhys* fun and relaxing, and that it supported getting inspiration, generating ideas, and designing iteratively. However, participants also struggled with consistently and accurately applying their own data mappings. Creating and reproducing multiple tokens of the same size, shape, texture, and roughness proved particularly challenging. Echoing findings from related studies [29, 30], our participants suggested that using some form of automation may help with addressing such issues (*P1, P4, P6, P7, P9*). However, *P9* associated automation with reduced flexibility and *P4* found it “*not as expressive*”. To this end, they wanted to keep the hands-on nature of working with clay and not fully automating it (*P4, P5, P9*).

To address the challenges of consistency and accuracy when mapping data to physical variables, and to offer agency over the process, we outline two implications for design.

Implication 1.A: Using machines to replicate tokens. Hybrid toolkits could let end-users define their own visual vocabulary by creating single tokens once (such as drawing a glyph), and then copy such tokens multiple times. Such approaches have been explored with glyph sketches in the visualization community, for example with *DataInk* [119] and *DataGarden* [83]. With clay, methods like 3D scanning [114] or fabrication techniques like vacuum forming [46] could help physicalization creators replicate tokens made by hand, enabling accuracy, consistency, and efficiency.

Implication 1.B: Using machines to produce scaffolds. Such scaffolds could be clay cutters, texture tools, and bead makers that enable creators to consistently and accurately create multiple marks. Parametric design tooling could streamline the process of generating customized 3D models by linking to physical variables such as size, shape, roughness, and patterns. *Deshpande et al.* [32] previously showed the effectiveness of using software to design and 3D print custom tools that can be used to facilitate manual craft practices, while maintaining creative exploration during manual making.

The two directions present a trade-off: it is not practically feasible to make custom tools for all variations (e.g., to represent quantitative data, the number of variations is potentially infinite), and, simply replicating once created tokens limit design variations. Studying this trade-off presents a future work direction for developers of data physicalization toolkits.

6.2 Implication 2: Defining Assembly Models for Interactive Physicalizations

Participants created data physicalizations with a variety of interactions involving both data actions (low-level ones like comparing and rearranging, and high-level ones like creating relatable metaphors and telling a narrative) and physical actions (passive ones like touching and grabbing, and active ones like planar motion and rotation). However, participants faced challenges in implementing their interactions (for example, rotating an object around an axis was difficult to implement, according to *P8*) and creating certain layouts (e.g., circular layout—*P4*).

Existing data physicalization toolkits address this interaction challenge by proposing structures to assemble tokens (also known as the assembly model [51]). For example, in *DataChest*, the toolkit includes trays that provide a clear location for attaching tokens and are used as segments of a timeline [116]. Similarly, *Pittarello et al.* [87] proposed a modular vertical tower structure to assemble the tokens when making a data physicalization. While these assembly structures facilitate the assembly process, they also prescribe interactions, constraining users in creating personalized and expressive interactions.

In our study, participants' interactions can be described using the concept of degrees of freedom (DoF) [109]—independent ways an object can move or be manipulated. Each action can be described based on the type of joint enabling those actions and the resultant data actions. For example, 1 DoF by rotation around an axis (revolute joint) enabled comparison and filtering, 1 DoF by sliding along a path (prism joint) enabled comparison and seeing distribution, or 3 DoF by planar movement (flat joint) that enabled moving and rolling the tokens to feel the properties of the token. Additionally, more degrees of freedom—and as a result wider ranges of interactions—can be supported by changing the shape of the token and by supporting rolling instead of slipping (e.g., a ball vs a cube). Some actions also involved reducing an object's DoF, such as when participants placed tokens inside a container to limit further movement.

The TUI literature has used the concept of DoF to show how tangible tokens can be used to interact with digital information [110]. Informed by such examples, we think that to help physicalization creators define their own interactions and assembly models, we could educate them about the concept of DoF. This can be achieved by scaffolding the learning process using either manual approaches or interactive approaches.

Implication 2.A: Scaffolding assembly model appropriation with handbooks. Similar to starter kit activities [100], we can leverage the handbook and the warm-up practices materials of *ClayPhys* as sites for introducing the concept of DOFs. For example, we could first familiarize creators with how to make structures with various DoFs (e.g., to make a revolute joint (1DoF) with wire and clay) as part of the warm-up practice; second, in the handbook, we could ask people to think about and specify the physical actions they expect the physicalization to support; third, we could ask them to specify the data actions they want to support in their data physicalization; and finally, we could ask them to iterate through this process to refine the interaction.

Implication 2.B: Fabricating custom assembly structures. Once creators have decided on their design, fabrication methods like 3D printing and laser cutting could be used to create dynamic and functional mechanisms with various DoFs [71, 73] that would be custom to the physicalization.

6.3 Implication 3: Supporting Low Threshold Entry Points and High Ceiling Explorations for Novices and Experts

Low-threshold entry points and high-ceiling explorations are two design principles proposed within the creativity support tools literature to broaden participation in creative activities [91]. Within data visualization and expressivity research, such principles have been addressed by providing flexibility to personalize data representations [93] using approaches like freeform sketching [68, 83, 96, 103, 119], using vector graphics [75, 119], and extracting elements from rasterized images [120].

Implication 3.A: Clay is a low-threshold material for data-physicalization, and *ClayPhys* supported the low-threshold principle both in terms of using the material and of integrating data visualization concepts. Warm-up activities and guidance material help physicalization makers start to work with the material, gain some basic techniques in working with the material, and tools (akin to starter kit activities in constructionist toolkits like Arduino [100]). Through such supports we observed that all participants could use techniques introduced in *ClayPhys* extensively in their physicalizations.

In terms of visualization concepts, we lowered the threshold by providing step-by-step guides on selecting data attributes, variables, and data mapping. We observed that participants with little experience in data visualization successfully created expressive data physicalizations. Although our participants were data visualization experts and designers, we observed that providing a list of variables and introducing constructive visualization and data sculpture concepts triggered thinking about and creating novel data representations.

Implication 3.B: Support high-ceiling explorations with making guidance. *ClayPhys*, offered limited support on the high-ceiling principle. We observed that although available tools facilitated creating a variety of form factors and enabled participants to think about more novel ideas (e.g., using wire armature to implement different interactions), one’s expertise in working with material played an important role in their success in implementing the more complex forms and ideas they had in mind. To overcome this challenge, participants suggested different strategies, such as complementing the clay object catalogue with step-by-step making instructions (P6), and providing construction steps and the required tools based on their physicalization idea, their selected variables, and the challenges they faced (P2, P4, P6, P9).

Digital fabrication techniques, and existing TUI techniques can expand the opportunities for offering low-threshold entry points and high-ceiling exploration. For example, to assist with the task of material manipulation, we can draw inspiration from previously demonstrated systems wherein artists can guide machines (such as robot arms [12], or an augmented throwing wheel [80]) to manipulate the material. To provide specific making instructions, we can draw inspiration from systems like MoveableMaker [1], which generate design-specific instructions for a specific project such as checking physical constraints for constructing the input physical object idea, and developing design files for fabrication.

6.4 Implication 4: Supporting Data Representation within Computational Fabrication Workflows

The HCI community increasingly relies on digital design and fabrication to create data physicalizations (e.g., [2, 3, 29, 31, 33, 37, 53, 82, 97, 104]). For example, some of these works discuss collaborative approaches in which end-users have interactions with both the machine and the material directly to leverage machine precision and expressive qualities of material like clay [13, 14, 35, 61, 80, 98, 107, 108, 114]. However, typical fabrication processes do not explicitly consider aspects of *data* as a core concept of design and fabrication process, although it is core to designing visualizations and physicalizations. For example, Kim et al. introduce compositional 3D printing by incorporating a middle layer of interaction (e.g., using physical objects as design input to modify the mesh) between the computer and the machine to support continuous interaction [61]. Similarly, Weichel et al. introduce “bi-directional fabrication” by considering iterations between digital interaction with the model and physical interaction with the material [114]. However, these examples of fabrication pipelines although useful to digitize toolkits like *ClayPhys*, it is not clear how data fits within such pipelines, and is a key consideration for systems that support data physicalization.

Implication 4.A: Explore ways to explicitly consider data in fabrication pipelines. In addition to enabling visualization creators to develop their own data encodings manually, we think integrating data in digital fabrication pipelines can also be considered to further support digitalization of hybrid toolkits like *ClayPhys*. For example, in our results, we observed that participants encoded data within geometry of the material (e.g., using shape), properties of material (e.g., using viscosity), and texture of the material (e.g., using roughness). Such data encodings can be supported through different fabrication processes. A) During *material preparation*, visualization creators can identify which type of material property they want to use for their encoding, and develop such material texture by modifying the smoothness, or brittleness of the material properties [10]. B) when generating the *fabrication file* (at the level of G-code and M-code), visualization creators can also programatically define the material-level encoding they want to use (e.g., shifting print layers based on data value, or making prints more or less porous vs rigid objects [101]). Lastly, c) during fabrication, visualization creators can also manipulate material (e.g., modifying a clay object when 3D printing it [14]) or after fabrication modify the final object [60, 114] to incorporate encoding of their choice.

Adapting digital fabrication pipelines to consider data in their workflow, not only makes these pipelines more suitable for data physicalization process, but also opens up more opportunities to use the expressive potential of material manipulation along with the benefits of digital fabrication such as accuracy and consistency.

7 LIMITATIONS AND FUTURE WORK

Our study had certain limitations that we think can be addressed in future work, to further expand knowledge in the area of data physicalization. Asking participants to use a tabular dataset might have encouraged one-to-one data mapping to the data points in the dataset, and consequently affected the data physicalizations created by participants. We might have identified different types of interactions and data mappings, had we used other kinds of data, such as a network or a geospatial dataset.

Even though clay is a freeform material, the specific properties of air-dry clay impose certain constraints. For instance, air-dry clay dries out over time, so participants had to use water to moisturize the clay and prevent drying. While mixing water afforded data mapping to the viscosity variable, it introduced some challenges in iteratively making the physicalization and refining in comparison to plasticine or polymer clay, which do not dry out over time. Further exploration of other freeform materials is needed to better understand the space of freeform physicalizations.

Finally, in this work, we explored clay as a freeform material to create expressive data physicalizations and discussed how our findings inform the design of higher-fidelity toolkits. However, clay might not be the best material to incorporate in every situation and environment [95]. For example, clay might not be a material of choice if wearability or dynamicity are important factors because of clay's fragility and weight. Clay might also not be appropriate in certain contexts such as outdoor settings, because of the nature of the material. Our study is a first step towards designing such toolkits and future work is needed to explore hybrid toolkits with alternative materials, as well as to explore the contextual dimensions and situatedness [16, 26] of data physicalization.

8 CONCLUSION

We introduced *ClayPhys*, a data physicalization toolkit designed to support the creation of personalized and expressive data physicalizations. Our evaluation of the toolkit in a one-day workshop with nine expert participants revealed that *ClayPhys* allowed participants to successfully create expressive physicalizations, by employing a wide range of physical variables, and incorporating diverse, personalized interactions. From these results, we further discussed four implications for technology integration that can further our low-fidelity toolkit: 1) supporting personalized physical vocabulary, 2) defining assembly models for interactive physicalizations, 3) supporting low threshold entry points and high ceiling explorations for novices and experts and 4) supporting data representation within computational fabrication workflows.

ACKNOWLEDGMENTS

This research was funded by NSERC RGPIN-2025-04477, NSERC RGPIN-2019-05422, and France-Canada Research Fund.

REFERENCES

- [1] Michelle Annett, Tovi Grossman, Daniel Wigdor, and George Fitzmaurice. 2015. MoveableMaker: facilitating the design, generation, and assembly of moveable papercraft. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*. 565–574.
- [2] Christoph Bader, Dominik Kolb, James C Weaver, Sunanda Sharma, Ahmed Hosny, João Costa, and Neri Oxman. 2018. Making data matter: Voxel printing for the digital fabrication of data across scales and domains. *Science advances* 4, 5 (2018), eaas8652.

- [3] S Sandra Bae, Takanori Fujiwara, Anders Ynnerman, Ellen Yi-Luen Do, Michael L Rivera, and Danielle Albers Szafir. 2023. A Computational Design Pipeline to Fabricate Sensing Network Physicalizations. *IEEE Transactions on Visualization and Computer Graphics* (2023).
- [4] S Sandra Bae, Clement Zheng, Mary Etta West, Ellen Yi-Luen Do, Samuel Huron, and Danielle Albers Szafir. 2022. Making data tangible: A cross-disciplinary design space for data physicalization. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–18.
- [5] Ali Baigelenov, Prakash Shukla, and Paul Parsons. 2025. How Visualization Designers Perceive and Use Inspiration. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [6] Bahare Bakhtiari, Aurélien Tabard, Sowmya Somanath, and Charles Perin. 2025. FlexPhys: A Workshop Cookbook for Operationalizing Data Physicalization Research Questions. In *IEEE Conference on Visualization and Visual Analytics (VIS2025)*.
- [7] Hannah K Bako, Xinyi Liu, Leilani Battle, and Zhicheng Liu. 2022. Understanding how designers find and use data visualization examples. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2022), 1048–1058.
- [8] Tove Grimstad Bang, Sarah Fdili Alaoui, Guro Tyse, Elisabeth Schwartz, and Frederic Bevilacqua. 2024. A Retrospective Autoethnography Documenting Dance Learning Through Data Physicalisations. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*. 2357–2373.
- [9] Fiona Bell, Erin McClure, Camila Friedman-Gerlicz, Ruby Ta, and Leah Buechley. 2024. Shape-Changing Clay-Dough: Taking a Material-Oriented Approach to 3D Printing Ceramic Forms. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–19.
- [10] Fiona Bell, Netta Ofer, and Mirela Alistar. 2022. ReClaym our Compost: Biodegradable Clay for Intimate Making. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [11] Jacques Bertin. 1983. *Semiology of graphics*. University of Wisconsin press.
- [12] Samuelle Bourgault, Alejandro Aponte, Megumi Ondo, Emilie Yu, and Jennifer Jacobs. 2025. WORM: Programming Collaborative Robots Through Manual Actions for Craft-Aligned Digital Fabrication. In *Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology*. 1–19.
- [13] Sam Bourgault and Jennifer Jacobs. 2024. Millipath: Bridging Materialist Theory and System Development for Surface Texture Fabrication. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*. 50–68.
- [14] Samuelle Bourgault, Pilar Wiley, Avi Farber, and Jennifer Jacobs. 2023. CoilCAM: Enabling parametric design for clay 3D printing through an action-oriented toolpath programming system. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16.
- [15] Matthew Brehmer and Tamara Munzner. 2013. A multi-level typology of abstract visualization tasks. *IEEE transactions on visualization and computer graphics* 19, 12 (2013), 2376–2385.
- [16] Nathalie Bressa, Henrik Korsgaard, Aurélien Tabard, Steven Houben, and Jo Vermeulen. 2021. What's the situation with situated visualization? A survey and perspectives on situatedness. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (2021), 107–117.
- [17] Nathalie Bressa, Jordan Louis, Wesley Willett, and Samuel Huron. 2024. Input Visualization: Collecting and Modifying Data with Visual Representations. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–18.
- [18] Hans Brombacher, Rosa Van Koningsbruggen, Steven Vos, and Steven Houben. 2024. SensorBricks: a Collaborative Tangible Sensor Toolkit to Support the Development of Data Literacy. In *Proceedings of the Eighteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–17.
- [19] Jeffrey Browne, Bongshin Lee, Sheelagh Carpendale, Nathalie Riche, and Timothy Sherwood. 2011. Data analysis on interactive whiteboards through sketch-based interaction. In *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*. 154–157.
- [20] Miguel Bruns, Stijn Ossevoort, and Marianne Graves Petersen. 2021. Expressivity in interaction: A framework for design. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [21] Alyxander Burns, Cindy Xiong, Steven Franconeri, Alberto Cairo, and Narges Mahyar. 2020. How to evaluate data visualizations across different levels of understanding. In *2020 IEEE Workshop on Evaluation and Beyond-Methodological Approaches to Visualization (BELIV)*. IEEE, 19–28.
- [22] Serena Camera and Elvin Karana. 2018. Experiential characterization of materials: Toward a toolkit. (2018).
- [23] Stuart Card. 2009. Information visualization. In *Human-computer interaction*. CRC press, 199–234.
- [24] Stuart K Card, Jock Mackinlay, and Ben Shneiderman. 1999. *Readings in information visualization: using vision to think*. Morgan Kaufmann.
- [25] Andrea Castaneda, Sowmya Somanath, and Charles Perin. 2025. Can Young Children Make Sense of their Own Data through Constructive Physicalization? A Qualitative Study. In *Proceedings of the 51st Graphics Interface Conference (Kelowna, British Columbia, Canada) (GI '25)*. Canadian Information Processing Society.
- [26] Silvia Cazacu, Stien Poncelet, Emma Feijtraij, and Andrew Vande Moere. 2025. The EnviroMapper Toolkit: An Input Physicalisation that Captures the Situated Experience of Environmental Comfort in Offices. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–14.
- [27] Victoria Clarke and Virginia Braun. 2017. Thematic analysis. *The journal of positive psychology* 12, 3 (2017), 297–298.
- [28] Andy Cockburn, Carl Gutwin, Joey Scarr, and Sylvain Malacria. 2014. Supporting novice to expert transitions in user interfaces. *ACM Computing Surveys (CSUR)* 47, 2 (2014), 1–36.
- [29] Foroozan Daneshzand, Charles Perin, and Sheelagh Carpendale. 2022. KiriPhys: Exploring New Data Physicalization Opportunities. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2022), 225–235.
- [30] Foroozan Daneshzand, Charles Perin, Navarjun Singh Grewal, Tatiana Losev, and Sheelagh Carpendale. 2025. Designing with Data: Supporting Design Processes in Physicalization Construction. In *Proceedings of the Nineteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–16.

- [31] Alexandre Abreu de Freitas, Walbert Cunha Monteiro, Thiago Augusto Soares de Sousa, Vinicius Favacho Queiroz, Tiago Davi Oliveira de Araújo, and Bianchi Serique Meiguins. 2022. A flexible pipeline to create different types of data physicalizations. In *2022 26th International Conference Information Visualisation (IV)*. IEEE, 73–78.
- [32] Himani Deshpande, Haruki Takahashi, and Jeeun Kim. 2021. Escapeloomb: Fabricating new affordances for hand weaving. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [33] Audrey Desjardins and Timea Tihanyi. 2019. ListeningCups: A case of data tactility and data stories. In *Proceedings of the 2019 on designing interactive systems conference*. 147–160.
- [34] Audrey Desjardins, Timea Tihanyi, Freesoul El Shabazz-Thompson, Brock Craft, and Julia Saimo. 2023. The inner ear: capturing and physicalizing home vibrations. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*. 594–607.
- [35] Laura Devendorf and Kimiko Ryokai. 2015. Being the machine: Reconfiguring agency and control in hybrid fabrication. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 2477–2486.
- [36] Evanthia Dimara and Charles Perin. 2019. What is interaction for data visualization? *IEEE transactions on visualization and computer graphics* 26, 1 (2019), 119–129.
- [37] Hessam Djavaherpour, Faramarz Samavati, Ali Mahdavi-Amiri, Fatemeh Yazdanbakhsh, Samuel Huron, Richard Levy, Yvonne Jansen, and Lora Oehlberg. 2021. Data to physicalization: A survey of the physical rendering process. In *Computer Graphics Forum*, Vol. 40. Wiley Online Library, 569–598.
- [38] Domestika. [n. d.]. Exploring Ceramics: The Slab Technique. https://www.domestika.org/en/blog/11240-exploring-ceramics-the-slab-technique?exp_set=1. Accessed: 2025-09-12.
- [39] Julia Dominiak, Anna Walczak, Evropi Stefanidi, Krzysztof Adamkiewicz, Krzysztof Grudzień, Jasmin Niess, and Paweł W Woźniak. 2024. ProtoBricks: A Research Toolkit for Tangible Prototyping & Data Physicalization. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference*. 476–495.
- [40] Pierre Dragicevic, Yvonne Jansen, and Andrew Vande Moere. 2020. Data physicalization. *Handbook of Human Computer Interaction (2020)*, 1–51.
- [41] Žarko Dumičić, Katja Thoring, Hermann W Klöckner, and Gesche Joost. 2022. Design elements in data physicalization: A systematic literature review. (2022).
- [42] Camila Friedman-Gerlicz, Deanna Gelosi, Fiona Bell, and Leah Buechley. 2024. WeaveSlicer: Expanding the Range of Printable Geometries in Clay. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–16.
- [43] Devon Frost, Raina Lee, Eun-Ha Paek, and Jennifer Jacobs. 2024. SketchPath: Using Digital Drawing to Integrate the Gestural Qualities of Craft in CAM-Based Clay 3D Printing. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–16.
- [44] Del Harrow. 2025. Air Breath, 2012. Slip cast porcelain, glaze, video, large drawing created using a graphite pencil attached to a CNC milling machine. <https://studiopotter.org/towards-aesthetic-digital-clay>. Accessed: 2025-09-12.
- [45] Trevor Hogan and Eva Hornecker. 2017. Towards a design space for multisensory data representation. *Interacting with Computers* 29, 2 (2017), 147–167.
- [46] Freddie Hong, Luca Tenders, Connor Myant, and David Boyle. 2022. Vacuum-formed 3D printed electronics: Fabrication of thin, rigid and free-form interactive surfaces. *SN Computer Science* 3, 4 (2022), 275.
- [47] Eva Hornecker, Trevor Hogan, Uta Hinrichs, and Rosa van Koningsbruggen. 2023. A Design Vocabulary for Data Physicalization. *ACM Transactions on Computer-Human Interaction (2023)*.
- [48] Dandan Huang, Melanie Tory, Bon Adriel Aseniero, Lyn Bartram, Scott Bateman, Sheelagh Carpendale, Anthony Tang, and Robert Woodbury. 2014. Personal visualization and personal visual analytics. *IEEE Transactions on Visualization and Computer Graphics* 21, 3 (2014), 420–433.
- [49] Samuel Huron, Sheelagh Carpendale, Jeremy Boy, and Jean-Daniel Fekete. 2016. Using viskit: A manual for running a constructive visualization workshop. In *Pedagogy of Data Visualization Workshop at IEEE VIS 2016*.
- [50] Samuel Huron, Sheelagh Carpendale, Alice Thudt, Anthony Tang, and Michael Mauerer. 2014. Constructive visualization. In *Proceedings of the 2014 conference on Designing interactive systems*. 433–442.
- [51] Samuel Huron, Yvonne Jansen, and Sheelagh Carpendale. 2014. Constructing visual representations: Investigating the use of tangible tokens. *IEEE transactions on visualization and computer graphics* 20, 12 (2014), 2102–2111.
- [52] Yvonne Jansen, Pierre Dragicevic, Petra Isenberg, Jason Alexander, Abhijit Karnik, Johan Kildal, Sriram Subramanian, and Kasper Hornbæk. 2015. Opportunities and challenges for data physicalization. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 3227–3236.
- [53] Lee Jones, Greta Grip, Boris Kourtoukov, Varvara Guljajeva, Mar Canet Sola, and Sara Nabil. 2024. Knitting Interactive Spaces: Fabricating Data Physicalizations of Local Community Visitors with Circular Knitting Machines. In *Proceedings of the Eighteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–14.
- [54] Lee Jones, Sara Nabil, Amanda McLeod, and Audrey Girouard. 2020. Wearable Bits: scaffolding creativity with a prototyping toolkit for wearable e-textiles. In *Proceedings of the Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 165–177.
- [55] Jess Joss, Julie Edwards, Nigel Wright, Alice Horne, Emma Forge, Alastair Laing, Kathie Hardwicke, Megan Lea, Kayla Dugger, Tom Forge, Nicola Powling, Lucy Philpott, David Almon, Igraine Roberts, Tom Morse, Sonia Charbonnier, Rajdeep Singh, Satish Gaur, Sunil Sharma, Dawn Henderson, Marianne Markham, Maxine Pedliham, and Mary-Clare Jerram. 2019. Complete Pottery Techniques: Design, Form, Throw, Decorate and More, with Workshops from Professional Makers. (2019).

- [56] Frédéric Kaplan and Isabella Di Lenardo. 2017. Big data of the past. *Frontiers in Digital Humanities* 4 (2017), 12.
- [57] Maria Karyda, Danielle Wilde, and Mette Gislev Kjærsgaard. 2020. Narrative physicalization: Supporting interactive engagement with personal data. *IEEE Computer Graphics and Applications* 41, 1 (2020), 74–86.
- [58] Kathleen Dustin. 2012. Spiral Eucalyptus Neckpiece (Polymer on Oxidized Sterling Silver). <https://kathleendustin.com/pastwork/spiralEucalNeck.php>. Accessed: 2025-09-12.
- [59] Helen Kennedy and Rosemary Lucy Hill. 2018. The feeling of numbers: Emotions in everyday engagements with data and their visualisation. *Sociology* 52, 4 (2018), 830–848.
- [60] Jee Eun Kim, Haruki Takahashi, Homei Miyashita, Michelle Annett, and Tom Yeh. 2017. Machines as co-designers: A fiction on the future of human-fabrication machine interaction. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. 790–805.
- [61] Jee Eun Kim, Clement Zheng, Haruki Takahashi, Mark D Gross, Daniel Ashbrook, and Tom Yeh. 2018. Compositional 3D printing: expanding & supporting workflows towards continuous fabrication. In *Proceedings of the 2nd Annual ACM Symposium on Computational Fabrication*. 1–10.
- [62] Nam Wook Kim, Hyejin Im, Nathalie Henry Riche, Alicia Wang, Krzysztof Gajos, and Hanspeter Pfister. 2019. Dataselfie: Empowering people to design personalized visuals to represent their data. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–12.
- [63] Nam Wook Kim, Eston Schweickart, Zhicheng Liu, Mira Dontcheva, Wilmot Li, Jovan Popovic, and Hanspeter Pfister. 2016. Data-driven guides: Supporting expressive design for information graphics. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 491–500.
- [64] George Lakoff and Mark Johnson. 2008. *Metaphors we live by*. University of Chicago press.
- [65] Carine Lallemand and Maud Oomen. 2022. The Candy Workshop: Supporting Rich Sensory Modalities in Constructive Data Physicalization. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. 1–7.
- [66] Amanda Lazar, Jessica L Feuston, Caroline Edasis, and Anne Marie Piper. 2018. Making as expression: Informing design with people with complex communication needs through art therapy. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–16.
- [67] David Ledo, Steven Houben, Jo Vermeulen, Nicolai Marquardt, Lora Oehlberg, and Saul Greenberg. 2018. Evaluation strategies for HCI toolkit research. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [68] Bongshin Lee, Rubaiat Habib Kazi, and Greg Smith. 2013. SketchStory: Telling more engaging stories with data through freeform sketching. *IEEE transactions on visualization and computer graphics* 19, 12 (2013), 2416–2425.
- [69] Bongshin Lee, Greg Smith, Nathalie Henry Riche, Amy Karlson, and Sheelagh Cappendale. 2015. SketchInsight: Natural data exploration on interactive whiteboards leveraging pen and touch interaction. In *2015 IEEE Pacific Visualization Symposium (PacificVis)*. IEEE, 199–206.
- [70] Kwangyoung Lee and Hwajung Hong. 2017. Designing for self-tracking of emotion and experience with tangible modality. In *Proceedings of the 2017 Conference on Designing Interactive Systems*. 465–475.
- [71] Danny Leen, Nadya Peek, and Raf Ramakers. 2020. Lamifold: fabricating objects with integrated mechanisms using a laser cutter lamination workflow. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology*. 304–316.
- [72] LES Collection. [n. d.]. Doris Josovitz. <https://lescollection.com/blogs/artists/doris-josovitz>. Accessed: 2025-09-12.
- [73] Jiaji Li, Mingming Li, Junzhe Ji, Deying Pan, Yitao Fan, Kuangqi Zhu, Yue Yang, Zihan Yan, Lingyun Sun, Ye Tao, et al. 2023. All-in-one print: Designing and 3D printing dynamic objects using kinematic mechanism without assembly. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [74] Yi-Na Li, Dong-Jin Li, and Kang Zhang. 2017. The impact of metaphors on information visualization. *Journal of visualization* 20, 3 (2017), 487–504.
- [75] Zhicheng Liu, John Thompson, Alan Wilson, Mira Dontcheva, James Delorey, Sam Grigg, Bernard Kerr, and John Stasko. 2018. Data illustrator: Augmenting vector design tools with lazy data binding for expressive visualization authoring. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [76] Dan Lockton, Delanie Ricketts, Shruti Aditya Chowdhury, and Chang Hee Lee. 2017. Exploring qualitative displays and interfaces. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. 1844–1852.
- [77] Giorgia Lupi. 2017. VIS capstone address data humanism: the revolution will be visualized. In *2017 IEEE conference on visual analytics science and technology (VAST)*. IEEE Computer Society, 1–1.
- [78] Giorgia Lupi and Stefanie Posavec. 2016. *Dear data*. Chronicle books.
- [79] Jennifer McCurdy. 2025. Capturing Movement Within Clay. <https://www.ecodiscipline.com/blog/capturing-movement-within-clay/>. Accessed: 2025-09-12.
- [80] Ilan E Moyer, Samuelle Bourgault, Devon Frost, and Jennifer Jacobs. 2024. Throwing Out Conventions: Reimagining Craft-Centered CNC Tool Design through the Digital Pottery Wheel. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–22.
- [81] Museum of Craft and Design. 2015. Data Clay: Digital Strategies for Parsing the Earth. <https://sfmcd.org/exhibitions/data-clay/>. Exhibition at Museum of Craft and Design, San Francisco; Accessed: 2025-09-12.
- [82] Bettina Nissen and John Bowers. 2015. Data-things: digital fabrication situated within participatory data translation activities. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. 2467–2476.
- [83] Anna Offenwanger, Theophanis Tsandilas, and Fanny Chevalier. 2024. DataGarden: Formalizing Personal Sketches into Structured Visualization Templates. *IEEE Transactions on Visualization and Computer Graphics* (2024).
- [84] Wyatt Olson, Freesoul El Shabazz-Thompson, Melanie Wells, Chuanzhe Xiong, Janey Yee, Julia R Saimo, Ocean Vu, Jonathan Narita, Brock Craft, Timea Tihanyi, et al. 2025. Stills from the Inner Ear Shorts: Collecting and Living with Data. In *Proceedings of the 2025 CHI Conference on Human*

- Factors in Computing Systems*. 1–20.
- [85] Daniel Pahr, Sara Di Bartolomeo, Henry Ehlers, Velitchko Andreev Filipov, Christina Stoiber, Wolfgang Aigner, H-Y Wu, and Renata G Raidou. 2025. NODKANT: Exploring Constructive Network Physicalization. In *Computer Graphics Forum*. Wiley Online Library, e70140.
- [86] Ben Piper, Carlo Ratti, and Hiroshi Ishii. 2002. Illuminating clay: a 3-D tangible interface for landscape analysis. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 355–362.
- [87] Fabio Pittarello and Manuel Semenzato. 2024. Experimenting with Dataphys, a Physicalization Toolkit for Representing Spatio-Temporal Environmental Data. In *Proceedings of the 2024 International Conference on Advanced Visual Interfaces*. 1–9.
- [88] Zachary Pousman, John Stasko, and Michael Mateas. 2007. Casual information visualization: Depictions of data in everyday life. *IEEE transactions on visualization and computer graphics* 13, 6 (2007), 1145–1152.
- [89] Roya Rad and Graham Dove. 2025. Making/Unmaking with Metaphors: Generative Co-design with People Living with Chronic Pain. In *Companion Publication of the 2025 ACM Designing Interactive Systems Conference*. 345–350.
- [90] Radical Craft. 2015. 01.15 Exhibition Opening: Data Clay: Digital Strategies for Parsing the Earth. <https://radical-craft.com/filter/ceramic/01-15-Exhibition-Opening-Data-Clay-Digital-Strategies-for-Parsing-the-Earth>. Page on Radical Craft about the "Data Clay: Digital Strategies for Parsing the Earth" exhibition at the Museum of Craft and Design, San Francisco; Accessed: 2026-02-01.
- [91] Mitchel Resnick, Brad Myers, Kumiyo Nakakoji, Ben Shneiderman, Randy Pausch, Ted Selker, and Mike Eisenberg. 2005. *Design Principles for Tools to Support Creative Thinking*. Technical Report. CMU.
- [92] Jonathan C Roberts, Benjamin Bach, Magdalena Boucher, Fanny Chevalier, Alexandra Diehl, Uta Hinrichs, Samuel Huron, Andy Kirk, Søren Knudsen, Isabel Meirelles, et al. 2022. Reflections and considerations on running creative visualization learning activities. In *2022 IEEE 4th Workshop on Visualization Guidelines in Research, Design, and Education (VisGuides)*. IEEE, 23–30.
- [93] Jonathan C Roberts, Chris Headleand, and Panagiotis D Ritsos. 2015. Sketching designs using the five design-sheet methodology. *IEEE transactions on visualization and computer graphics* 22, 1 (2015), 419–428.
- [94] Joellyn Rock. 2015. Narrative Ceramics: Early Work. <https://joellynrock.com/portfolio/narrative-ceramics/>. Portfolio page showcasing early narrative ceramics by the artist; Accessed: 2025-09-12.
- [95] Kim Sauvé, Miriam Sturdee, and Steven Houben. 2022. Physecology: a conceptual framework to describe data physicalizations in their real-world context. *ACM Transactions on Computer-Human Interaction* 29, 3 (2022), 1–33.
- [96] David Schroeder and Daniel F Keefe. 2015. Visualization-by-sketching: An artist's interface for creating multivariate time-varying data visualizations. *IEEE transactions on visualization and computer graphics* 22, 1 (2015), 877–885.
- [97] Ticha Sethapakdi, Laura Huang, Vivian Hsinyueh Chan, Lung-Pan Cheng, Fernando Fuzinato Dall'Agnol, Mackenzie Leake, and Stefanie Mueller. 2023. Polagons: Designing and fabricating polarized light mosaics with user-defined color-changing behaviors. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [98] Monica Silva Lovato, Jeff Suina, Jared Tso, Alexis Kaminsky, Camila Friedman-Gerlicz, and Leah Buechley. 2025. American Indian Pottery and Clay 3D Printing: An Exploration of Opportunities and Risks in Professional Practice. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–23.
- [99] Lauren Sinclair. 2025. Map Elevation with Play Clay. <https://learn.arcgis.com/en/projects/map-elevation-with-play-clay/>. ArcGIS tutorial; last tested March 20, 2025; Accessed: 2025-09-12.
- [100] Sowmya Somanath, Laura Morrison, Janette Hughes, Ehud Sharlin, and Mario Costa Sousa. 2016. Engaging 'at-risk' students through maker culture activities. In *Proceedings of the TEI'16: Tenth International Conference on Tangible, Embedded, and Embodied Interaction*. 150–158.
- [101] Sowmya Somanath, Ron Wakkary, Omid Ettehadi, Henry Lin, Armi Behzad, Jordan Eshpeter, and Doenja Oogjes. 2022. Exploring the composite intentionality of 3D printers and makers in digital fabrication. *International Journal of Design* 16, 3 (2022), 77–95.
- [102] Anselm Strauss. 1987. Qualitative analysis for social scientists. *Cambridge University* (1987).
- [103] Miriam Sturdee, Soren Knudsen, and Sheelagh Carpendale. 2022. Data-painting: Expressive free-form visualisation. (2022).
- [104] Saiganesh Swaminathan, Conglei Shi, Yvonne Jansen, Pierre Dragicevic, Lora A Oehlberg, and Jean-Daniel Fekete. 2014. Supporting the design and fabrication of physical visualizations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3845–3854.
- [105] Art teacher mcr. 2025. The Art Teacher. <https://theartteacher.net/2021/06/01/ks3-easy-clay-project-textured-vessels/>. Accessed: 2025-09-12.
- [106] Alice Thudt, Uta Hinrichs, Samuel Huron, and Sheelagh Carpendale. 2018. Self-reflection and personal physicalization construction. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–13.
- [107] Iremnur Tokac, Herman Bruyninckx, Corneel Cannaearts, and Andrew Vande Moere. 2019. Material sketching: Towards the digital fabrication of emergent material effects. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–6.
- [108] Iremnur Tokac, Benay Gursos, Herman Bruyninckx, and Andrew Vande Moere. 2022. Craft-inspired digital fabrication: A study of interactive robotic clay carving. In *Proceedings of the 7th Annual ACM Symposium on Computational Fabrication*. 1–14.
- [109] John Joseph Uicker, John J Uicker Jr, Gordon R Pennock, and Joseph E Shigley. 2023. *Theory of machines and mechanisms*. Cambridge University Press.
- [110] Brygg Ullmer, Hiroshi Ishii, and Robert JK Jacob. 2005. Token+ constraint systems for tangible interaction with digital information. *ACM Transactions on Computer-Human Interaction (TOCHI)* 12, 1 (2005), 81–118.
- [111] Rosa Van Koningsbruggen, Luke Haliburton, Beat Rossmly, Ceenu George, Eva Hornecker, and Bart Hengeveld. 2024. Metaphors and Tacit Data: the Role of Metaphors in Data and Physical Data Representations. In *Proceedings of the Eighteenth International Conference on Tangible, Embedded, and*

- Embodied Interaction*. 1–17.
- [112] Jagoda Walny, Samuel Huron, and Sheelagh Carpendale. 2015. An exploratory study of data sketching for visual representation. In *Computer Graphics Forum*, Vol. 34. Wiley Online Library, 231–240.
 - [113] Xiaoyu Wang, Hannah van Iterson, S Sandra Bae, and Rong-Hao Liang. 2025. Reflecting on Solo Dining Behavior with Annotated Data Physicalization. In *Proceedings of the Nineteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–8.
 - [114] Christian Weichel, John Hardy, Jason Alexander, and Hans Gellersen. 2015. ReForm: integrating physical and digital design through bidirectional fabrication. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*. 93–102.
 - [115] ASK Wijayawardena, Ruvan Abeysekera, and MWP Maduranga. 2023. A systematic review of 3d metaphoric information visualization. *International Journal of Modern Education and Computer Science* 15, 1 (2023), 73.
 - [116] Jelle Wijers, Hans Brombacher, and Steven Houben. 2024. DataChest: a Constructive Data Physicalization Toolkit. In *Proceedings of the Eighteenth International Conference on Tangible, Embedded, and Embodied Interaction*. 1–7.
 - [117] Wesley Willett and Samuel Huron. 2016. A constructive classroom exercise for teaching infovis. In *Pedagogy of Data Visualization Workshop at IEEE VIS 2016*.
 - [118] Jacob O Wobbrock. 2012. Seven research contributions in HCI. *Intelligence* 174, 12-13 (2012), 910–950.
 - [119] Haijun Xia, Nathalie Henry Riche, Fanny Chevalier, Bruno De Araujo, and Daniel Wigdor. 2018. DataInk: Direct and creative data-oriented drawing. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. 1–13.
 - [120] Jiayi Eris Zhang, Nicole Sultanum, Anastasia Bezerianos, and Fanny Chevalier. 2020. DataQuilt: Extracting visual elements from images to craft pictorial visualizations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.
 - [121] Jack Zhao and Andrew Vande Moere. 2008. Embodiment in data sculpture: a model of the physical visualization of information. In *Proceedings of the 3rd international conference on Digital Interactive Media in Entertainment and Arts*. 343–350.
 - [122] Ran Zhou, Jianru Ding, Chenfeng Gao, Wanli Qian, Benjamin Erickson, Madeline Balaam, Daniel Leithinger, and Ken Nakagaki. 2025. Shape-Kit: A Design Toolkit for Crafting On-Body Expressive Haptics. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–26.
 - [123] Torre Zuk and Sheelagh Carpendale. 2006. Theoretical analysis of uncertainty visualizations. In *Visualization and data analysis 2006*, Vol. 6060. SPIE, 66–79.
 - [124] Torre Zuk, Lothar Schlesier, Petra Neumann, Mark S Hancock, and Sheelagh Carpendale. 2006. Heuristics for information visualization evaluation. In *Proceedings of the 2006 AVI workshop on BEyond time and errors: novel evaluation methods for information visualization*. 1–6.

A FINAL CREATIONS OF ALL PARTICIPANTS FOR EVERY ITERATION

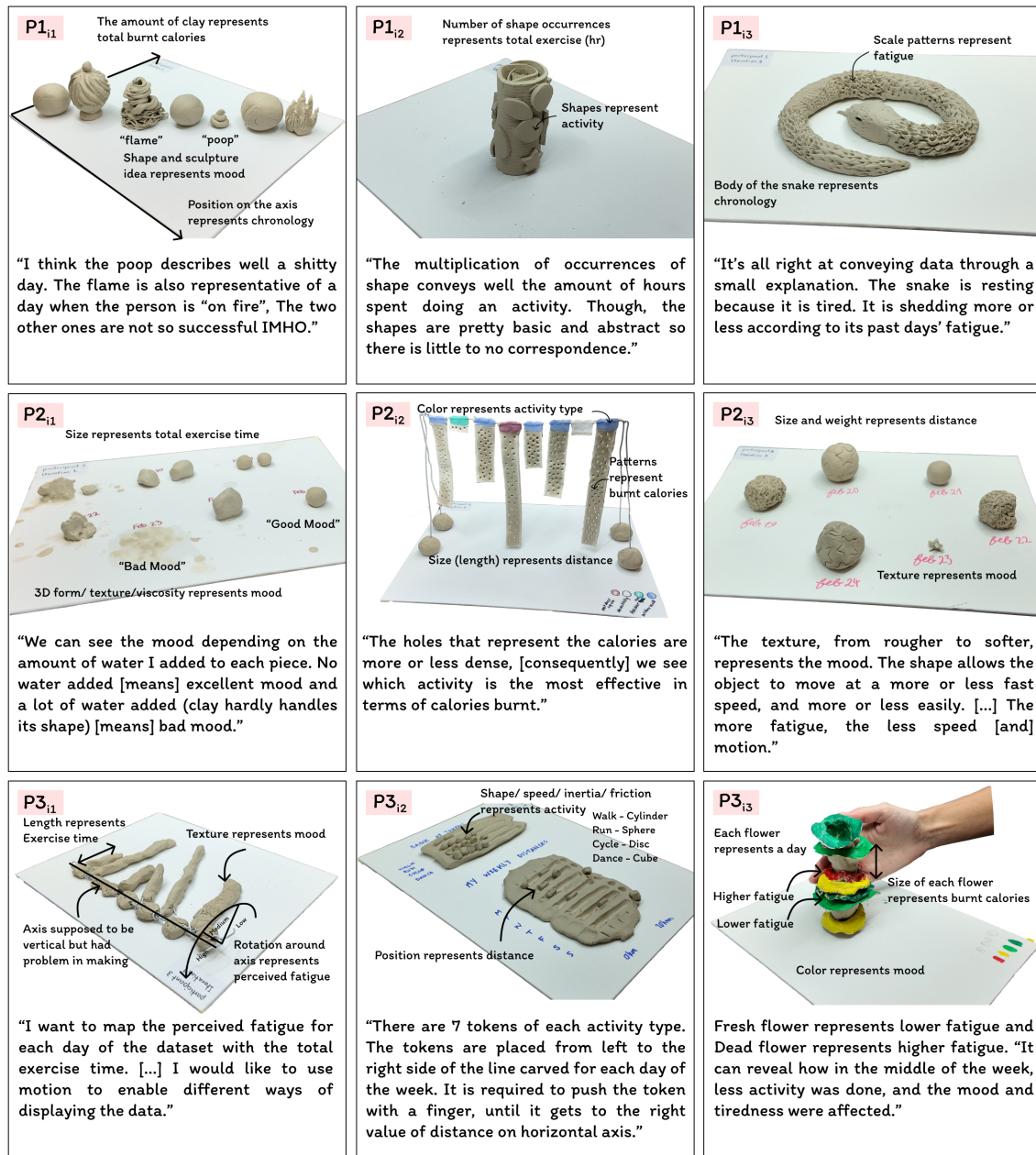


Fig. 12. Data physicalizations created by P1, P2, and P3 in all three iterations and the description of each physicalization.



Fig. 13. Data physicalizations created by P4, P5, and P6 in all three iterations and the description of each physicalization.



Fig. 14. Data physicalizations created by P7, P8, and P9 in all three iterations and the description of each physicalization.