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Reciportrait: a Data Humanism Approach for Collaborative Sensemaking of Personal Data

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Figure 1: Participants making sense of the personalized visualizations both individually and collaboratively, by using Reciportrait. The toolkit's name is inspired by "reciprocal portrait drawing," a collaborative practice where two artists create portraits of each other, influenced by their mutual movements and emotions.

Abstract

Data Humanism has gained prominence in personal visualization and Personal Informatics, advocating for a subjective and slow approach to engage with personal data. Collaborative sensemaking has great potential for aiding the understanding of personal data, yet little is known about addressing requirements of structure and coordination when integrating Data Humanism into collaborative visualization. In this paper, we propose design principles for creating both subjective and effective collaborative visualizations, while coordinating the slow sensemaking process and promoting data awareness and communication. We operationalize these principles into a personal visualization toolkit, which we evaluate with an observational study involving 16 university students (8 pairs) analyzing each other's screen-time data. Our findings reveal that implementing the proposed design principles: (1) facilitated data comparison from shared subjective perspectives, (2) helped coordinate sensemaking while allowing time for understanding personal data, and (3) helped the contextualization of data patterns, in turn aiding self-reflection.

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CCS Concepts

• **Human-centered computing → Empirical studies in visualization**; **Empirical studies in HCI**.

Keywords

data visualization, Data Humanism, collaborative sensemaking

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1 Introduction

In the field of data visualization, Data Humanism has emerged as an approach that emphasizes gaining personalized and meaningful experiences from data. Rather than merely simplifying and quantifying data, Data Humanism encourages exploring data in connection with broader contexts—such as stories, people, and behaviors—to derive a deeper understanding of the data [9, 15, 40]. This approach has gained traction in personal visualization and Personal Informatics (PI), in which the potential of visual and tangible representations of personal data to facilitate self-reflection on personal behaviour and experiences have been investigated [12, 37, 67]. Existing personal data visualizations that apply Data Humanism have involved digital platforms [e.g., 73], or analog approaches such as sketching [e.g., 57] and the use of tangible tokens [e.g., 27]. These applications of Data Humanism emphasis understanding personal data through imperfect and personalized data representations for subjective data analysis and interpretation [32], and a slow and thoughtful sensemaking process for in-depth engagement and comprehension of personal data [39].

While Data Humanism advocates for a subjective and deliberate exploration of personal data, recent work by Friske et al. [18] has highlighted how collaboration introduces subjective analysis and interpretation of personal data, through social communication and data comparison. This idea of collaborative sensemaking has long been recognized as beneficial in facilitating understanding and reflection on data [28], and these benefits also hold in the context of personal data [5, 11, 55]. Encouraging collaboration on personal data provides alternative perspectives for comparison, which can reveal previously invisible data patterns during individual analysis [11, 52]. The social communication can engage individuals in explaining and interpreting personal experiences [55] by integrating interpersonal perspectives, especially for fostering self-reflection. This process can reveal the interconnected self—a self-image that is linked to broader social contexts—which is essential for developing a comprehensive understanding of oneself. Yet, with the exception of a few recent works [16, 18, 52], very few personal visualization tools have explored to facilitate collaborative sensemaking.

However, integrating Data Humanism into collaborative personal visualization poses challenges of conflicting requirements. First, collaborative visualization requires a common structure for both organising and visualizing personal data among all individuals to facilitate inter-personal comparison and shared understanding [28], while Data Humanism requires personalised representations that might be distinct for each individual for affording subjective analysis and interpretation [32]. Second, Data Humanism encourages engaging users at a slow pace that allows the individual creating or viewing the visualizations to immerse themselves in the data and reflect on their observations and insights—what Lupi [39] calls "personal engagement". The pace at which different individuals engage with the data or visualizations may thus be different. However, collaborative personal visualization requires coordination between creators [11, 17]. This creates conflicting requirements as a pace that works for one collaborator may not work for another. To investigate these challenges, we ask: **How can the process of personal visualization design balance the need of Data Humanism approach and collaborative sensemaking for facilitating sensemaking of personal data?**

To address this research question, we propose four design principles based on prior research on Data Humanism, personal visualization, and collaborative sensemaking. These principles ensure a subjective yet structured frame for enabling collaborative visualization while aiding a Data Humanism approach. They also enable coordination of deliberate slowness in sensemaking while fostering awareness and communication around the personal data. We then introduce a collaborative personal visualization toolkit, Reciportrait, by applying the proposed four design principles. To evaluate the proposed design principles and toolkit, we conduct an observational study of 16 university students in 8 pairs, who used the toolkit and made sense of each other's data. We use smartphone screen time data as the context for the study as a representation of individual and personal behaviour. We analyse the created visualizations, the collaborative sensemaking process, and the insights derived from their joint efforts.

Our findings reveal three key insights. First, participants create diverse collaborative visualizations by modifying elements such as marks, channels, and data types, enabling comparisons from both shared and personalized perspectives. Second, the toolkit particularly supports slowness during the externalization and discussion of visualization solutions, the sketching of proposed solutions, and the comparison of data patterns after overlapping sketched visualizations. Third, the participants engage in iterative sensemaking processes and activities that helped them generate four types of insights: data insights, behavioral patterns, contextual factors between experiences, and self-recognition. We discuss the role of the design principles in facilitating the development of collaborative visualizations, the coordination of the sensemaking process, and the insights that emerge as outcomes of this process. In summary, our work makes the following contributions:

(1) We propose four design principles to facilitate collaborative sensemaking of personal data, balancing the needs of both Data Humanism and collaborative sensemaking.
(2) We introduce the design of Reciportrait, a collaborative personal visualization toolkit that operationalizes the proposed design principles.
(3) Through a user study, we evaluate the design of Reciportrait, and examine how the toolkit—and in turn the design principles—facilitates collaborative visualization and sensemaking, as well as insights about personal data and behavior.

2 Related Work

Our work aims to address the challenge of balancing the need of Data Humanism and collaborative sensemaking in facilitating understanding and reflection on personal data. In this section, we provide an overview of related work on Data Humanism, collaborative sensemaking, and personal visualization to explain the challenge in detail.

2.1 Data Humanism and Personal Data

Data Humanism is an approach first suggested by Lupi [39], who argued that making sense of data requires considering the underlying contexts and offering a subjective perspective for data collection, analysis, visualization, particularly when the data pertains to people. Data Humanism advocates gaining personalized and meaningful experiences from data by exploring its organization and connecting it to stories, knowledge, people, and behaviours, instead of simplifying and quantifying it [9, 15, 39]. This approach has gained traction in personal visualization and personal informatics, which have explored how visual and tangible representations of personal data can aid in understanding one's behavior, thereby facilitating self-reflection and behavior change [18, 32]. Within these fields, Data Humanism approach has been used for enhancing understanding of data from two perspectives: data representation and the sensemaking process. Each of these perspectives can be described as follows:

(1) **Data Representation.** Data Humanism advocates complex and personalized representations for enhancing the understanding of data. Here, the "complex" refers to creating visualizations that go beyond standard forms, allowing the creation of metaphors that add new and unexpected insights to the main narrative in the data [32, 39]. Personalization involves providing structures that allow users to define and organize data according to their subjective conceptual boundaries, revealing insights that are directly relevant to their experiences [9, 10]. Additionally, incorporating context during the collection, analysis, and display of data is essential, as the underlying contexts contribute to constructing personal narratives [18, 68]. This approach to data representation design aligns with existing data visualization literature on expressiveness, which advocates for visualizations that represent multifaceted and nuanced narratives, rather than simply focusing on quick and simple information delivery [73].
(2) **Sensemaking process.** Data Humanism acknowledges that making sense of and gaining a deep understanding of data requires deeper engagement. As Lupi [39] states, *"creating new points of view or uncovering something new typically cannot happen at a mere glance; this process of revelation often needs and requires an in-depth investigation of the context."* Lupi also advocates for embracing the imperfection and approximation of data. Engaging in the process of researching, translating, and envisioning data representations can help people not only understand data but also connect to the stories of themselves and others [41]. This approach also aligns with the concept of slow technology [24], which emphasizes that slow interaction can help individuals unconsciously amplify the presence of confronted details and provide more cognitive space for moments of reflection. This "slowness" does not imply inefficiency, but rather denotes a deliberate pace of interaction that allows for deeper engagement and thoughtful interpretation of information.

Recent research in personal visualization has explored the integration of Data Humanism approaches to enhance the understanding of personal data for individuals. First, a set of studies have investigated sketch-based visualization authoring tools, which leverage the free-form and intuitive nature of sketching for people to design personalized visualizations [41, 57, 66]. Second, constructive visualization offers non-actuated token-based physical data representations for people to construct and manipulate data representations [26, 27, 63]. Third, there are digital visualization tools designed to help individuals develop personalized and expressive visualizations that convey qualitative personal contexts and information [32, 73].

Previous Data Humanism work advocates for designing subjective data representations and slow sensemaking processes to deepen the understanding of personal data. In this paper, we explore how Data Humanism approaches can be integrated into collaborative personal visualization design.

2.2 Collaborative sensemaking on personal data

Collaborative sensemaking encompasses interactions between individuals and data, during which they collectively search for, externalize, and analyze relevant information, develop shared representations, and generate and evaluate hypotheses [28, 70]. In personal data visualization and personal informatics, there exists a consistent theme underscoring the need for incorporating collaborative sensemaking of personal data [5, 11, 55, 74]. Benefiting from the social interaction around personal data, collaborative sensemaking can help individuals construct the interconnected self—a key facet of self-image often neglected in personal informatics but necessary for comprehensive understanding of oneself [55].

To support collaborative sensemaking of personal data, prior work in collaborative sensemaking, personal visualization and PI has highlighted requirements from two perspectives: data representation and the sensemaking process.

(1) **Data Representation.** Shared representations—in the context of this paper, visualizations that are created and interpreted together by individuals working together—serve as the key instrument to present relevant information. A shared representation requires effective structure to illustrate data in a format that is not only understandable to one individual but also relatable and accessible to others [53, 70]. When presenting personal data, this shared representation should facilitate comparison of both the data as well as personal behaviors [16, 52]. Such a comparison helps individuals identify subtle differences in their behaviors and experiences that might be overlooked or remain invisible in individual analysis, thus triggering further reflection upon themselves.
(2) **Sensemaking process.** Within the sensemaking process, careful coordination is required to facilitate communication among individuals to maintain awareness of other's progress, outcomes, and perspectives [3, 44]. The collaborative communication around personal data, such as data explanation, inquiry and interpretation, can help integrate one's subjective perspective with alternative viewpoints from others [18]. This enriches data analysis and supports the recall and reconstruction of personal narratives. To balance individual and shared perspectives, providing individual and shared workspaces is an effective strategy that enhances communication while minimizing disruptions to personal work [2, 25, 59]. To foster deeper levels of reflection, such as dialogic and transformative reflection that reveals relationships between past experiences and alter users' mental schemas, further guidance is needed to coordinate subjective

and interpersonal perspectives [17], thus finding the "right sort of experiences" that is particularly reflective [11, 64].

These previous work has identified the needs to structure collaborative visualizations and coordinate the process of collaborative sensemaking of personal data, which conflict with the core requirements of Data Humanism. Yet, only a few personal visualization toolkits have explored facilitating collaborative sensemaking of personal data [5, 11]. The most common approaches comprise personal visualization tools that offer standard visualizations and design the interaction with data around comparison [16, 52]. For instance, Puussaar et al. [52] designed a collaborative personal informatics tool for co-workers to compare and annotate each other's data. One notable direction is Participatory data physicalization [22, 48, 49, 62], which is "a physical visualization that allows for a co-located audience to physically participate in the creation of the visualization by directly encoding their data while following predetermined rules". For example, Sauvé et al. [62] engaged individuals in creating a personal data physicalization using colorful wooden tokens to represent their food consumption, allowing them to reflect on their habits within the contexts of multiple cohorts. A recent work by Friske et al. [18] involves two participants collaboratively knitting and interpreting personal data representations. The personalized nature of the knitting representations encouraged reciprocal inquiry and interpretation of each other's data and personal narratives, fostering self-reflection.

In summary, current personal visualization design encounters challenges in balancing the personal and subjective focus of Data Humanism with the coordination required in collaborative sensemaking. These challenges include: 1) providing structure for developing shared data representations in complex and subjective formats while effectively facilitating comparison between collaborators, and 2) coordinating the sensemaking process to allow for deliberate, slow-paced investigation of data while ensuring individuals remain aware of and support others' perspectives and outcomes to achieve meaningful reflection.

3 Toolkit Design

We introduce four design principles developed to address the research gap, and the collaborative visualization toolkit, Reciportrait, where we apply these principles.

3.1 Design Principles

We employed a structured, multi-phase process to propose the design principles. First, we reviewed literature on Data Humanism [9, 10, 18, 24, 32, 39, 41–43, 68] and collaborative sensemaking of personal data [11, 16, 18, 25, 28, 44, 52, 55] to identify key requirements for effective data sensemaking. From this review, we synthesized essential requirements from two perspectives: data representation and sensemaking processes. Next, we analyzed existing research on personal data visualization [6, 12, 14, 22, 26, 32, 41, 48, 49, 57, 61–63, 66] to evaluate how current approaches align with or deviate from these requirements, identifying both strengths to build upon and tensions to address. Finally, we integrated these insights to formulate a set of design principles that balance the subjective, slow-paced focus of Data Humanism with the coordination required for collaborative sensemaking.

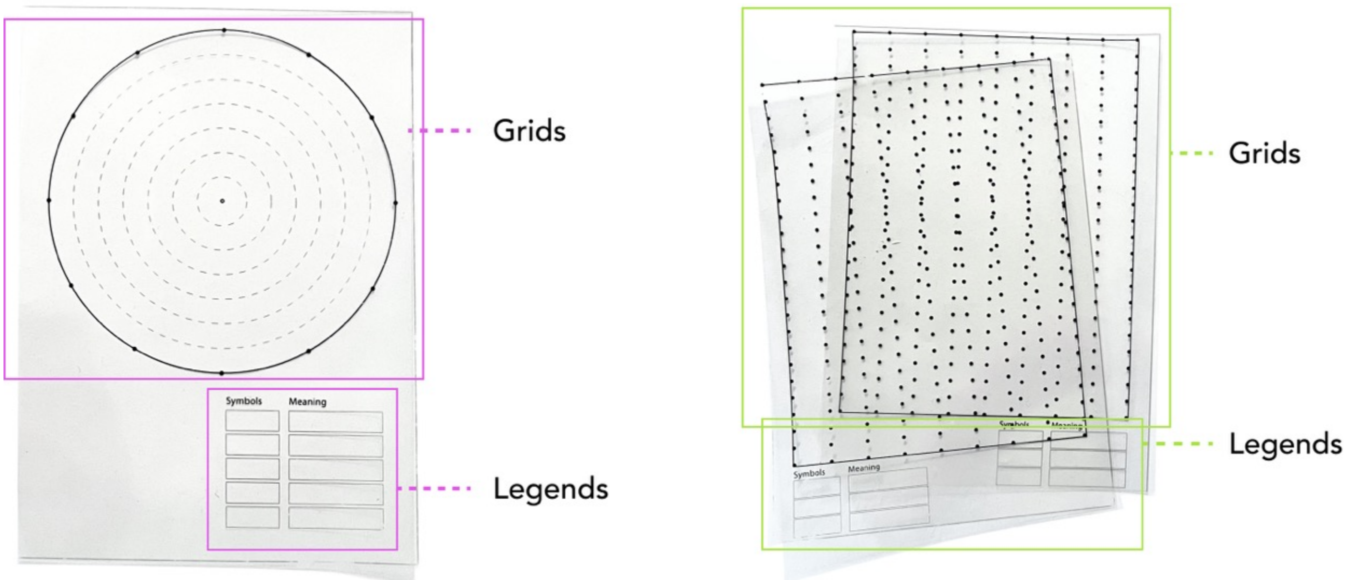
Specifically, we propose four design principles: **DP1** (Enable Personalized Visual Encoding Methods) and **DP2** (Guided Visualization Authoring) to facilitate creating subjective and imperfect collaborative visualizations while providing a structure for effectively illustrating data patterns among collaborators; and **DP3** (Support for Deliberate Slow Interaction) and **DP4** (Collaborative and Individual Working Spaces)to ensure a thoughtful sensemaking approach while helping maintain awareness of and support for each other's progress and outcomes, thereby fostering reflection.

DP1: **Enable Personalized Visual Encoding** calls for supporting personalized visual encoding methods, allowing users to author data representations that reflect their subjective perspectives and experiences. In line with Data Humanism approaches, data is regarded as ontological units rather than fixed objects [42]. Understanding data requires a localized resolution, where individuals segment it based on personal boundaries and connect it to broader organizational structures while incorporating personal contexts related to the captured data [42, 43]. Engaging individuals in encoding data and authoring visual representations is an effective approach for analyzing and representing data that meet their personal interests and information needs [57, 66], while also connecting data to life activities and broader contexts [18, 32].

DP2: **Support Guided Visualization Authoring** calls for providing structure to assist users in creating visualizations. Designing a (personal) visualization involves a complex process, including defining design goals, processing data, visual encoding data, and presenting visualizations [10, 57]. Offering structure is essential to guide users in developing effective visualizations that clearly illustrate data patterns while ensuring the system's usability [61]. When creating collaborative visualizations for enhancing sensemaking of personal data within a group, additional structure focused on guiding comparisons is necessary, which leverages others' data in revealing behavioural patterns and anchoring self-reflection [16, 52].

DP3: **Afford Deliberate Slow Interaction** calls for deliberate slow interaction to facilitate deeper engagement and thoughtful interpretation of data. It encourages mindfulness, helping individuals to unconsciously focus on and amplify details and providing ample cognitive space for reflective moments [24]. This slow-paced interaction does not imply inefficient mechanisms that merely extend the time spent, but rather involves a carefully controlled pace that allows users to reflect on how and why things work. It is helpful for guiding the reflection based on personal data [11]. Bentvelzen et al. [6] highlight that offering instructions is helpful for preventing aimless data exploration, and save more cognitive space necessary to foster reflection.

DP4: **Offer Collaborative and Individual Working Spaces** calls for shared and individual working spaces to keep collaborators informed about each other's data sensemaking processes and outcomes while minimizing disruptions to individual reflection. Deep self-reflection on personal data



(a) An example of circular visualization grid

(b) Two overlapped rectangular visualization grids

Figure 2: The transparent visualization grids

requires not only collaborative efforts but also careful coordination between individual and joint analysis, questioning, and relating personal experiences [17]. On one hand, facilitating data-related communication—such as inquiry, explanation, and interpretation—is crucial for uncovering the context behind the data [14] and engaging in a reciprocal process of data analysis to foster reflection [18]. On the other hand, it is essential for individuals to engage deeply with their own data, recalling past experiences and generating and evaluating hypotheses [12]. A combination of shared and individual working spaces is required: the shared space facilitates timely conversations and keeps collaborators informed about each other's progress, while the individual space allows users to focus on their personal analysis without interruptions [44].

3.2 Implementation

We apply these design principles in a collaborative personal visualization toolkit, Reciportrait. It consists of three components blending the design principles: visualization grids, visualization example cards, and a data reflection canvas.

3.2.1 Visualization grids. They provide users with templates that balance freedom and guidance in personalizing data visualizations (**DP1, DP2**). They consist of two elements: grids and legends (see Figure 2b). We chose two types of grids—circular (Figure 2a) and rectangular (Figure 2b), which together show several visualizations based on polar coordinate systems (e.g. pie charts, radar charts, chord diagrams, etc.) and cartesian coordinates (e.g., bar charts, line charts, scatterplots, histograms, etc.). The legends consist of two columns of boxes, prompting users to define and personalize the symbols and their meanings.

The visualization grids are printed on transparent paper, enabling a manual, sketch-based interaction with data (**DP3**) which can foster reasoning [21] and externalizing thoughts [71]. Each user is provided with identical visualization grids, with legends positioned at the bottom left and bottom right corners, respectively (**DP4**). The transparency of the grids and the deliberate placement of the legend areas allow for easy overlapping, facilitating the comparison of data patterns (see Figure 2b).

3.2.2 Example cards. The four example cards are designed to offer diverse solutions for developing effective visualizations for comparison (**DP2**). The back of each card includes an inspirational question that indicates insights into the behaviors and experiences addressed by the corresponding visualization solutions. The front side features an example visualization with a brief description at the top. The example cards use screen time data as their context, which will be explained in more detail in the method section 4.1. To highlight comparisons between two users, the example visualizations use two distinct colors, green and purple. Detailed descriptions of each card are provided below. The example visualizations offer four distinct perspectives on illustrating data patterns—daily fluctuations(card1), variations in categorical activities(card2), chronological usage sequences(card3), and behavior time summaries(card4)—proven effective for analyzing and reflecting on behavior [34, 56, 67].

3.2.3 Data reflection canvas. The data reflection canvas provides individual annotation areas to support slow sketching (**DP3**) and a shared working space to structure comparison and discussion (**DP4**), enabling individual and collaborative reflection on both data and personal experiences. The data reflection canvas (Fig. 4), consists of two elements: shared data comparison spaces and individual annotation spaces. The shared data comparison space features three

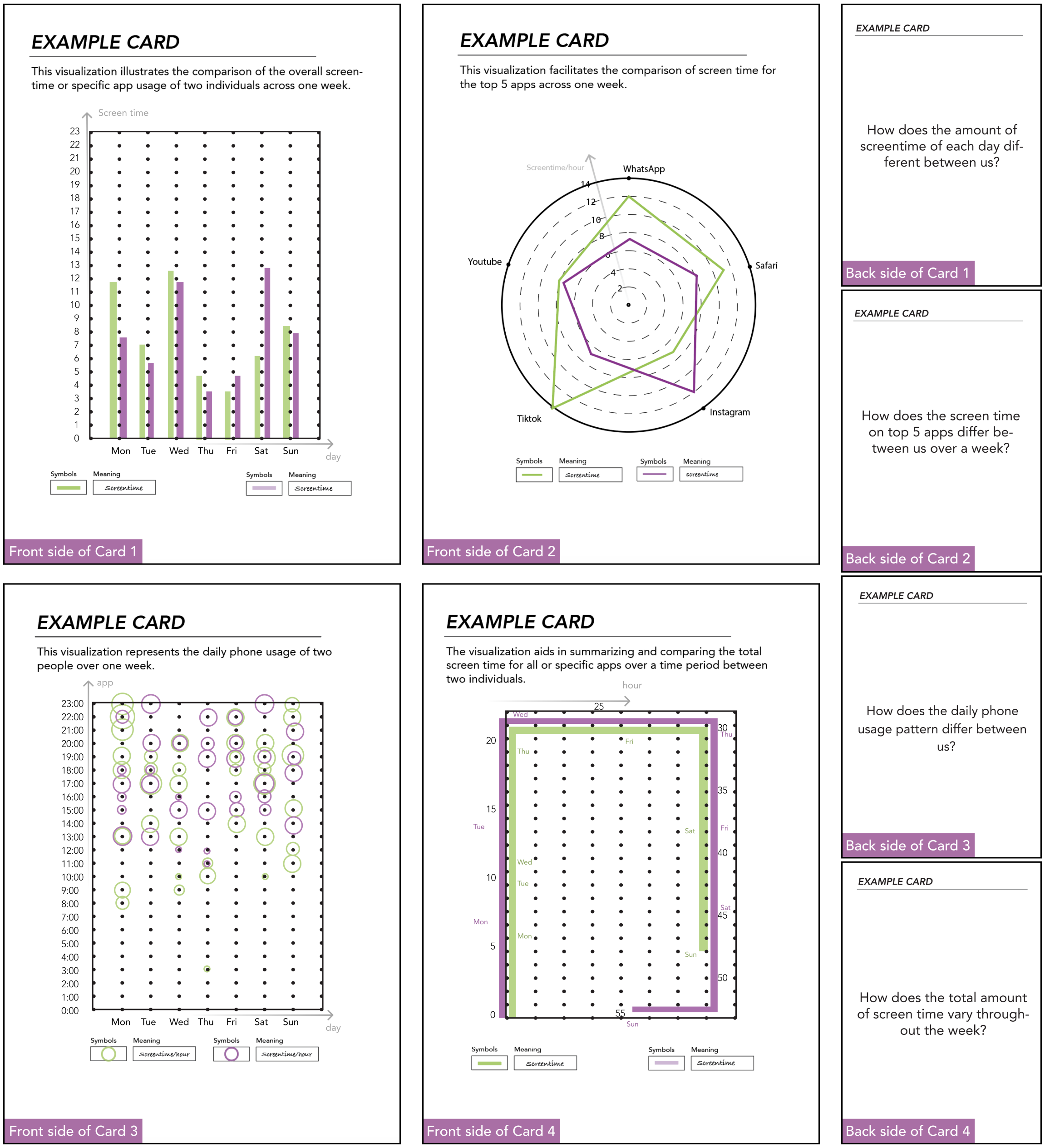


Figure 3: Example cards provided to participants. The data represented in these cards all relate to smartphone screen time. The example cards represent a diverse set of visualizations such as grouped bar chart, radar chart, bubble chart, and a type of grouped bar chart wrapped around a rectangular spiral for compactness, reminiscent of W.E.B. du Bois' design [8]. These examples are meant to encourage participants to explore diverse representations of their own data.

white blocks, each matching the size of the visualization grids, positioned centrally on the canvas. Users can overlap their sketched visualization grids within these white blocks, allowing for detailed comparison of data patterns. On either side of the canvas, each user has an individual annotation space, marked in green and purple. These annotation spaces are designed with empty areas to encourage users to record their insights and personal reflections.

4 Method

We conducted an observational lab user study with Reciportrait, to examine how the proposed design principles and the toolkit help people collaboratively make sense of their personal data.

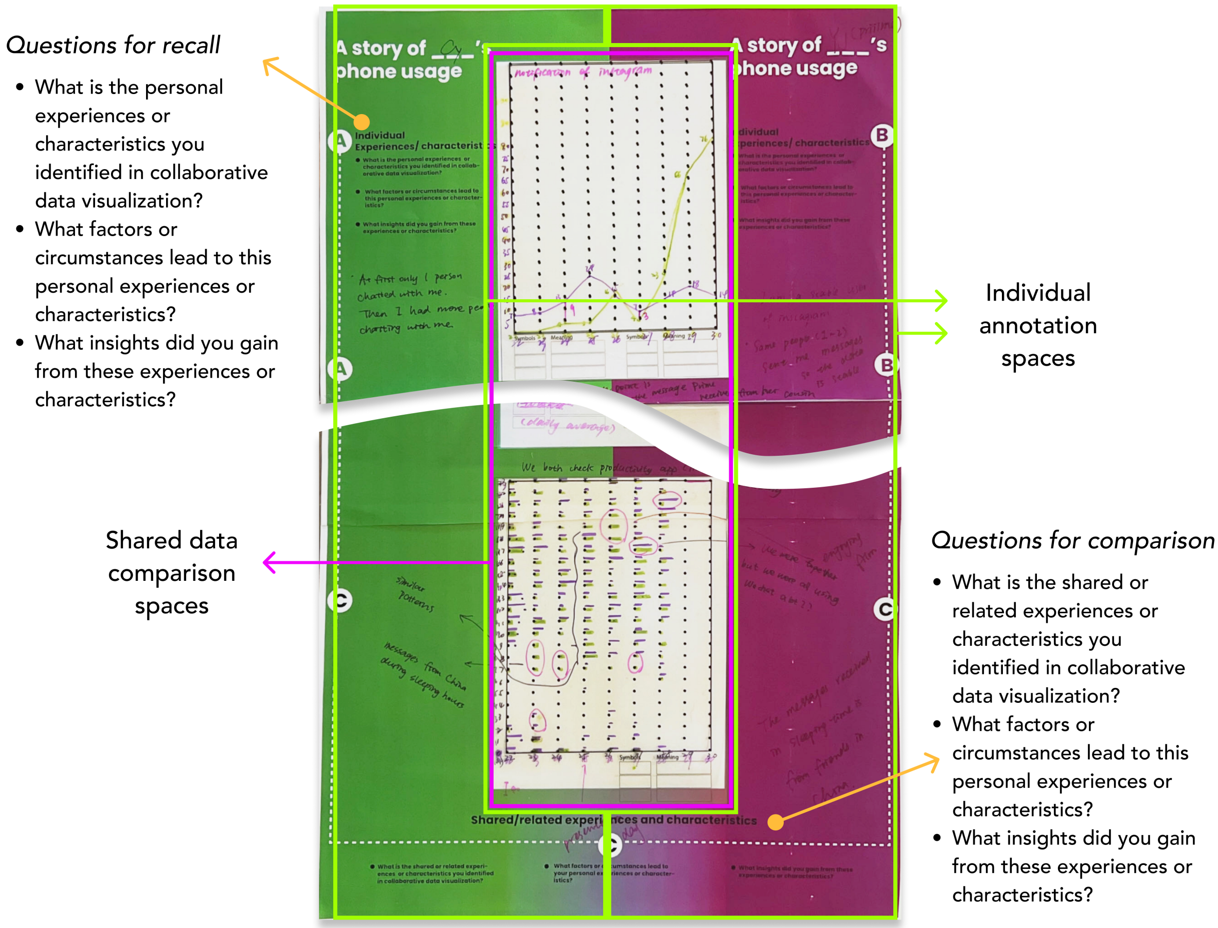


Figure 4: The data reflection canvas. This canvas includes individual annotation spaces and shared data comparison spaces. Reflective questions at the top and bottom of the canvas guide users through three levels of reflection: recalling past experiences and comparing behaviors, relating these patterns to contextual factors, and summarizing insights in relation to self-identity, based on Fleck and Fitzpatrick [17].

4.1 Context

We selected screen time data as the context for designing our personal data visualization toolkit for two main reasons. First, as screen time has become a ubiquitous aspect of modern life, with individuals spending increasing amounts of time on digital devices like smartphones [36, 54], screen time data offers a meaningful and engaging way for users to explore and manage their digital behaviors [38, 51]. Despite the widespread use of screen time data in PI tools, most of these tools offer only standard and simplified visualizations [58, 69], which contrasts with the richer and more subjective approach advocated by Data Humanism. Second, screen time data is a form of time series data [58], making it particularly effective for tracking behavioral patterns, identifying trends, and observing fluctuations over time [34, 67]. The temporal nature of this data allows users to recall past behaviors and reflect on their experiences more easily.

4.2 Participants

We recruited 16 university students, forming 8 pairs. We restricted our inclusion criteria to students who were self-declared friends and had shared classes or activities within the previous weeks, because involving people with shared experiences can foster a sense of relatedness, facilitating making sense of and reflecting on each other's data [13, 51]. All participants had collected their screen time data via their smartphones for at least 14 days before the study. The participants' ages ranged from 21 to 29 (*median=24, avg=23.9*) and included 4 bachelor's students and 12 master's students. Detailed demographic data are provided in Table 1. Our institution's Human Research Ethics Committee and Privacy Team reviewed and approved our study.

4.3 Study set up and procedure

The observational user study with the toolkit was conducted in a dedicated user study room. As shown in Figure 5, the data reflection

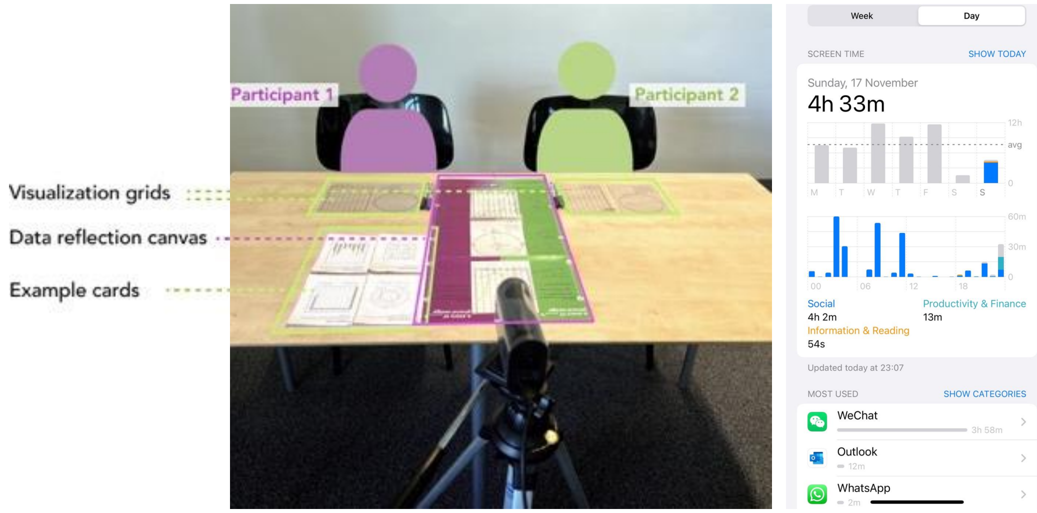


Figure 5: Study setup and example of screen time visualization. The left image illustrates the study setup, where participants sit side-by-side in front of the data reflection canvas, with a video camera capturing their interactions with the Reciportrait toolkit. The right image shows a screenshot of participants' screen time visualization from an iPhone.

Table 1: Details of study participants in pairs. *Gx* refers to a pair of participants using the toolkit, with the suffix *-1* or *-2* distinguishing participants within each pair.

Group		Age	Biological Sex	Education level	Academic Background
G1	G1-1	26	Male	Master	Design
	G1-2	24	Female	Master	Design
G2	G2-1	24	Female	Master	Design
	G2-2	23	Female	Master	Design
G3	G3-1	25	Female	Master	Design
	G3-2	23	Female	Master	Design
G4	G4-1	26	Female	Master	Design
	G4-2	29	Female	Master	Design
G5	G5-1	23	Male	Master	Mechanical Engineering
	G5-2	24	Female	Master	Mechanical Engineering
G6	G6-1	22	Male	Bachelor	Design
	G6-2	21	Female	Bachelor	Design
G7	G7-1	24	Male	Master	Design
	G7-2	26	Male	Master	Design
G8	G8-1	21	Male	Bachelor	Applied Science
	G8-2	21	Male	Bachelor	Applied Science

canvas was centrally positioned on a table, allowing both participants to sit side by side for effective collaboration. Each participant was provided with three rectangular and three circular visualization grids on their side of the table, along with green and purple pens that matched the color scheme of the toolkit's workspace. The example cards were placed adjacent to the canvas. To document participant behavior and interactions with the toolkit, a camera was positioned in front of the table, recording the entire session.

Each pair of participants was invited to a 60-minute session to use the toolkit, with actual session duration ranging from 45 to 90 minutes. During the session, participants explored and co-authored collaborative visualizations based on each other's phone screen time data visualizations. As illustrated in Figure 5, these data visualizations were presented as standard bar and line charts, displaying trends in total screen time, specific app usage, and notifications across 24-hour and weekly periods. Participants began with a 10-minute tutorial, during which researchers explained how to access screen data visualizations and use the toolkit. As shown in Appendix A.1, this instructions focused on explaining the functionality of each toolkit element without prescribing specific individual or collaborative usage, allowing participants the flexibility to determine their own collaboration approach. After familiarizing with the toolkit, all participants engaged in a blend of collaborative and individual work throughout the process. Following the session, we conducted a 20-minute post-hoc interview with each pair. During the interview, participants were asked to explain their sensemaking process, share the insights they generated, and describe their experiences and challenges while using the toolkit collaboratively.

This session allowed us to capture three types of data: 1) a picture of the canvas containing all created collaborative data visualizations, 2) the video recordings capturing the collaborative sensemaking process, and 3) the voice recordings of interviews.

4.4 Data Analysis

We conducted the data analysis in three phases. The first two phases focused on understanding the development of visualizations and the collaborative sensemaking process, while the third phase examined the insights generated as the outcome of the sensemaking process.

4.4.1 Phase 1: Identifying Types of Collaborative Visualizations. We examined the canvas photographs to categorize the different types of data visualizations based on their level of customization relative to the provided examples. The first author reviewed all images and classified the collaborative visualization according to modification of their visualization elements, including channels, marks, and data types [45]. We used the interview data to understand data patterns participants identified from these visualizations.

4.4.2 Phase 2: Identify Collaborative Sensemaking Activities and Sub-processes. This analysis focused on identifying specific activities and sub-processes participants engaged in while using the toolkit to derive insights. Drawing on the sensemaking framework proposed by Pirolli and Card [50], we applied the grounded theory analysis method as outlined by Glaser et al. [20], following three steps.

Step 1 **Open Coding:** Two coders independently analyzed video recordings from the first three groups to identify sub-activities in the second column of Table 2. For example, participants scrolling through each other's phones to read data was labeled "review data."

Step 2 **Axial Coding:** The coders grouped sub-activities into broader categories based on shared goals (see the first column of Table 2). For example, "data analysis" included reviewing data, comparing data, and identifying patterns. After merging these codes into a consolidated list, one coder used it to categorize activities from the remaining groups, identifying new sub-activities until saturation was reached after the eighth group.

Step 3 **Selective Coding:** The collaborative sensemaking sub-processes (see Figure 8) were identified by grouping activities according to their goals. For example, activities aimed at exploring interesting data for visualizations were classified as "data exploration." The coders reflected on the activities from Step 2, resulting in four sub-process types, which were then applied to the remaining groups.

To understand the distribution of activities within sub-processes, we calculated the proportion of each activity by dividing its frequency by the total number of activities observed in that sub-process across all eight groups. For instance, the proportion of "data analysis" activities was determined by dividing its frequency by the total number of activities within the "data exploration" sub-process. Additionally, to gain insights into the overall experiences of collaborative sensemaking with the toolkit, the second author conducted a semantic analysis of the interview transcriptions.

4.4.3 Phase 3: Analyze Insight Moments. In this phase, we identified and analyzed "insight moments" where participants reported gaining new personal insights, following a three-step process. First, two coders independently reviewed the video recordings to pinpoint moments where participants explicitly expressed that they had generated new personal insights (*e.g., "I didn't notice that (on) the days when I sleep longer, I have more interruptions"*). To ensure a comprehensive understanding, we also reviewed the post-hoc interviews transcriptions and the corresponding data visualizations. Second, two coders discussed all identified insight moments and categorized them based on insights types and reflection levels as outlined in prior research [12, 17], resulting in four distinct insight categories. The second coder then revisited all insight moments across the eight groups to refine and apply these categories. Finally, we analyzed the occurrence of these insight moments by tracing the sequences of sub-activities and corresponding sub-processes identified in Phase 2.

5 Findings

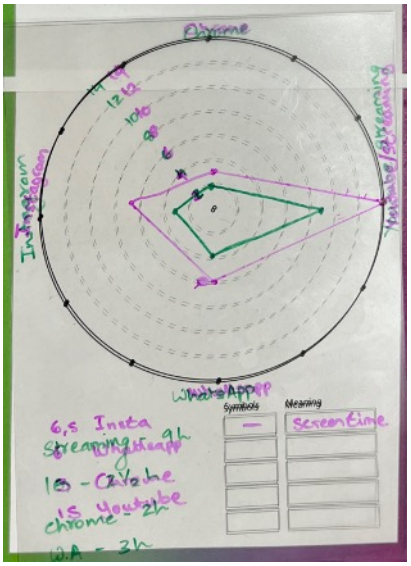
We present our observations of (1) the collaborative sensemaking process enabled by Reciportrait, by reporting the developed collaborative visualizations in Section 5.1 and the collaborative sensemaking activities and sub-processes in Section 5.2, and (2) the outcomes of this process by demonstrating the gained personal insights in Section 5.3.

5.1 Developed Collaborative Visualizations

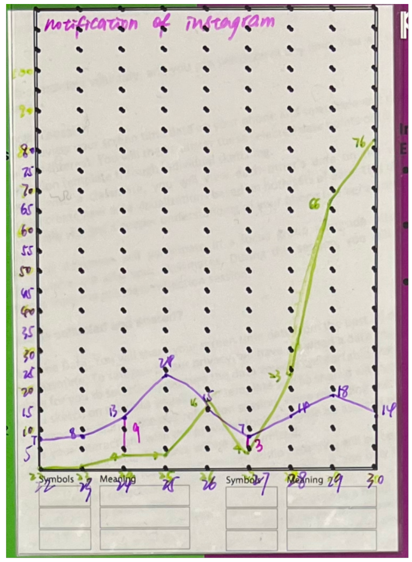
All eight groups successfully authored the required three collaborative visualizations, each representing an overlap of two sketched individual visualization grids (as described in Section 3.2.1). These collaborative visualizations demonstrated a variety of modifications based on the provided examples (as described in Section 3.2.2), including 1) alterations to data types, scales, marks, and channels; 2) changes to channels; and 3) designs that closely emulated the provided examples. We describe how these collaborative visualizations facilitated participants' sensemaking of each other's data.

5.1.1 Modifying Data Types, Scales and Marks. In several cases, participants chose different data types and categories within each other's datasets, represented the data at scales that diverged from the provided examples, and, in some instances, also altered the marks and channels used to visualize the data. These are further subcategorised below. We observed these change in 13 of the 24 visualizations. Of the 13, four visualizations modified the marks, and two modify the channels. This type of collaborative visualization enabled participants to align with their subjective interests and information needs during the sensemaking process.

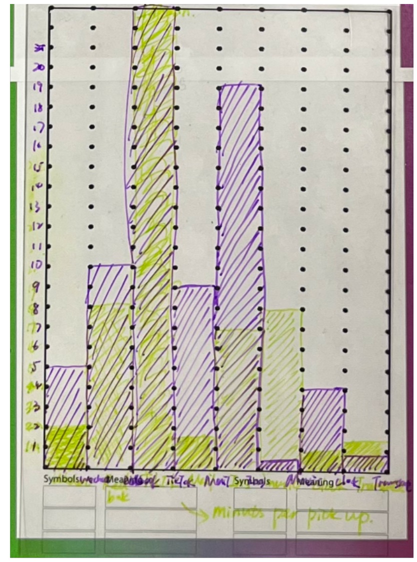
(1) *Modifying Data Categories:* In visualizations altering data granularity, participants adjusted the axis to include different types of apps according to their shared interests. For instance, Figure 6a shows a radar chart comparing the top four apps used by two individuals, G8-1 (purple) and G8-2 (green). Participants present four apps on the angular axes of the chart based on their shared experiences, and screen time represented radially. This resulted in similar shapes for both participants, with G8-1's plot (purple) notably larger than G8-2's, indicating similar relative interests in the apps, but different screen times.
(2) *Modifying Data Attributes:* Participants incorporated alternative data (e.g., time spent and notifications) provided by their phones but not utilized in the provided examples. For



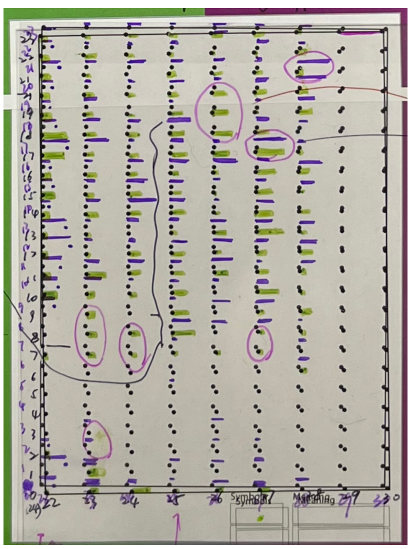
(a) An example of visualization with modified data categories (Participants G8)



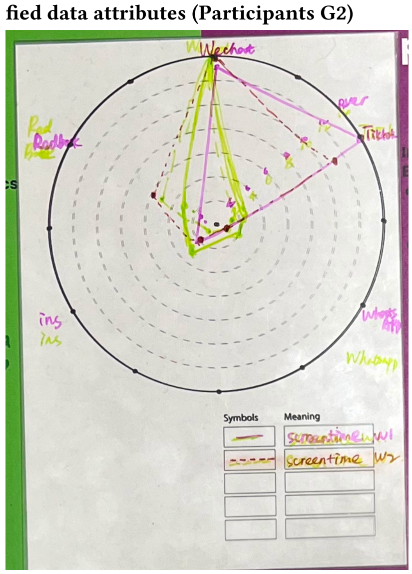
(b) An example of visualization with modified data attributes (Participants G2)



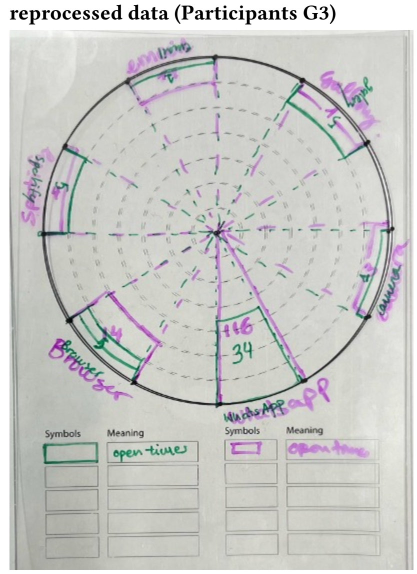
(c) An example of visualization incorporate reprocessed data (Participants G3)



(d) An example of visualization with modified marks (Participant G3)



(e) An example of visualization incorporating additional channel (Participant G7)



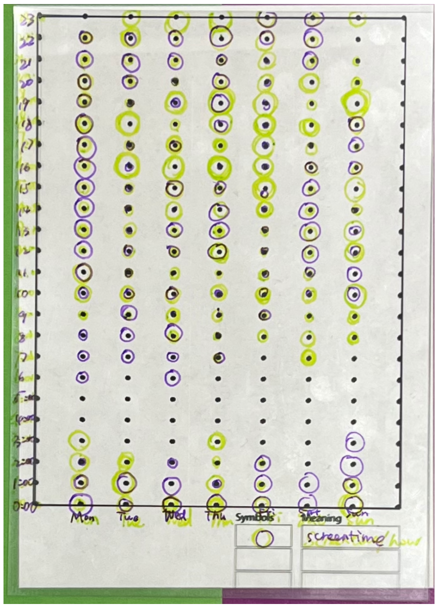
(f) An example of visualization with changed channels (Participant G7)

Figure 6: Example Visualizations with Modifications in Data Types, Scales, Marks, and Channels

instance, in Figure 6b, a line chart is depicted using Instagram pickup times as the y-axis and dates as the x-axis. After noticing differences in pickup times on the 24th and 27th, marked by the pink numbers 9 and 3 respectively, Participant G2-1 (green) realized that these messages were from her cousins, which contrasted with her initial belief that her only Instagram contact was Participant G2-2.

(3) *Incorporating Reprocessed Data*: We observed one group reprocessed data provided by their phones and incorporated them into the visualization. As shown in Figure 6c, the participants (G3) used average screen time per pickup (in minutes) as the y-axis, calculated by dividing the total screen time by the number of pickups, with app categories (e.g., TikTok, Clock, Music) on the x-axis. This visualization revealed that both participants spent over 30 minutes each time they opened TikTok (third bar from the left), while G3-2 (purple) averaged 20 minutes per pickup on Email (fifth bar).

(4) *Modifying marks:* Participants incorporated subjective marks into this type of visualization to emphasize relevant data characteristics. Our analysis identified 8 out of 24 visualizations that incorporated changes in marks, with only two exclusively altering marks, while others also adjusted data



(a) An example of visualization that emulating example design from card 3 (Participants G8)

(b) An example of visualization that emulating example design from Card 1 (Participants G2)

Figure 7: Visualizations that emulating example design.

types and channels. As illustrated by the bar chart in Figure 6d, participants maintained the design from example card 3 (Figure 3) but added a horizontal line to compare phone usage within each hour. The varying lengths of the green and purple lines, highlighted by pink circles, revealed unique phone usage patterns for each participant.

5.1.2 Modifying Channels. In this category of visualizations, participants changed or modified channels, often resulting in visualizations different from the provided examples on the example cards. Our analysis identified 4 visualizations involving changes in channels, with 3 of them also incorporating modifications in markers, granularity, and marks.

(1) *Incorporating Additional Channels:* In this type of visualization, participants primarily added more channels to present additional relevant information. For instance, in the radar chart in Figure 6e, participants extended the time period from one week (as offered by the example visualization design) to two weeks by adding one more channel, representing the phone usage of the second week in dotted lines. This visualization illustrates that participant G3-1 exhibits similar usage across four apps within two weeks, while participant G3-2 increased her usage on Red and decreased usage on TikTok in the second week.
(2) *Change of Channels:* In some cases, participants changed the channels used to represent the data. For instance, Figure 6f shows how participants (G7) visualized screen time across different days using a circular stacked bar chart (with the outside circumference as a baseline) as opposed to the standard bar chart offered by their phones. The "position" channel of the bar chart is now changed to an "angle" while the bars themselves represent different apps. The length of each stacked bar (colored by user) represents pickup time. Participants admitted that the visualizations were not entirely accurate (see the lengths of the blocks representing '34' and '116' in Fig. 6f), but they reported that the process of creating the visualization helped them engage with and think about the data.

5.1.3 Emulating Example Design. This type of visualization replicated the design of provided examples with participants' own data. Our analysis revealed 8 out of 24 visualizations falling into this category. For example, Figure 7a illustrates a visualization that follows the design from card 3 (see Figure 3). This visualization highlights phone usage patterns such as both participants (G2) staying up late until 2-3 AM, and participant G4-2 (purple) using the phone less after 5PM. Similarly, Figure 7b replicates the design in card 1 (Figure 3), illustrating that participant G2-2 (green) consistently has longer screen time than G2-1 (purple). Although this approach doesn't introduce new designs, participants reported that incrementally sketching data points helped them engage more deeply with the data, leading to a better understanding.

5.2 Collaborative Sensemaking Activities and Sub-processes

We outline the collaborative sensemaking activities during the use of Reciportrait in Table 2, categorized based on participants' objectives in the creation of collaborative visualizations. Table 3 describes the sub-process of the collaborative sensemaking process, with the usage of both individual and shared working spaces of Reciportrait.

Table 2: Collaborative sensemaking activities. This table presents five sensemaking activities, each grouping multiple sub-activities according to the same goals when interacting with the Reciportrait toolkit. Icons on the left of the "Activity" column correspond to the icons in Table 5.

	Activity	Sub-activity	Description
DA	**Data Analysis**	Review data	Read and explore each other's data provided by their phones.
		Compare data	Articulate the similarities and differences between each other's data.
		Discuss data type	Discuss to identify engaging data types for collaborative visualizations.
		Identify insights	Point out and describe the pattern in each other's data.
		Process data	Re-calculate data from standard charts to fit common interests.
		Relate data	Identify patterns in one visualization and relate them to another visualization.
DC	**Data Contextualization**	Comment data	Share opinions on the patterns observed in each other's data.
		Explain data	Explain personal contexts and information behind data.
		Inquire data	Raise questions upon anomalous data points.
		Interpret data	Provide hypothetical explanations on each other's data.
VC	**Visualization Conceptualization**	Define axis meaning	Discuss the data characteristics (e.g., category, range) for the axis.
		Define axis scale	Work together to specify the range and units represented by the axis.
		Propose Vis design	Comment on example cards or suggest new ideas for visualization designs.
		Define marks	Discuss the design of marks, such as symbol type, orientation, and size.
		Envision Vis	Imagine visualization possibilities and potential data patterns.
VS	**Visualization Sketching**	Sketch Vis	Sketch data on the provided visualization grids.
		Revisit Vis design	Confirm the details of the defined visualizations together.
		Comment sketches	Share opinions on the physical activity of sketching data.
		Annotate data	Individually add notes to the canvas regarding identified data patterns.
		Sketch Vis possibility	Explore potential visualizations together by sketching data points in the grids.
RD	**Reflective Discussion**	Inquiry	Ask about behaviors and experiences not captured by the data.
		Explain behavior	Explain behaviors underlying data with habits, life conditions, and events.
		Reason behavior	Clarify behaviors and experiences based on personal desires and opinions.
		Compare behavior	Identify related or different behavior and experiences between each other.
		Value judgment	Share personal opinions and values on events or phenomena.

Table 3: Sub-processes with the use of individual and shared working spaces: This table outlines the sub-processes involved when participants create and reflect upon collaborative visualizations using Reciportrait. The individual working space is referred to as the "visualization grids" in Section 3.2.1, and the collaborative working space is referred to as the "Data Reflection Canvas" in Section 3.2.3.

Sub-process	Description	Use of Individual & Shared Working Space
Data Exploration	Identify relevant data type and instances for collaborative visualization by reviewing each other's data.	Participants analyzed data directly on each other's phones, without using visualization grids.
Visualization Design	Design the collaborative visualization by brainstorming and discussing elements like data types, axes, and marks.	Participants discuss and sketch their visualizations ideas on the individual visualization grids of a dominant participant.
Visualization Implementation	Create the designed visualization by sketching data onto the provided grids.	Participants sketch their data in their individual visualization grids while occasionally communicating and reviewing each other's progress.
Reflection	Reflect on each other's data by comparing and relating behaviors and experiences.	Participants overlay their individual visualization grids on the shared canvas, then discuss data patterns and annotate their observations.

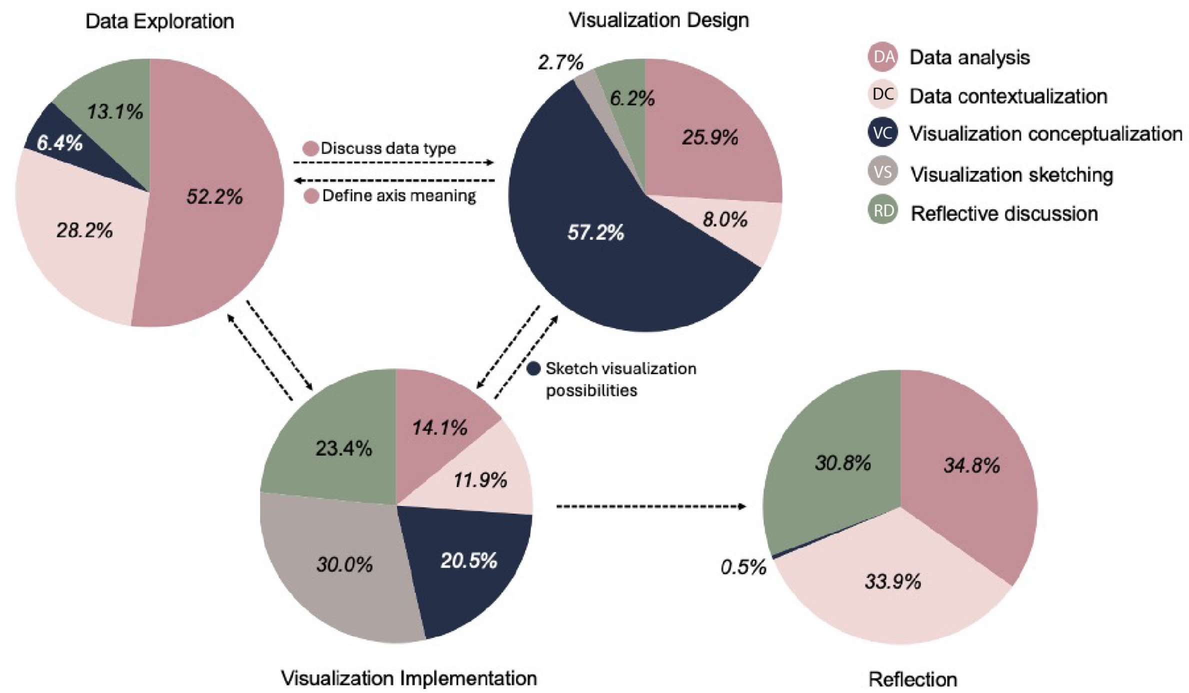


Figure 8: The overall collaborative sensemaking process, highlighting the distribution of activities across four distinct sub-processes. The four pie charts represent the frequency of sensemaking activities outlined in Table 2, within each sub-process. Activities that frequently cause transitions between sub-processes are highlighted between the bar charts.

In this section, we present our observations of the collaborative sensemaking process enabled by Reciportrait, by introducing (1) the overall collaborative sensemaking process and its sub-processes, and (2) the collaborative sensemaking activities within each sub-process.

As illustrated in Figure 8, we found that the overall collaborative sensemaking process is iterative, involving three key sub-processes: data exploration, visualization representation, and visualization sketching. Each sub-process is driven by specific activities, while reflection occurs at the end of the iterative process. The shift from data exploration to visualization representation was often marked by the activity of discussing data types (DA), helping participants identify relevant data points and move into the process of visualization design. Conversely, the shift from visualization design to data exploration was typically prompted by defining axis meanings (VC), after which participants reviewed and compared data to refine the axis. Moreover, participants often revisited the visualization design process (VS) after assessing and refining their visualizations, identifying more nuanced features that prompted further adjustments. We report the detailed activities within each of the four sub-processes in the following.

In the sub-process of **data exploration**, participants primarily engaged in data analysis activities, which accounted for 52.4% of the total amount of the activities, with additional activities including data contextualization (28.2%), visualization conceptualization (6.4%), and reflective discussions (13.1%) taking a smaller part.

In the sub-process of **visualization design**, as shown in Figure 8, participants predominantly engaged in visualization conceptualization activities (57.2%), with a notable portion allocated to data analysis activities (25.9%). Participants frequently worked individually on conceptualizing visualizations, such as defining axis meanings and envisioning layouts, while sketching and referencing data. These activities often spurred both participants back to data analysis activities (e.g., discussing data type, reviewing data). This back-and-forth between visualization conceptualization and data analysis slowed the design process but facilitated deeper data understanding through collaborative sensemaking. For instance, when defining the axis of the visualization in Figure 6c, participant G3-1 suggested adding a new data type, prompting the reprocessing of data by dividing total notifications by pickup times. This helped uncover differences in average notifications across days.

> G3-2:"Or we can use the notifications per pickup time instead of the daily notifications across a week. For instance, I see we both have the daily pickup times of Instagram."

In the sub-process of **visualization implementation**, participants usually engaged in visualization sketching activities (VS), while collaboratively discussing, contextualizing and reflecting upon the identified data points. As illustrated by figure 8, we observed that the visualization sketching activities (VS) is the major activity taking 30.0% of the total account of activities. The slow interaction offered by this activity enabled the spontaneous collaboration on visualization conceptualization (20.5%), data analysis

Table 4: Insights Definitions and Example Quotes

Insight Into ...	Definition	Example Quote
Data	Identification of trends, outliers, correlations, or other patterns within each other's datasets.	"We noticed a significant increase in app usage during weekends."
Behavioral patterns	Understanding of behavioral tendencies represented by the data.	"The consistent late-night usage suggests a tendency to procrastinate."
Experiences	Contextual factors (e.g., environmental and personal circumstances) that influence experiences.	"The spikes in activity coincide with periods of high stress at work."
Self-recognition	Self-knowledge that augments, corrects, or develops participants' recognition of themselves.	"Seeing the actual data made me realize I spend more time on social media than I thought."

(14.1%), data contextualization (11.9%) and reflective discussion (23.4%). Participants reported that explaining and communicating identified data patterns during this sub-process was fun and engaging.

> G3-2:"It is fun to do this, as you can share the insights you gain immediately with someone... and it is also fun to hear from others."

In the final sub-process **reflection**, participants overlay their individual visualization grids to compare data patterns and engage in discussions about their past behaviour and experiences based on observed data patterns. Five of the eight participant groups reported that this moment of overlapping their sketches was the most exciting part of the collaborative sensemaking process. The iterative work leading up to this stage had built participants' curiosity and interest in comparing and reflecting on each other's data. Consequently, participants engaged in data analysis (34.8%), data contextualization (33.9%), and data reflection (30.8%) activities, focusing on explaining and reflecting on each other's data and experiences, with little involvement in conceptualization or sketching activities (see Figure 8).

5.3 Insights

In this study, we observed that all 8 groups experienced moments of insight, leading to a total of 30 occurrences. We categorized these insights into four distinct types, as shown in Table 4. Additionally, we provide a detailed account of how these insights emerged through a sequence of activities, outlined in Table 5. In this section, we explain the observed insights and how the execution of activities contributes to different types of insights in detail.

5.3.1 Gaining insights into data through visualization sketching and data analysis. As shown in Table 5, row 1 to row 9, insights into data emerged primarily during the sketching, visualization design, and reflection sub-processes, with only one occurrence during the data exploration sub-process. These insights were mainly triggered by two types of activities: visualization sketching (VS) and data analysis (DA), followed by contextualization activities (DC). These two activities led to insights into data in different ways.

First, during the sub-process of visualization implementation, sketching (VS) helped participants immerse themselves in detailed data points, uncovering patterns and facilitating personal reflections. For example, in Table 5, row 1, participant G3-2 sketched her screen time using purple circles, as depicted in Figure 6d. Repeatedly sketching these circles deepened her recognition of data patterns, leading her to share insights with her partner:

> "It is too tiring to sketch the screentime, because I have been using my phone constantly throughout the day... The circles are all total (representing one hour each)... I feel guilty" (G3-2).

Second, comparing data (DA) and contextualization (DC) with a friend helped uncover hidden data patterns. For example, in row 8, Participant G2 compared visualizations of "Instagram pick up times" and noticed the same number of notifications on a specific day (see Figure 6b). This pattern prompted them to remember that it was the day they attended the same event together, since they used Instagram chiefly to contact each other:

> "Look at the 26th. Do you remember that's the final day of EI?" (G2-1)
> "Hahaha, yes, we were together." (G2-2)

5.3.2 Gaining insights into behavioural patterns through data analysis, visualization sketching, and data contextualization. Insights into behavioral patterns predominantly emerged during the sub-processes of sketching and reflection. As shown in Table 4, rows 12 to 15, these insights typically began with data analysis (DA) and visualization sketching (VS), followed by data contextualization activities (DC). Some emergence of these insights was further facilitated through reflective discussions (RD), as observed in rows 10 to 12. We explain how these two initial activities work together with subsequent ones in different ways, leading to insights into behavioral patterns.

First, during sketching (see examples in rows 11 and 12), the slow-paced interaction enabled by visualizations (VS) allowed participants to discuss the data (DA) and reason about the behaviors represented (RD), leading to deeper insights. Second, in the process of reflection, participants first identified data patterns (DA) after overlaying visualizations, then contextualized and explained the data based on their experiences (DA), often reasoning through these reflections (RD). For example, in row 12, participant G4-1 noticed a pattern in G4-2's data, and through inquiry, further explained the behavior:

> G4-2: "Oh, reading is your main activity on your phone! This makes me realize that I also spend a lot

Table 5: Types of insight with leading activities. This table presents the types of insights with leading activities during "insights moments" across 8 groups. Each insight is categorized by type in the "Insights into..." column, with the sequences of activities detailed in columns "1," "2," "3," "4," and "5".

	Group	Insight into...	1	2	3	4	5	Activities	Sub-proc.
1	G3		VS	VS	DC			Sketch visualization + Commenting on sketching activity + Explain data	Vis Impl.
2	G8		VS	DA				Sketch visualization + Identify data pattern	Vis Impl.
3	G8		VS	DA				Sketch visualization + Identify data pattern	Vis Impl.
4	G7		DA					Compare data	Reflection
5	G5	Data	DA	DA				Compare data + Identify data pattern	Reflection
6	G8		DA	DA				Review data + Identify data pattern	Vis design
7	G4		DA	DA	DC			Review data + Explain data	Data expl.
8	G2		DA	DC				Compare data + Explain data	Vis design
9	G4		DA	DC	DC			Compare data + Inquire data + Explain data	Vis design
10	G1		VS	DC	RD			Sketch visualization + Inquire data + Reasoning behavior	Vis Impl.
11	G2		VS	DC	RD			Visualization Sketch + Explain data + Reasoning behavior	Vis Impl.
12	G4	Behavior	DA	DC	RD			Identify data pattern + Inquire data + Explain behavioural pattern	Reflection
13	G4		DA	DC				Identify data + Explain data	Reflection
14	G7		DA	DC				Identify data pattern + Interpret data	Reflection
15	G6		DA	DC	DA	DC		Review data + Explain data + Review data + Explain data	Reflection
16	G1		VS	DC	RD	RD		Sketch visualization + Interpret data + Reasoning behavior + Relating behavior	Vis Impl.
17	G3		DA	DC				Identify data pattern + Interpret data	Reflection
18	G1		DA	DC	RD			Identify data pattern + Interpret data + Reasoning behavior	Reflection
19	G3		DA	DC	RD			Identify data pattern + Explain data + Reasoning behavior	Reflection
20	G3	Experiences	DA	DC	RD			Compare data + Interpret data + Relate behavior	Reflection
21	G5		DA	DC	RD			Compare data + Interpret data + Relate behavior	Reflection
22	G2		DA	DC	DA	RD		Identify data pattern + Explain data + Compare data + Relate behaviour	Reflection
23	G5		DA	RD	DC	RD	RD	Compare data + Interpret data + Explain data + Reasoning behavior + Relate behavior	Reflection
24	G4		DA	RD	RD			Identify data + Compare behavior	Reflection
25	G5		RD	RD	RD			Inquire behavior + Explain behavior + Relate behavior	Reflection
26	G1		RD	RD				Explain behavioral pattern + Share opinion	Reflection
27	G1	Self-recognition	RD	RD	RD			Non-data inquiry + Explain behavioral pattern	Reflection
28	G2		DA	DC	RD	RD	RD	Identify data pattern + Interpret data + Explain behaviour + Share opinion	Reflection
29	G3		DA	DA	RD	RD		Identify data pattern + Explain data + Explain behaviour pattern + Relate behaviour	Reflection
30	G4		DA	DC	RD	DA	RD	Compare data + Explain data + Inquire behaviour + Review data + Share opinion	Reflection

of time reading while using TikTok, but you won't see."
G4-1: "While using TikTok? You spend a long time on it, Hahaha"
G4-2: "Yes, you know some video is just explaining a book. As you can see here, I spent a long time on TikTok, because some videos are very long when explaining a book."

5.3.3 Gaining insights into experiences through a specific sequences of sensemaking activities. Insights into experiences mainly appeared during the reflection process, except for one instance that occurred during the sketching process (see row 16 to row 24 in Table 4). Most of these insights were facilitated by a sequence of activities, including data analysis (DA), data contextualization (DC), and reflective discussion activities (RD).

Despite similar activity patterns, the reflective discussion (RD) at the end plays an important role in leading participants to insights into their behavioural patterns. First, participants engaged in reasoning about and relating behaviors (RD), typically occurring at the end of the activity sequence (e.g., rows 16 to 25). This allowed them to connect contextual aspects of their experiences with the behaviors they recalled while explaining identified data patterns. Second, interpreting data prompted participants to generate hypothetical explanations based on past events and observed behaviors in both their own and others' data, which led to further reasoning about those events and behaviors. For example, in row 23, both participants (G5) identified a pattern indicating differing sleep durations (DA), which prompted participant G5-1 to hypothesize about G5-2's habit in allocating studying hours(DC). In elaborated on a contextual factor—the upcoming homework deadline—that was influencing their sleep patterns. This prompted G5-1 to connect G5-2's behavior to her own experiences, recognizing that both of them tend to relax before embarking on big assignments (RD).

> G5-2:"Both of us stay up very late in the evening..."
> G5-1:"Yeah, I didn't know you also stay up very late until 2, 3 'o clock... and you get up 2 hours earlier than me..."
> G5-1:"Is it because you work from Monday to Friday, thus you need some rest on Friday night?"
> G5-2:"Not really. I want to prepare my slides and presentation from Saturday, thus I want to take some rest on Friday."
> G5-1:"Oh, so you tend to relax more before a big thing happens! I do the same!"

5.3.4 Gaining insights into self-recognition reflective in a sequence of activities with iterative reflective discussion.

Insights into self-recognition only occurred during the reflection process. Reflective discussion (RD) played an essential role in facilitating these insights in two main ways.

First, as shown in rows 26 and 27, participants generated insights into self-recognition by engaging in reflective discussions (RD). These discussions began with inquiries about each other's behaviors and experiences, which sparked deeper reflection. Second, from row 28 to 30 in Table 5, insights often began with data analysis (DA), followed by reflective discussions (RD), where participants explored each other's behaviors. These inquiries and explanations helped participants connect their actions and experiences to their self-identity. For example, in row 30, participant G4-1 noticed that G4-2 spent significant time on WeChat (DA). After discussing their data, G4-1 reflected on her own behavior, revisited her data, and renewed her self-understanding by linking her identity to the behavior under investigation.

> G4-2:"WeChat surprised me. I spent 24 hours on it last week."
> "Oh, you spend time with your boyfriend on WeChat. (G4-1)"
> "Yes, but you also spent 20 hours on WeChat. (G4-2)"
> "With whom? I don't even know! (G4-1)"
> "Haha, why? Do you check moments? (G4-2)"

Participant G4-1 reviewed her data and WeChat chat logs on her phone to investigate further. Not finding any specific person with whom she spent a long time chatting, she concluded:

> "I am not the type of person who likes to socialize with people in person. (G4-1)"

6 Discussion

To understand how our personal visualization toolkit, applying the proposed design principles, balances the demands of Data Humanism with collaborative sensemaking, we first reflect upon the proposed design principles in facilitating the personal data sensemaking process. We then discuss the personal insights derived from using our visualization toolkit.

6.1 Balancing Data Humanism and Collaborative Sensemaking for Personal Data Understanding and Reflection

6.1.1 Reflecting upon DP1 and DP2 for the development of collaborative visualizations.

Our findings suggest that supporting personalized visual encoding methods (DP1) while offering guidance for visualization design (DP2) foster the co-authoring of collaborative visualizations, thus facilitating collaborative sensemaking in two ways.

Firstly, the implementation of these two principles enabled users to co-create diverse collaborative visualizations that facilitated data comparison from shared subjective perspectives (aligning with Data Humanism principle DH1 detailed in Section 2.1). Our findings in Section 5.1.1 suggest that changing data categories, data attributes and incorporating reprocessed data led to meaningful comparisons from shared subjective viewpoints. Participants also explored subjective perspectives in analysing each other's data by changing, replacing, or adding new channels. Together, the implementation of these principles allowed participants to compare levels of interest in areas of common interest (Section 5.1.1 example 1), verify beliefs (Section 5.1.2 example 2), and observe similarities (Section 5.1.2 example 3) and differences (Section 5.1.2 example 4) in behaviour.

Secondly, the two principles also empowered users to co-author visualizations, which in turn increased their willingness to engage with and analyze data patterns. Most of the visualizations created in Section 5.1—such as those emulating example designs, modifying granularity, or adjusting marks—did not involve significant deviations from the provided example cards, yet they helped participants reveal data patterns. In some cases, while the collaborative visualizations themselves—such as the one that introduced a new channel (Sec. 5.1.2 example 2)—were not effective in illustrating data patterns, the process of designing them encouraged participants to collaboratively analyze data patterns.

These findings highlight the importance of empowering people to author (even imperfect) visualizations, rather than solely focusing on creating purely effective and accurate visualizations. These findings echo the goals of Data Humanism approaches [10, 41]. Going beyond the benefit of engaging people deeply with their data, this self-authoring process also introduced an "IKEA effect" [46, 47]—where individuals place greater value on self-created objects due to personal investment, increasing their curiosity and willingness to further analyse and reflect upon their data. In contrast to work on personal visualizations enabling simple data comparisons [16, 52], we argue that future personal visualization toolkits should also support co-authoring of visualizations. This can facilitate the alignment of subjective interests in exploring and analyzing data among individuals and increase people's willingness to engage with and explore each other's data. The collaborative discussion around these visualization elements can lead to more extensive and meaningful modifications in visualization design for collaborators (see Section 5.1.2), enhancing the collaborative sensemaking process.

6.1.2 Addressing the tension of coordinating individual and collaborative perspectives in the sensemaking process while maintaining engagement. Our findings in Section 5.2 suggest that providing both individual and shared working spaces (DP4) helps coordinate slowness in collaborative sensemaking (DP3), engaging participants in understanding and reflecting on each other's data.

Firstly, offering identical individual working spaces—the visualization grids—slows down the process of discussing visualization design possibilities. During the sub-process of *visualization design*, participants were involved in intensive externalizing, articulation, and discussion of visualization design ideas on one of their visualization grids. This helped them understand how the visualization "can work", i.e., how it can be designed to better present each other's data. Participants also experienced shifts between the sub-processes of data exploration and visualization implementation (see Fig. 8), where they predominantly used one visualization grid to discuss the data type and define axis meaning to refine a collaborative visualization design. These findings align with two of the five ways of slowness introduced by Hallnäs and Redström [24, p. 203]—*"learn how it works"* and *"understand why it works the way it works"*, which emphasize the value of taking time for understanding the functionality and rationale behind a system.

Secondly, the identical individual working spaces enable real-time communication while sketching detailed data points. In *visualization implementation* (see Section 5.2 and Table 2), the slow process of sketching data points on identical visualization grids allows participants to simultaneously communicate and reflect on the insights they uncover. This finding illustrates another way of slowness—"see what it is" [24, p. 203]—which highlights the value of slowness in enhancing the observed details.

Finally, overlapping the individual visualization grids onto a shared working space after a long sensemaking process builds users' curiosity and encourages deeper engagement in analyzing and reflecting upon data. During the *Reflection* sub-process (see Section 5.2), participants reported that the series of sensemaking activities that they performed on their separate visualization grids gradually built their curiosity and interest to compare and reflect on each other's data on the shared working space. This finding aligns with yet another way of slowness - "find out the consequences of using it" [24, p. 203], which highlights that slowness can result from a design that emphasizes reflective and mindful interaction with the technology.

To the best of our knowledge, while Data Humanism approaches have highlighted the importance of slowness in making sense of personal data, insights into how to coordinate slowness within a collaborative setting have been limited. Our study leverages the strategy of using individual and collaborative working spaces [25, 59] and suggests their flexible usage to coordinate slowness in the collaborative sensemaking process, which can be extended to different scenarios. For instance, the slowness of "seeing what it is," can be incorporated into sketch-based visualization authoring tools [7, 65] by offering identical individual working spaces to engage more people to communicate data insights while sketching (personal) visualizations. The individual and shared visualization grids we introduce in this work can also be extended to apply to constructive visualization [26, 63, 72] in which tokens could be used to construct visualizations in identical individual and shared working spaces. This could enable participants to discuss visualization construction possibilities and construct collaborative visualization that best illustrate data patterns. Finally, in line with the idea of slowness in "finding out the consequences of using it," participatory data physicalization [22, 48], could consider revealing the final collaborative data representation in a gradual manner to build stakeholders' curiosity and enhance their willingness to analyze and reflect upon the data.

6.2 Personal Insights Enabled by Balancing Data Humanism and Collaborative Sensemaking

6.2.1 Insights into Data and Behavioral Patterns. Our findings in Section 5.3.1 demonstrate that insights into data are typically triggered by two key activities—visualization sketching (VS) and data analysis (DA), and sometimes follow up with data contextualization activities (DC). These activities can happen in the sub-process of visualization implementation, visualization design, and reflection when participants are designing, sketching and comparing their individual visualizations. These results suggest offering individual and shared working spaces (DP4) amplify the benefit of slow sensemaking (DP3) in revealing data pattern—in line with the reflection level R1-description outlined by Fleck and Fitzpatrick. These findings also support the three ways of slowness in data sensemaking discussed in Section 6.1.2, extending beyond traditional patterns of insight generation—flexible data manipulation [1, 34, 60].

As detailed in Section 5.3.2, insights into behavioral patterns emerged mainly through two processes: 1) participants sketching data on individual visualization grids while discussing data patterns, and 2) overlaying the visualization grids and contextualizing the data. These findings indicate that providing both shared and individual working spaces (DP4) within a slow sensemaking process (DP3) can help individuals identify and contextualize data patterns, leading to insights into their past behaviors. This process aligns with Fleck and Fitzpatrick's [17] concept of "descriptive reflection"—recalling, justifying, and explaining actions—which can be enhanced through social interaction that encourages users to articulate their reason behind behaviors. In personal informatics and visualization, a key objective has been to facilitate the recall and explanation of past experiences through data [31, 67]. Existing methods have achieved this by presenting personal data chronologically [11, 67], utilizing machine-driven explanations [19, 23, 30], and only a few cases involving collaborative data communication [14, 18]. Our findings suggest a promising alternative approach: involving a slow, collaborative sensemaking process (DP3) to identify data patterns, then coordinating the process by integrating both individual and shared working spaces (DP4). This triggers data contextualization between people, leading to explanations of and insights into behavior patterns.

6.2.2 Insights into experiences and self-recognition. As shown in Table 5, participants experienced self-recognition and insights into experiences, corresponding to Fleck and Fitzpatrick's[17] definitions of Dialogic Reflection and Transformative Reflection.

As detailed in Section 5.3.3 and Section 5.3.4, insights into experiences and self-recognition followed a specific sequences of activities: starting with data analysis (DA), moving to data contextualization (DC), and concluding with reflective discussions (RD) (see rows 18–21, 28, and 30 in Table 5). These two types of insights are not the result of isolated sensemaking activities but occur mainly at the sub-process of reflection. This reflection occurs after a long and iterative process of data exploration, visualization design, and implementation, as illustrated in Figure 8. These findings suggest that the combination of the four design principles plays a crucial role in facilitating these insights. Specifically, DP1 and DP2 support the creation of collaborative visualizations that capture both shared and individual perspectives on data patterns, thus revealing meaningful insights into experiences. Meanwhile, DP3 and DP4 foster continuous dialogue about data and personal experiences throughout the collaborative sensemaking process, finally contributing to an understanding of themselves (i.e., self-recognition). These findings are consistent with the reflection literature, which posits that achieving higher levels of reflection requires intentional coordination of lower-level reflection activities [11, 17]. They also align with existing research on collaborative sensemaking [44] and personal data insights [12], emphasizing how gaining insights requires a complex process of generating and discussing hypotheses from data.

Within the fields of personal visualization and personal informatics, facilitating higher levels of reflection, particularly dialogic and transformative reflection, has long been considered challenging [11]. Our findings suggest that integrating these design principles—personalized visualization (DP1 and DP2) and iterative, collaborative sensemaking (DP3 and DP4)—provides a promising approach to achieving meaningful reflection.

6.3 Broader implications of the co-authoring Feature in HCI

As discussed, our personal visualization toolkit offers two key benefits for making sense of personal data through its co-authoring feature. First, this authoring feature allows users to create their own visualizations, fostering a sense of connection and ownership with their personal data, which in turn motivates them to explore and reflect on it (see Section 6.1.1). Second, the collaboration aspect provides a reciprocal approach that actively engages users in exploring and reflecting on their personal data in detail (see Section 6.1.2). These two benefits have the following broader implications for HCI research and applications.

Increasing visualization literacy among lay people: One significant challenge in HCI is the limited visualization literacy among lay people, which often hinders their ability to make informed decisions based on data [4, 35]. Our toolkit integrating the principles of Data Humanism and collaborative sensemaking, offering two key forms of support: (1) learning from peers: by incorporating co-authoring into design, future visualization tools can foster discussion and peer learning, and (2) a deliberate, reflective process for understanding and exploring data: by visualizing personal experiences, such tools can enhance learners' understanding of data representation and interpretation. This approach empowers learners to cultivate critical data literacy skills over time.

Increasing engagement in Personal Informatics contexts: Traditional personal informatics tools often struggle to engage users, especially teenagers who prioritize self-expression and individuality [51]. Static and standardized visualizations typically do not resonate with their interests, limiting long-term engagement. Our toolkit has the potential to be used in educational settings, enabling students to create personalized visualizations with metaphors that reflect their unique experiences and perspectives. This customization can foster deeper engagement while promoting peer learning. Through collaboration, students can share insights, reflect on their digital behaviors, and learn from one another—an approach that supports social learning and self-identification, crucial during adolescence. Additionally, the tangible aspects of the toolkit enhance engagement by providing hands-on experiences for students.

6.4 Limitations

One limitation lies in the level of personalization available in the toolkit. While we offer visualization grids that can serve as foundations for various types of visualizations, these options still restrict users' ability to create more personalized visualizations, as suggested by [33, 41]. Future work could explore the development of additional visualization templates to incorporate more personalized visual elements suitable for a collaborative setting. Additionally, the design of the example cards leans towards more standard visualizations, with less emphasis on personalization. This choice was made to help users easily understand, modify, and compare the data based on the example visualizations; however, future research could investigate offering visualization examples and metaphors that are both easy to adapt and more personalized.

Another limitation relates to the participant recruitment process, particularly concerning their educational background and familiarity with data visualizations. Despite our efforts to recruit a diverse group, the sample was skewed toward individuals with university students in fields such as design and engineering. While all participants reported a basic understanding of visualizations—primarily attributed to their daily use of phone screen time data and educational experiences—we did not collect detailed information about their specific familiarity with data visualization concepts. This lack of detailed context may have influenced our understanding of how they engaged with the data and created visualizations. To improve the generalizability of our findings, future studies should aim for a more diverse participant pool that includes individuals with varying levels of expertise in design and data visualization.

Lastly, this study is limited by the use of standard phone visualizations as a starting point for collaborative visualization design, which may have influenced both the visualization output and the generation of insights. Prior research on "causing fixation" [29] highlights how initial examples can shape subsequent designs. The bar chart format of the phone visualizations likely biased participants toward similar designs, despite our efforts to mitigate this by providing diverse example cards. Furthermore, there is a challenge in distinguishing the source of insights—whether they originated from the phone visualizations or the collaborative process. While the phone visualizations primarily served as prompts for discussion, we intentionally reported only those insights that emerged through collaborative exploration. However, fully disentangling their origins remains difficult due to the inability to observe participants' internal thought processes.

7 Conclusion

In conclusion, this research advances personal data visualization by addressing the challenge of balancing the needs of Data Humanism and collaborative sensemaking. We introduced a set of design principles, which facilitate the collaborative visualizations to be both subjective (DP1) and effective (DP2), while coordinating the slow sensemaking process (DP3) and promoting data awareness and communication (DP4). We applied these principles in the design of a personal visualization toolkit, Reciportrait, and evaluated it through an observational study with 16 university students working in the context of smartphone screentime data.

Our findings suggest that supporting personalized visual encoding (DP1) and guiding visualization authoring (DP2) enable users to create visualizations that align with both shared and subjective perspectives in data analysis. The flexible use of individual and shared working spaces (DP3) helps coordinate the slow sensemaking process (DP4) in three key ways: 1) enabling focused individual data analysis to uncover detailed patterns, 2) fostering collaborative discussions to understand the mechanism and outcome of visualization authoring, and 3) cultivating curiosity through data comparison and reflection in a slow, iterative visualization process. Additionally, our results indicate that the proposed design principles extend existing insight gaining patterns by integrating conversation into data manipulation and engaging users in a reciprocal and structured sensemaking process.

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A Appendix

A.1 User study instruction

Welcome to the Collaborative Visualization Session! In this session, you will use our toolkit to collaboratively create visualizations based on your screen time data from your phone.

A.1.1 Accessing Your Screen Time Data.

(1) Please open your phone and navigate to your screen time data.
(2) Go to *Settings* > *Screen Time* > *See All App and Website Activity.*
(3) Here, you can view your screen time on a daily or weekly basis. You may also explore additional features available in this section.

A.1.2 Introduction to Example Cards. You will find example cards showcasing collaborative visualizations, with personal data from each participant represented in green and purple. These examples illustrate the potential end products you can create during this session and demonstrate various ways to compare each other's data. Please review the four examples and feel free to ask any questions if something is unclear. Keep in mind that these comparisons are not meant to evaluate the quality of your data or behavior; rather, they are designed to help you identify differences and similarities.

A.1.3 Explanation of Visualization Grids. To create your collaborative visualization, use the provided circular and rectangular visualization grids to sketch your personal data and overlap them. For effective overlap, both of you should select the same type of visualization grid and align your data to illustrate shared patterns. You will create three collaborative visualizations, and you are encouraged to explore various methods to personalize the visualizations beyond the provided examples, as long as the approach makes sense to both of you.

A.1.4 Overview of the Data Reflection Canvas. The data reflection canvas includes three white blocks for overlapping your individual visualization grids. Each of you also has a personal annotation space that provides questions to guide you in annotating the data patterns in the collaborative visualizations, as well as discussing and reflecting on personal experiences that extend beyond these patterns. Please answer the questions one by one and provide brief annotations for your responses.