Beyond Screens: Exploring Alternative Forms of Personal Data Visualisation Through Co-Creation

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While sensor technologies have grown and become democratised, so have the collection of data relating to the individual. But the presentation of such data, if it exists, is typically made interpretable to all. In this paper, we present results from the first of a series of co-design workshops, during which we prompted participants to reflect and co-create novel alternative forms of data representations that felt more personal. We found that personal data covers many categories, with no simple rules for what should be private, semi-private or public: in some cases, sharing personal data was described as desirable. This co-creation workshop allowed individuals to explore physical design spaces and produce their own abstractions. This is the first step to understanding such personal metaphors, leading to further exploration of reflexivity and actionability for individuals that goes beyond traditional visualisation practices and media.

Data visualisation, Data physicalisation, Co-design workshop, Personal informatics

1. INTRODUCTION

Portable, ambient, and wearable technologies provide sophisticated tools for harvesting and tracking personal data that incorporate a range of activities. People increasingly use such devices and sensors to collect, analyse and monitor data about themselves, enabling further recording of activities and behaviours within personal and networked connections (Harari et al. 2016). This "*self-tracking*" practice varies in motivation (Lupton 2014) and form, from Citizen Science initiatives to health and wellbeing metrics such as steps taken in a day or calories burned (Chan et al. 2025).

These data are typically visualised on small private screens, expressed as charts and numeric visuals, known as "*micro visualisations*" or "*glanceable visualisations*" (Blascheck et al. 2021). By displaying time spent in states of being or acting, they often provide observations and insights into personal mental and physical situations. The purpose of which is then to inform behaviours and influence habits presented as beneficial, e.g., health and/or wellbeing changes. As such, while other works have focused on "*personal data*" as data about an individual collected by third parties for monetary profits such as ad revenue (Gomez Ortega et al. 2024), in this paper, we explore "*personal data*" as observations or facts about an individual collected by themselves for their own benefits.

The aims of this project are to understand what data participants collect about themselves, the motivations for collecting and reviewing this data, and to understand different levels of privacy and values users assign to collecting data. All of which to inform how to materialise the collected data in a way that is meaningful and purposeful to the original owner-creator. This paper discusses a co-design workshop that explored, through user-shaped perspectives, ideas for pooling personal data sets and producing new ways to consider mapping the data towards interpretive models of display.

The challenge was to think about data in unexpected ways and to make it more physical in form. The approaches engaged in this work invited consideration of how we imagine personal framing of our data in 2D form, taking influence from the works of David McCandless in *Information is Beautiful* (2009), and progressing to questioning possibilities for imagining 3D physicalisation and devices, akin to the LOOP system (Sauvé et al. 2020) or Activity Sculpture (Stusak et al. 2014).

Bakhtiari et al. recently published outcomes from a similar workshop (Bakhtiari et al. 2026), proposing a taxonomy of expressive data physicalisation. Other

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recent works have shown the emergence of data physicalisation tools and methodologies as practical means for users to reflect on their self-tracking practice (Akbaba et al. 2026; Wijers et al. 2024). Our work is distinguishable in that we aim to explore how data owner-creator design and construct visual and physical metaphors for their own private data, and how such artefacts might be displayed publicly.

2. CO-DESIGN OF PERSONAL DATA WORKSHOP

We invited participants to collaborate within a workshop designed to deconstruct the ways in which we are increasingly collecting data about ourselves, and to question how data might benefit us as individuals. Through a co-design workshop, considering how data is used, presented and represented in alternative forms, participants were encouraged to develop a "*user/owner*" perspective to self-tracking.

Co-design is the creative practice of bringing people into the development of products, tools and systems achieved through creative and constructive platforms that reduce perceived barriers and increase inclusion of all alternative ways of design thinking, problem-solving and manifesting solutions (Fleischmann, 2013; Winton, 2021). Co-design invites playful consideration of problems or opportunities with an understanding that when rules are reformed or reimagined through imaginative means, "serious play" can result in serious and purposeful outcomes.

The workshop embraced these ideas to structure a three-stage process of playful and collaborative investigation. Within **stage 1**, participants were challenged to think about the type, structure and value of most of their personal data collection. These concerns commonly stay under-considered or even hidden from users within their personal devices, apps or in the cloud. Hence, while the exercise asked questions to individuals, we encouraged participants to discuss in groups and inspire each other to reflect on what type of personal data they collect about themselves, actively and passively. We also prompted participants to describe data they wished they would collect about themselves and why.

During **stage 2**, participants reflected on the nature of their personal data by rating it across seven quality dimensions, expressed as semantic differential scales. In this stage, participants were also working in groups, placing sticky notes (each representing a type of data identified in stage 1) on a common sheet of paper (Figure 1). This group activity was chosen to foster think-aloud reflections and debate between participants. Individuals could still rate their own items against the mainstream collective thoughts.



Figure 1: *In stage 2, participants discussed and proposed ratings for personal data items elicited in stage 1.*

The seven quality dimensions were chosen and reflected amongst researchers to enquire about the nature of their privacy, the mode of collection, their perceived usefulness, and the agency participants have over the data collection (Lupton 2014):

- **Privacy**: from *private* to *public*;
- **Frequency**: from *occasional* to *frequent*;
- **Automation**: from *manual* to *fully automated*;
- **Accuracy**: from *approximate* to *accurate*;
- **Actionability**: from *informative* to *actionable*;
- **Desirability**: from *I have to* to *I want to*; and
- **Enjoyability**: from *I hate to* to *I love to*.

We designed these first two stages to provoke participants into active awareness and reflection surrounding the data that they collect about themselves, ultimately eliciting the producer, owner and user perspectives required for the final co-creation stage. This also allowed us to capture (a) an overview of the type of data individuals collect, and (b) human-centred perceptions and judgements about these data.

Finally, **stage 3** engaged participants in creative hands-on activities that encouraged the conceptual understanding of frameworks created in the first two stages to explore, physically, new ways of representing personal data. The methods encouraged creative thinking through the physical forming of ideas in off-screen models, producing tangible considerations of how these insights might exist or perform as reconsidered digital interventions or as physical representations that could exist away from screen devices.

This stage took place in two parts. First, participants were given blank canvases, coloured pencils and acrylic geometrical shapes, with instructions to create free-form, two-dimensional representations of any of the data or combination of data identified in the previous stages. For this, participants chose whether to work individually or in pairs. At the start of the creation process, participants were also given a sheet of paper



Figure 2: *In stage 3, participants co-designed, in 2D and then 3D, new ways to represent and display their personal data.*

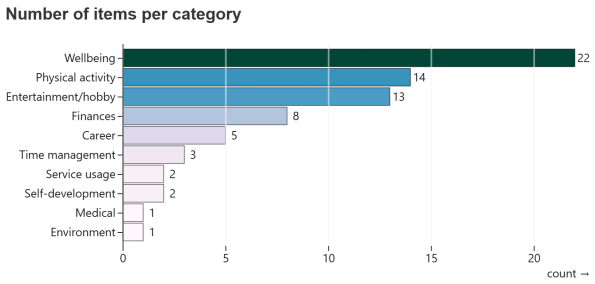

Figure 3: *Number of items per category of personal data.*

instructing them to provide a key to understanding their design and an overview of the creative reflection behind their display. Second, we handed modelling clay to participants, instructing them to replicate the same exercise, this time in three dimensions (Figure 2).

The workshop concluded with a round of discussion amongst participants and organisers. Participants took turns to present their design, and individuals were invited to express their perception of other designs.

This paper leans into the creative participation of user groups to discuss their generation of ideas and the scope for expanding to new concepts for further exploration.

3. WORKSHOP RECRUITMENT

We recruited participants through advertising within our university and invited people to sign up through an online event platform. This was to ensure that as many diverse parties as possible could be recruited based on their own desire to investigate the workshop theme. We outlined that the workshop would involve personal- and collective-focused inquiry utilising creative practices.

More than 20 people signed up to take part in the workshop, with 11 turning up at the event. All participants received an Information Sheet documenting processes and were asked to sign consent forms to participate. We randomly split participants into two groups to make discussions less intimidating, and each group had one facilitator guiding the co-creation process (Visser et al. 2005). Participants did not receive rewards for taking part, although refreshments were provided throughout the workshop. In total, the workshop ran for 2 hours.

We did not gather demographic information about our participants, beyond confirming that all participants were of legal age to give consent and in full capacity to complete the workshop activities. This was to (a) minimise data collection as per data protection regulations, (b) lower barriers to participation for marginalised participants, and (c) reflect co-design practice and treat participants as "*experts of their experience*" (Visser et al. 2005). However, our recruitment strategy favoured a student community, typically in their 20s, which reveals limitations that we discuss below.

Ethical approval for this study was granted by our institution's ethics committee, covering recruitment techniques, methodological approach, and data collection. Generative AI (Grammarly) was used in the writing process for proofreading. All text was reviewed by the authors for correctness and appropriateness.

4. COLLABORATIVE DATA CONSTRUCTION

In this section, we present and discuss the information collected in stages 1 and 2 of our workshop. We take initial steps towards a reflexive approach to summarising and interpreting the themes extracted from these stages (Rigby and Iacovides 2026).

As authors/researchers, our collective interests are wide but contained within HCI. We bring expertise in human-centred design, wearable technologies and data visualisation. With the aim of our workshop, we also recognise ourselves as user-owners of our own personal data, with expectations regarding the types of data we consider personal and our views on privacy, actionability, accuracy, etc. Thus, our constructive analysis is not only shaped by participants' accounts but also reflects on hypotheses we built before and after the workshop.

4.1. What type of data do participants collect about themselves?

As shown in Figure 1, participants wrote free-form descriptions of the data they collect about themselves on sticky notes. We coded emerging themes and present them in Table 1 and Figure 3.

The most frequent category was **wellbeing**, especially mobile *screen time* recorded by the OS or dedicated apps. Other wellbeing data included *sleep* (cycles or duration) and, less often, *diet*.

The second most frequent category, also health-related, was **physical activity**. Contrary to expectations that

Categories	Sub-categories
Wellbeing	screen time; sleep; diet
Physical activity	workouts; steps; calories
Entertainment/hobby	music; movies; games; collections; photos
Finances	expenses
Career	job applications; education
Time management	events; tasks
Service usage	energy; data
Self-development	language learning
Medical	heart rate
Environment	air quality

Table 1: *Categories of personal data collected by our participants.*

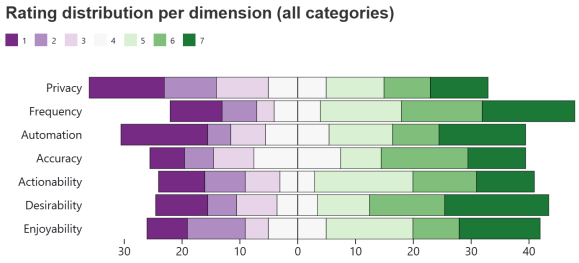

Figure 4: *Distribution of ratings per quality dimension.*

steps would dominate, *workout routine* was mentioned equally often. *Calories spent*, despite the spread of wearable fitness trackers, appeared only twice.

Participants also tracked **entertainment** and **hobbies**: *music* listened to, *games* played (often via streaming platforms), and *movies* watched (usually logged manually). Two participants tracked collectable card *collections* (such as Pokemon cards), and one detailed tracking their *photography* hobby.

Other common categories were **finances** (i.e., *expenses*) and **career**, including *job* applications and *education* tasks such as college applications and study time.

These categories largely matched our expectations, though financial expenses were more prominent than anticipated. With the strong focus on wellbeing, these themes highlight emerging concerns in our participant pool. We had not predicted items such as service usage and environment, but these align with concrete concerns for the participants' generation.

4.2. How private is personal data?

Figure 4 shows the distribution of ratings across our seven quality dimensions. Generally speaking, most ratings were shifted towards personal data being collected more frequently, automatically and accurately, while being more actionable, desired and enjoyable.

The ratings on privacy showed more balance. This itself demonstrates a noteworthy finding: **personal data is not necessarily seen as private**. Participant 5 laid out interesting remarks in that regard: "[making my data public] *is okay if it is anonymous, it can help others*". It highlights the stance that personal data can sometimes be seen as beneficial for the public good; hence, there can be willingness to make it public under certain conditions.

However, data related to wellbeing and finances were largely categorised as private (Figure 5). This confirmed the initial postulate of our research, that **there are data items that user-owners want to gather and consume privately**.

Meanwhile, physical activity tends to be more balanced, and entertainment data is seen as mostly public. It showcases the social bonds users build around personal data, as described by Lupton (2014). Several participants explained this choice in two ways: hobbies are meant to be shared to build relationships and common experiences; meanwhile, physical exercises and sports are sometimes shared competitively, to motivate oneself and others to match or outperform each other. Generally speaking, **collecting and displaying personal data is also a social activity**.

4.3. How do quality dimensions coincide?

Generally, we only observed moderate concordance between a few dimension pairs. Privacy and desirability showed a Kendall's τ of 0.28, indicating that participants considered data they *have to* collect as more private. Other noteworthy pairs were enjoyability and accuracy, frequency and automation, automation and accuracy, and frequency and actionability (all with $\tau = 0.25$). However, these don't consider the categories of items, and our methodological design may inflate single-rater halo effects.

With Figure 5, we can inspect how quality dimensions interact in the top 5 categories of data items.

There is a positive trend between automation and frequency, suggesting that the more automated the collection method is, the more frequently data is collected. Physical activity is an exception: it tends to be collected frequently but in a less automated fashion.

One assumption might be that data collected by automated means, such as mobile devices, wearables, or online services, would be seen as more accurate. However, we did not observe a strong link between the two dimensions. With finances, we observe the opposite: data is gathered manually in most cases, which turns out to reassure participants regarding its accuracy.

Desirability and enjoyability were also qualities we expected to see strong connections between. Yet, there is a weak positive correlation between the two. Upon closer inspection of the data, we noticed that the biggest



Figure 5: *Rating counts for the top categories of personal data.*

category of data, screen time, was slightly high on the desirability scale (meaning participants *want* to collect it), while strongly low on the enjoyability scale (meaning participants *hate* collecting it). This shows a type of data that participants are not enthusiastic to gather, but from which they recognise the benefits of reflecting upon. It also confirms our intuition that both dimensions should be considered separately.

Finally, actionability – whether participants perceived the data item as something they can act upon – allows us to see two forms of personal data. We initially targeted personal data that user-owners gather to reflect on and consume to improve themselves, and we found those in categories like wellbeing, physical activity and finances, which were rated as actionable. However, entertainment tends to be less actionable while being highly desired and enjoyed. Thus, we should not underestimate the value of these types of data, sometimes collected for pleasure only, and perhaps worth considering more when designing displays.

4.4. Participant pool and methodology limitations

Comparing our early hypotheses and the items returned by participants, we noticed types of data which were absent, revealing methodological limitations.

While health was a prevalent theme (with wellbeing and physical activity), actual medical data was absent from the items relayed by our participants. Part of our initial intent for this workshop concerned the relationship user-owners form with intimate data, such as tracking health conditions (Ramesh et al. 2026). We believe this to be the result of two methodological flaws: our workshop setting (a) attracted younger participants less likely to have chronic conditions for which they would collect data and (b) did not provide a space sufficiently safe for participants to feel comfortable discussing such intimate aspects of their lives.

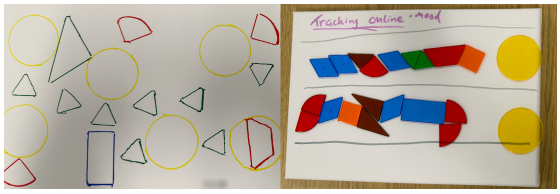

Figure 6: *Example of abstract 2D visualisation designs produced by participants.*

We also anticipated more diversity of items, and more generally, wider description differences. We postulate again a possible limitation posed by our pool of participants and the methodology used: putting participants in groups did foster meaningful conversation and initially a breadth of themes, but also created influence and quickly narrowed exploration. Coupled with the low number of participants, the results we gathered from these first stages must be seen as only initial findings within a larger research.

5. NEW DESIGNS FOR PERSONAL DATA

This section presents the designs created by participants in the third stage of our workshop. While initially remaining close to traditional data visualisation designs, we found that translating the exercise in a 3D design space allowed participants to express newer, more personal forms of design.

5.1. 2D Designs

In 2D, participants generated five designs in total (some participants worked in pairs). Two designs were generally close to traditional dashboarding concepts: either showing sleep, expenses and calories as a scatter plot, bar chart or radar plot, respectively; or imagining the consumption of entertainment (games, movies, music) as a report with progress information.

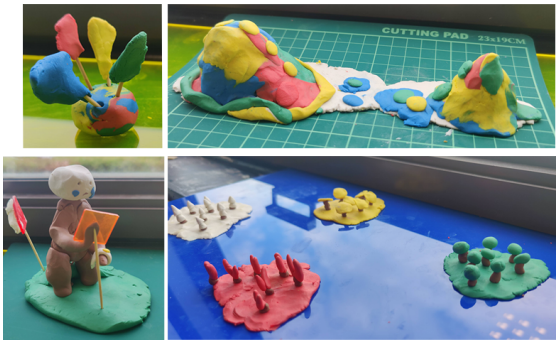

Figure 7: *Examples of 3D visualisation designs created by participants using modelling clay.*

A third design adopted a more typical meaning attached to "*personal data*" and proposed a display separating data that must remain private vs. data that is shared to improve services.

The final two designs (Figure 6) conceptualised novel design approaches for personal data visualisations. On the left, two participants considered a complete persona and the data attached to it as a complex network of information. From there, they formed abstract shapes to display "**clusters of data**", their interconnectedness, currency and threats. This is reminiscent of motif techniques, often used to simplify the display of patterns in large networks (Dunne and Shneiderman 2013, Wulms et al. 2026). The second design, on the right, also abstracted data as simple shapes and composed these shapes to form a "**mosaic of emotions**" which could be leveraged to track online mood.

5.2. 3D Designs

Using modelling clay as the main medium, we then instructed participants to continue their creative process and imagine novel 3D representations for their personal data. Nine designs were proposed, and we found three strategies: *geometry*, *personification* and *landscaping*.

Geometry follows traditional data visualisation principles. One design proposed a "**mood ball**" (Figure 7, top left), where each colour represents a mood and the importance of a colour in the marbled surface indicates a mood's propensity. Another design suggested a "**pyramid of fitness**", where the pyramid incrementally builds throughout the day as fitness and wellbeing goals are achieved. A final design proposed a 3D circular bar chart tracking achievements across activities.

Personification designs directly modelled a humanoid meant to represent the person within its data environment. One design imagined a pair of statues, one representing an individual and the other depicting AI. The height difference between the two symbolises the usage of AI tools. The other personification design envisioned a person with surrounding objects (Figure 7, bottom left): a smartwatch to indicate personal goals, a flag to symbolise achievements or a mobile phone to explore social circles. Its face is also used to display emotions.

The final angle used landscape and nature analogies to symbolise personal data. First, the "**social landscape**" (Figure 7, top right) envisioned online media consumption and interactions as an evolving landscape, where topography features activity and geology displays sentiment. The other two designs both targeted growth and symbolised it with trees. In one case, a central tree figure would grow as your learning in several skills grew. In a second design, data was again clustered in smaller islands (Figure 7, bottom right), each with different forests. As data grows, so do the forests and islands.

While earlier research has produced data mapping classifications (Bakhtiari et al. 2026), this shows strategies for how participants situate themselves with their personal data, and which metaphors are desirable when considering potential public displays.

6. DISCUSSION AND CONCLUSION

This co-design workshop was the first step in ongoing research aiming to understand how individuals produce and consume data about themselves. While we acknowledge limitations in our experimental design, it provided initial results that will support the scoping of future research directions.

What is *personal* data remains an open question. While we tried to form an initial set of categories, we also need to realise that each individual has their own affinity to what is worth recording, exploring and sharing. We, however, found some evidence that most personal data, to some degree, has shareable value and can play a role in the social bonds we form, at multiple levels of closeness. In that regard, future workshops need to consider both the experience of participants and the setting within which they feel comfortable disclosing personal and intimate topics.

The co-design exercises for novel visualisation techniques also revealed that our workshop structure was successful. Our staged methodology gave participants time to reflect on their personal data, and the tools we provided for design revealed strategies that created meaningful visual metaphors. While it may typically be labelled as bad practice by data visualisation research, in the eyes of the user-owner these metaphors are valid and reflective. Hence, our future research direction aims to further understand these metaphors and explore the extent to which they permit reflexivity and actionability for user-owners: by themselves, within their close circles, and even when displayed publicly.

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