PAIRcolator: Pair Collaboration for Sensemaking and Reflection on Personal Data

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DOI
10.1145/3706598.3713332

Publication date
2025

Document Version
Final published version

Published in
CHI 2025

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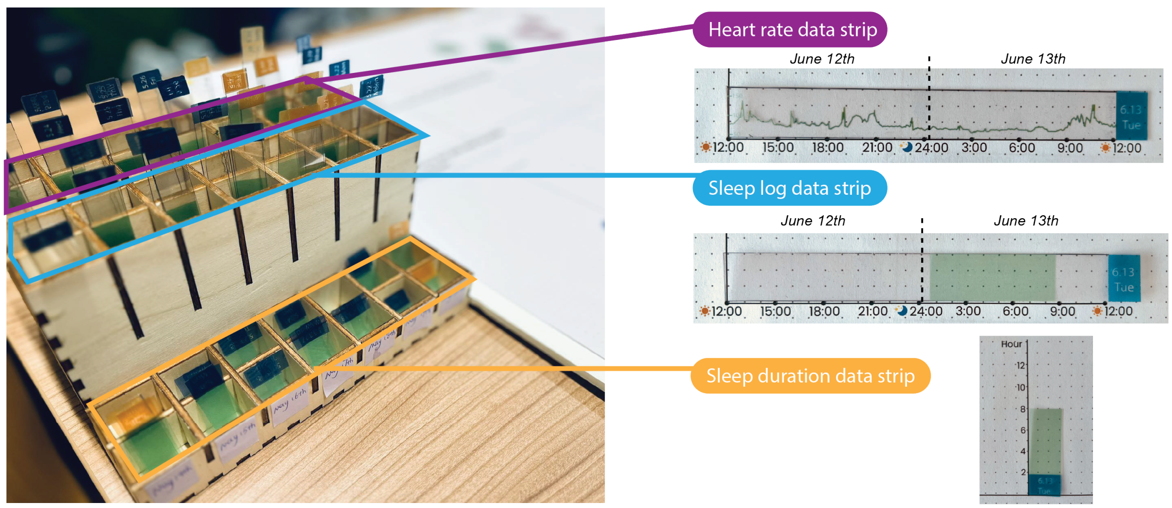


Figure 1: A set of transparent data strips in a wooden holder (left), core component of the data PAIRcolator toolkit. The toolkit took its name from the "percolator", brewing coffee and connecting people. The PAIRcolator bring people in pairs to *brew* insights from their data. In this example, the strip holder hosts 14 days of personal data to combine heart rate, sleep log and sleep duration data strips.

Abstract

This paper explores pair collaboration as a novel approach for making sense of personal data. Pair collaboration—characterized by dyadic comparison and structured roles for questioning and reasoning—has proven effective for co-constructing knowledge. However, current collaborative visualization tools primarily focus on group comparisons, overlooking the challenges of accommodating pair collaboration in the context of personal data. To address this gap, we propose a set of design rationales supporting subjective data analysis through dyadic comparison and mixed-focus collaboration styles for co-constructing personal narratives. We operationalize these principles in a tangible visualization toolkit, PAIRcolator. Our user study demonstrates that pairwise collaboration facilitated by the toolkit: 1) reveals detailed data insights that are effective for recalling personal experiences, and 2) fosters a structured, reciprocal sensemaking process for interpreting and reconstructing personal experiences beyond data insights. Our results shed light on the design rationales for, and the processes of pair sensemaking of personal data, and their effects to foster deep levels of reflection.

CHI '25, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/25/04
https://doi.org/10.1145/3706598.3713332

CCS Concepts

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

Keywords

Collaborative sensemaking, personal data visualization, self-reflection

ACM Reference Format:
Di Yan, Jacky Bourgeois, Yen-Chia Hsu, and Gerd Kortuem. 2025. PAIRcolator: Pair Collaboration for Sensemaking and Reflection on Personal Data. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 20 pages. https://doi.org/10.1145/3706598.3713332

1 Introduction

Personal visualization [2, 43] and Personal Informatics (PI) [18, 45], play a crucial role in helping individuals make sense of their personal data, enabling them to understand past behaviors and reflect on underlying experiences [11, 46, 68, 70]. This sensemaking process, however, is inherently challenging due to the subjective and contextual nature of personal data. Individuals need to explain their data with the nuances of their personal lives [20, 51], and engage in analysis and interpretation according to their subjective conceptual boundaries [52, 53]. Personal visualization, focusing on the design of interactive data representations of personal data [33], has been used as an effective tool for facilitating sensemaking of personal data. Existing visualization designs have explored both digital and tangible approaches, such as integrating contextual information through (machine-generated) annotations [47, 54], and enabling subjective analysis through agentive manipulation of time components [2, 18, 43]. Tangible toolkits further enhance sensemaking by fostering direct and haptic interaction, promoting intuitive exploration and deeper reflection [3, 69].

Recent work by Friske et al. [23] has highlighted the benefits of pair collaboration in facilitating subjective analysis and interpretation of personal data, fostering reflection on personal experiences. This idea of pair collaboration, often involving two peers working together to search, organize, and discuss relevant information within a shared representation, has long been recognized for enhancing sensemaking [1, 71]. Through dyadic comparisons, this approach can uncover detailed patterns that might remain hidden during group comparison [41], providing effective anchors for recalling and reflecting on underlying personal experiences [12]. Additionally, the flexibility of dyadic interaction—ranging from closely coupled to loosely coupled collaboration [37]—allows participants to naturally adopt and switch roles, assisting each other in questioning and reasoning about relevant information [1]. Despite these advantages, current collaborative personal visualization tools predominantly focus on designing data representation for group comparisons [28, 57, 60], which are often limited to establishing norms [21] and lack the coordination to integrate individual and collaborative perspectives [11, 22].

However, facilitating pair sensemaking in the context of personal data presents challenges. First, data representations require an effective structure that supports both participants in segmenting and analyzing data from their subjective perspectives [2, 53], while also revealing personally meaningful data patterns in dyadic comparisons. Second, the pair sensemaking process requires careful coordination between tightly-coupled and loosely-coupled collaboration [37], facilitating individual perspectives for subjective data analysis and interpretation [10] while encouraging communication to interpret, enrich, and reconstruct each other's personal narratives [23]. To address these challenges, our research focuses on the following question: **How can pair-wise collaboration facilitate sensemaking of personal data?**

To investigate this research question, we present a set of design rationales (DR) for facilitating pair-wise sensemaking of personal data, derived from existing literature on sensemaking of personal data, pair sensemaking and personal visualization. We applied these design rationales and introduce PAIRcolator, a pair-wise tangible personal visualization toolkit. This toolkit affords subjective data analysis through dyadic comparison (DR1) and offers guidance for developing effective data representations for meaningful reflection (DR2). It also coordinates the subjective analysis of personal data (DR3) with collaborative conversations focused on interpreting and reconstructing each other's personal narratives (DR4).

We conducted an observational user study focused on sleep data, which is closely linked to social dynamics and personal life. We recruited 28 university students, paired into 14 groups, to investigate the use of the Toolkit and the pair sensemaking process. Our findings highlight the unique advantages of pair collaboration facilitated by our toolkit in fostering self-reflection on personal data. First, the dyadic and agentive comparison aids in uncovering detailed data insights that are effective for recalling personal experiences. Second, the pair sensemaking process fosters a structured, reciprocal interaction between participants, enabling deeper reflection through the reinterpretation and re-evaluation of experiences beyond the identified data insights. Our study contributes to personal visualization and PI research by introducing pair collaboration as a promising approach for fostering self-reflection on personal data.

In summary, our contribution is two-fold:

- We propose a novel approach to pair sensemaking of personal data, which encompasses a set of design rationales synthesized from the literature on sensemaking of personal data, pair sensemaking and personal visualization, and a tangible collaborative personal visualization toolkit that operationalizes these rationales.
- Through a user study, we provide empirical insights into the application of our approach—pair sensemaking of personal data. We also reflect on how the toolkit, and consequently the underlying design rationales for fostering reflection on personal data.

2 Related Work

Our work aims to address the challenges of facilitating pair sensemaking of personal data. In this section, we provide an overview of related work on collaborative sensemaking of personal data, sensemaking of personal data, and pair sensemaking to explain the challenges in detail.

2.1 Collaborative personal visualization

Personal visualization is defined as "the design of interactive visual data representations for use in a personal context" [33]. In personal visualization [2, 43] and Personal Informatics [18, 45], sensemaking of personal data is a vital activity for people to understand their past behaviors and experiences, and to support self-reflection [46, 68, 70] and behavioral change [11]. Collaborative sensemaking, involving individuals who collaborate in searching and externalizing relevant information, creating shared representations, and generating and evaluating hypotheses [36, 72], has been considered beneficial for understanding and reflection on personal data [11, 61]. The data representations that incorporate comparisons between one's data and others' can uncover patterns that might remain hidden in individual analyses [16, 21, 60]. Furthermore, the sensemaking process can benefit from incorporating interpersonal perspectives to encourage the explanation and interpretation of personal experiences underlying personal data [55, 60].

Despite the substantial body of personal visualization work facilitating individual sensemaking of personal data, only a few personal visualization studies have investigated collaborative sensemaking. Common approaches include digital personal visualization tools designed to facilitate data comparisons within groups [16, 21, 60]. Similarly, participatory data physicalization [28, 57, 59] supports group comparison by enabling individuals to collaborate in creating shared representations through encoding their data into tangible tokens under predefined rules [28, 65]. The comparison with aggregated group data is primarily beneficial for defining norms [21]. Only recent research by Friske et al. [23] has begun to investigate pair sensemaking. Their study demonstrates that pairs can play entangled roles as both "makers" and "interpreters" in questioning and reasoning about crafted data representations, which helps reconstruct personal narratives.

Previous research underscores the benefits of collaborative sensemaking in enhancing understanding and reflection on personal data. However, only a few personal visualization tools have focused on collaborative sensemaking, primarily focusing on group comparisons. Our work contributes to the collaborative sensemaking of personal data by introducing pair collaboration as a novel approach.

2.2 Sensemaking and reflection on personal data

Within the field of personal visualization and PI, personal data is regarded as both subjective and contextual, prompting the exploration of various tangible and digital approaches to accommodate this nature.

(1) **Subjective nature:** The subjective nature of personal data emphasizes the need for analysis and interpretation that aligns with individuals' personal conceptual boundaries. Any attempt to define meaning from data involves the performance of "agential cut", where people separate data into elements from a dataset according to their subjective conceptual boundaries [53]. To accommodate the subjective nature of such data, visualization approaches that integrate features for agential time manipulation have been considered effective for empowering users to visually explore, segment, and interpret their data [2, 18, 43]. For instance, tangible visualization has introduced tangible data tokens that allow users to construct, organize, and manipulate blocks of data freely [34, 35], fostering more intuitive and engaging interactions with data [38]. Furthermore, providing structure and guidance is crucial for facilitating the development of effective visualizations, thereby allowing users to allocate more cognitive resources to self-reflection [6].

(2) **Contextual nature:** The contextual nature of personal data refers to the situational aspects embedded in the data, which encompass information about individuals' daily lives and underlying experiences that may not be directly represented in the data itself [10, 20, 51]. To address this, existing visualization approaches have employed storytelling techniques, such as crafting narratives along timelines [68], reconstructing personal experiences into personalized visualizations [42, 51], and incorporating (machine-driven) annotations and interpretations [47, 54]. These techniques help users situate their data within (re)structured narratives, enriching their understanding by connecting raw data with personal and contextual experiences.

Previous research in personal visualization highlights the contextual and subjective nature of personal data, emphasizing specific sensemaking requirements: (1) enabling subjective data analysis to uncover personally meaningful insights, and (2) supporting the interpretation and reconstruction of personal and contextual information into coherent narratives. Building on these insights, our work addresses these requirements in pair sensemaking of personal data.

2.3 Pair Sensemaking

Pair sensemaking, where two individuals work together to solve problems, share insights, and reflect on data, has long been recognized for its potential to enhance knowledge construction and decision-making [1, 71]. The nature of pair collaboration offers distinct advantages in data representation and sensemaking process, which are beneficial for making sense of personal data.

(1) **Data representation:** Dyadic comparison offers a focused and detailed lens for data analysis by limiting comparisons to two individuals [41]. This lens reduces the complexity typically found in group scenarios, allowing for a more effective allocation of visual dimensions, such as color and marks, to analyze the information that the data entails. This approach facilitates the revelation of detailed data patterns [23], which serve as effective anchors for triggering the recall of past experiences, as well as for generating and evaluating hypotheses related to personal experiences [12].

(2) **Sensemaking process:** Dyadic interactions within the sensemaking process can take various forms, ranging from tightly-coupled to loosely-coupled collaboration [37, 67]. Through these different collaboration styles, individuals adopt reciprocal roles in questioning and reasoning, facilitating knowledge construction [1, 71, 72]. In particular, loosely-coupled collaboration provides individuals with the space to work independently, fostering a more focused and engaging experience without undue influence from others [37, 66]. Conversely, tightly-coupled collaboration increases the likelihood of continuous and real-time conversation and feedback, which helps uncover tacit knowledge that might otherwise remain unarticulated [71].

In summary, pair collaboration presents a promising approach to enhance data representation and sensemaking process for fostering the understanding and reflection on personal data. However, facilitating pair sensemaking in the context of personal data presents challenges in accommodating its subjective and contextual nature. Specifically, these challenges include: 1) structuring the data representations to support subjective segment and analysis of data while affording dyadic comparisons to reveal personally reflective data insights for the two participants, and 2) coordinating tightly and loosely coupled collaboration to facilitate individual data analysis and interpretation while leveraging collaborative perspective to enrich and reconstruct personal narratives.

3 The PAIRcolator Toolkit

To address the challenge highlighted in Section 2.3, we introduce the four Design Rationales (DR) and the PAIRcolator toolkit operationalizing these design rationales.

3.1 Design Rationales

We adopted a structured, iterative, multi-phase approach to derive design rationales for pair sensemaking of personal data. This process drew on literature from three key areas: personal visualization and PI, collaborative sensemaking and pair sensemaking. The process unfolded in four interconnected steps:

- *Identify benefits of collaborative sensemaking:* We reviewed and synthesized research on personal visualization, personal informatics, and collaborative sensemaking, identifying two key aspects that collaboration enhances in personal data sensemaking: data representation [16, 21, 28, 60, 65] and the sensemaking process [23, 36, 61, 72].
- *Identify techniques for pair sensemaking:* Drawing on research into pair collaboration and the beneficial aspects identified in Step 1, we defined two key techniques: supporting dyadic comparisons [23, 37, 41] and enabling mixed-focus collaboration styles [37, 66].
- *Identify techniques for subjective and contextual personal data:* From the personal visualization literature, we identified the key characteristics of personal data—its subjective and contextual nature. We then reviewed visualization techniques that accommodate these characteristics, leading to the identification of agential manipulation of time components [2, 6, 18, 34, 43] and narrative reconstruction [10, 20, 51, 68].
- *Synthesize:* We synthesized the identified pair collaboration techniques and visualization strategies, leading to the development of four design rationales for pair sensemaking of personal data.

To develop effective data representations, we propose *affording dyadic and agential comparison* (DR1) to enrich the revelation of personally reflective data insights, and *supporting guidance-based construction* (DR2) to ensure effective data representation while freeing up cognitive resources for meaningful reflection.

DR1 **Affording dyadic and agential comparison:** This design rationale focuses on segmenting data into small, interpretable units to facilitate collaborative exploration between two individuals. By enabling agential manipulation of personal data, the design provides multi-dimensional visual elements in small data units, empowering users to reorganize and prioritize information that is personally meaningful [2, 53]. These units also support dyadic comparison, which focuses on detailed data insights [41], aiding in the recall of past experiences [12]. The combination of agential manipulation and dyadic comparison enhances the effectiveness of the process by integrating subjective perspectives, allowing individuals to uncover personally reflective insights for both individuals, thereby fostering reflection on their experiences.

DR2 **Supporting Guidance-based Construction:** This rationale calls for providing structured guidance to support dyadic comparisons and agential manipulation of personal data. Individual agential manipulation of personal data is inherently complex and requires effective structures to successfully uncover data patterns [42]. Combining it with dyadic comparison introduces additional challenges, particularly in integrating the perspectives of both individuals [41]. Clear and well-defined guidance can reduce the cognitive effort needed for constructing data representations, allowing users to allocate more mental resources to meaningful reflection, extending beyond merely uncovering data insights [6].

To coordinate the sensemaking process, we propose *facilitating individual and shared narrative construction with data* (DR3) to foster the individual and collaborative interpretation of personal data and experiences, and *prompt pair dialogue around inquiry and interpretation* (DR4) to encourage collaboration in reflecting on personal experiences beyond the data insights.

DR3 **Facilitating Individual and shared narrative construction with data:** This rationale emphasizes the coordination of individuals to construct personal narratives from their data while also enabling the collaborative development of shared narratives. Building personal narratives is essential for articulating and reflecting on personal contexts and generating meaningful insights [10]. Through mixed-focus collaboration, pair collaboration can balance the need for individual sensemaking with the benefits of information exchange in pairs, enhancing knowledge construction [1, 37]. Coordinating the individual and shared narrative construction preserves subjective analysis and interpretation of personal data while leveraging others' perspectives to enrich and diversify the interpretation of personal experiences.

DR4 **Prompt pair dialogue around inquiry and interpretation:** This rationale highlights the importance of fostering dialogue between pairs to encourage timely and reciprocal inquiry and interpretation of each other's data and experiences. Close-coupled collaboration is essential in the pair sensemaking process, where effective conversation occurs, leading to enhanced understanding of data and related phenomena [36]. In the context of personal data, dialogue—encompassing data inquiry, explanation, and interpretation—is crucial for reconstructing personal narratives [23]. Within a pair dynamic, reinterpreting personal data can shift the focus from deriving a single "true" narrative to developing multiple interconnected narratives that inform and enrich one another in an ongoing process of understanding.

3.2 Design Implementation

The toolkit consists of three main components blending the design rationales: transparent data strips, a data exploration canvas, and a question card deck.

3.2.1 Transparent Data Strips. The transparent data strips present data in small units with a structured format that allows for overlaying to illustrate data patterns (DR1, DR2). The toolkit includes a set of transparent data strips for each user based on their data, with a distinctive color to facilitate the comparison. Figure 1 illustrates a set of data strips made of sleep logs, sleep duration, and heart rate data over two weeks, placed in three laser-cut wooden boxes. Each box contains data strips for two weeks (one week for each row), with several copies of each strip to enable multiple uses of each data point. Each single data strip is designed as a discrete entity (e.g., heart rate of a single day) of the entire dataset. Specifically, the sleep log strip utilizes bars to depict sleep stages; the colored area represents asleep, and the transparent area indicates awake periods. The heart rate strip shares the same time range (24 hours) as the sleep log strip and illustrates heart rate changes using a line chart. The sleep duration strips consist of a bar representing the 24 hours of the day, featuring a small handle at the bottom. These three types of data strips can be overlaid flexibly in different ways to illustrate data pattern, as illustrated by Figure 2, 3, 4.

3.2.2 Data Exploration Canvas. The data exploration canvas provides a set of grids to guide users in constructing data strips (DR2), and working spaces for constructing both individual and shared data representations for inquiry and interpretation each other's data (DR3, DR4). As depicted in Figure 5, the two equal individual working spaces (blue blocks) are adjacent in the upper left and right corners. This arrangement strategically places users in an equal position to view and discuss each other's data. We include a keyword space to trigger people to summarize their personal insights generated from individual data representations. The collaborative workspace (i.e., the orange block) is located near the users' seats at the bottom of the canvas, offering four types of grids for constructing and communicating collaborative visualizations.

The inclusion of individual working spaces and the design of strips that present data in small units empower users with flexible control over data sharing. These individual working spaces provide a relatively intimate and safe environment for users to plot their data, allowing them to gain insights into their information before sharing. Users can selectively remove any strips containing information they prefer not to share during the collaboration. This design approach aligns with personal data privacy research that emphasizes the importance of engaging with one's data to understand its sensitivity and intimacy [26, 56], while also facilitating agential privacy control [15].

3.2.3 Question Card Deck. The question card deck provides instructions for constructing collaborative data representations and guiding reflective conversations (DR3, DR4). It consists of numbered question cards that correspond to the grids in the collaborative working space, with each card featuring a reflective question designed to inspire users to create data representations on the corresponding grid. We designed two types of questions to facilitate data construction. The first type guides users in comparing their data with questions like, "How does your sleep duration differ daily over the past two weeks?" This prompts users to plot their sleep duration on grid number one, sum the data, and compare totals. The second type encourages users to create representations that capture more information about their behaviors and experiences, facilitating inquiry into each other's data. For example, a question like, "How fragmented is your sleep? What factors lead to sleep interruptions?" invites deeper exploration. A complete list of card questions is available in Table 3 in the Appendix.

4 Method

We conducted an observational study investigating the pair sensemaking process and the usage of the PAIRcolator toolkit.

4.1 Context

We focused our study on university students' sleep data for several reasons. First, sleep is crucial for health and well-being, and research highlights significant sleep issues among students [29, 31, 50]. Second, sleep is influenced by social dynamics and the living environment, in addition to individual physical conditions [29, 39, 73]. Collaborative reflection on sleep data has been shown to enhance self-awareness of sleep patterns and related experiences [62]. Our dataset includes sleep log data, which tracks sleep stages (awake or asleep) and total sleep duration in the day. We also incorporated heart rate data to understand daily activities that may impact sleep behavior.

4.2 Participants

We recruited 28 university students, organized into 14 pairs through snowball sampling. Our promotion efforts included announcements on Twitter, Facebook groups, and the university's advertising platform. Participants were required to have collected their sleep and heart rate data via smartwatches for at least 14 days before the study.

The participants' ages ranged from 23 to 32 years (median = 26.5, average = 26.9) and included 14 master's students and 14 PhD candidates. To facilitate relevant discussions and reflection on each other's data and sleep experiences, we paired participants based on their educational degree (as shown in Table 1), and along with their voluntary participation in sleep data collection. We consider this pair strategy sufficient for two reasons. First, relatedness between participants (e.g., shared interest in collecting data, related sleep experiences) is key for triggering reflection [13, 40, 74]. Second, comparison serves as a means to trigger self-reflection, making any potential comparison bias less critical.

4.3 Study Setup and Procedure

4.3.1 Preparation of each Pair Session. We obtained informed consent and provided participants with a brand-specific manual for exporting their heart rate and sleep data from their smartwatch accounts (Apple, Garmin, or Xiaomi) over a 14-day period. Before sharing their data, participants are encouraged to review the personal visualizations from their smartwatches to gain an overview of their data. We informed them that they would be collaborating with another university student whom they did not know and confirmed their willingness to share their data. Only those who agreed to share

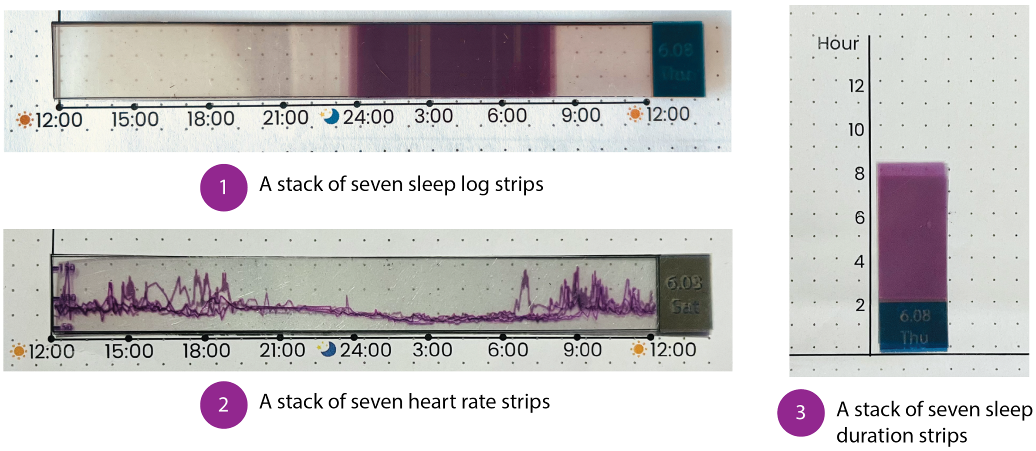


Figure 2: Stacking the same type of data strips: This type of stack contains several data strips of the same type, which allows users to discover data patterns over a customized time range.

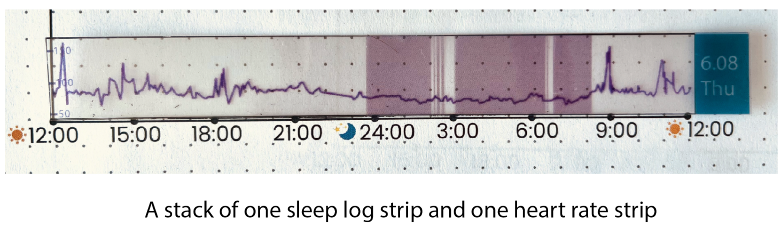


Figure 3: Stacking different types of data strips: This stack includes two data strips of different types, allowing users to explore patterns of various sleeping behaviors.

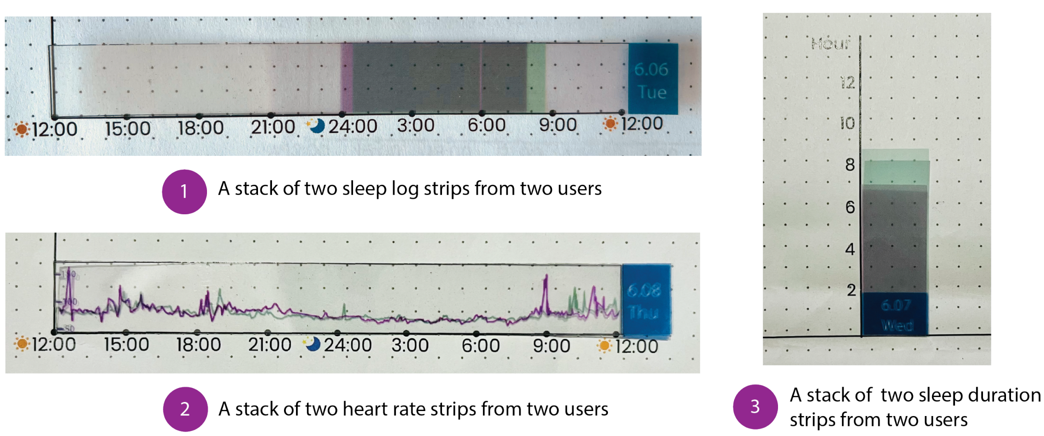


Figure 4: Stacking data strips from two persons: This type of stack contains data strips from two different users, helping users identify and discuss the differences and similarities in their behaviors.

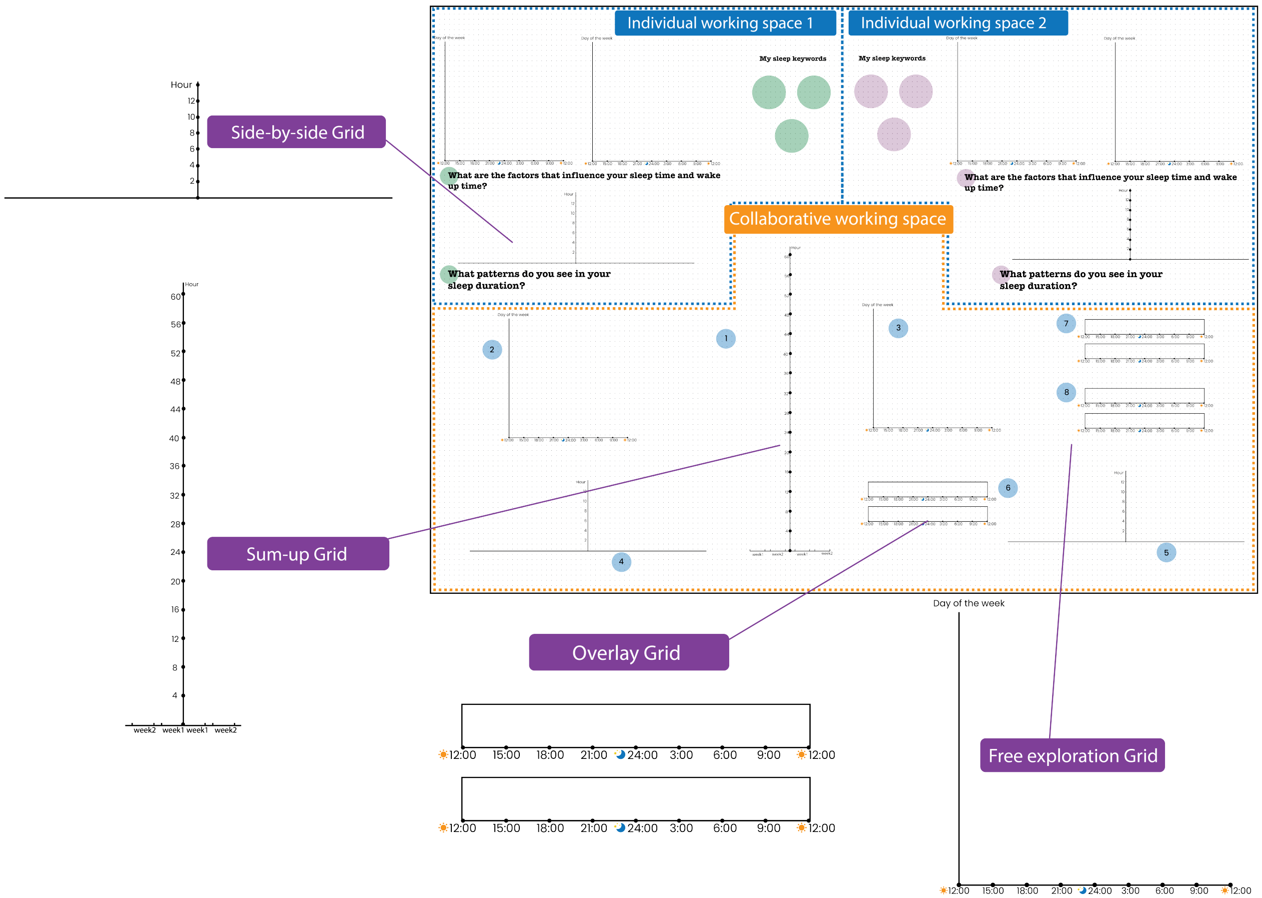


Figure 5: The data exploration canvas contains four types of grids – free exploration, side-by-side, overlay an sum-up – for users to work individually and collaboratively with guidance. The Free Exploration Grid is designed for users to distribute or overly multiple types of data strips freely. It only provides coordinates on the x-axis with a time unit (e.g., 24 hours) and leaves the y-axis open. It prompts users to distribute or overlay sleep logs and heart rate stripes to explore patterns over a week or overlay multiple data stripes differently. The Side-by-Side Grid encourage users to group data according to customized principle and place it side by side for comparison. It utilizes time units (e.g., hours) as the y-axis and leaves the x-axis empty, allowing users to distribute or overlay sleep duration stripes based on their preferences. The Overlay Grid is designed to prompt users to overlay multiple data stripes into one consolidated view. It comprises two blocks, each featuring a time unit (24 hours) on the x-axis. This design encourages users to overlay multiple data stripes, regardless of the types and from which person. The Sum-Up Grid prompts users to sum up and compare the data of two people by distributing them on both sides of the grid. It utilizes the time unit as the y-axis while leaving the x-axis empty on both sides, indicating that two users should align their data stripes on either side to calculate the total amount.

their data and view that of other university students were recruited for the study. Participants then shared their exported data with us via a shared OneDrive file (our University's IT infrastructure). The first author analyzed this data and created visual representations for each participant. All activities were reviewed and approved by our institution's ethics committee and privacy team.

4.3.2 Setup and Procedure of the Pair Session. As shown in Figure 6, pair sessions were conducted with the data exploration canvas centered on a table, where two participants sat side-by-side. Each received a set of personal data strips (see Section 4.3.1), placed on their respective sides of the canvas. To capture interactions, we set up two cameras: one facing the table to record participant interactions and another providing a top-down view to focus on hand movements and toolkit engagement.

Each session was planned for 60 minutes, with actual durations ranging from 45 to 90 minutes. The first 10 minutes were dedicated to a tutorial on the PAIRcolator toolkit, where the first author explained its design and demonstrated construction possibilities using the participants' data strips (see Appendix A.0.1). Then, participants are asked to use the toolkit collaboratively, without seeking further assistance from the research team. After the pair session,

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	Participant	Age	Biological Sex	Occupation	Device	Academic Background
G1	G1-1	26	Male	PhD candidate	Apple Watch	Design
	G1-2	31	Male	PhD candidate	Apple Watch	Design
G2	G2-1	27	Female	PhD candidate	Garmin Watch	Mechanical Engineering
	G2-2	31	Female	PhD candidate	Garmin Watch	Design
G3	G3-1	25	Male	Master student	Apple Watch	Mechanical Engineering
	G3-2	23	Female	Master student	Garmin Watch	Design
G4	G4-1	30	Female	PhD candidate	Apple Watch	Applied Physics
	G4-2	29	Female	PhD candidate	Apple Watch	Mechanical Engineering
G5	G5-1	23	Male	Master student	Apple Watch	Applied Physics
	G5-2	24	Female	Master student	Apple Watch	Mechanical Engineering
G6	G6-1	30	Male	PhD candidate	Apple Watch	Civil Engineering
	G6-2	30	Female	PhD candidate	Garmin Watch	Design
G7	G7-1	29	Male	PhD candidate	Apple Watch	Applied Physics
	G7-2	34	Male	PhD candidate	Xiaomi Watch	Civil Engineering
G8	G8-1	24	Female	Master student	Apple Watch	Aerospace Engineering
	G8-2	24	Female	Master student	Apple Watch	Design
G9	G9-1	24	Female	PhD candidate	Xiaomi Watch	Mechanical Engineering
	G9-2	26	Male	Master student	Apple Watch	Computer Science
G10	G10-1	24	Female	Master student	Apple Watch	Design
	G10-2	25	Male	Master student	Apple Watch	Applied Physics
G11	G11-1	30	Female	PhD candidate	Apple Watch	Computer Science
	G11-2	30	Male	PhD candidate	Apple Watch	Aerospace Engineering
G12	G12-1	23	Female	Master student	Garmin Watch	Civil Engineering
	G12-2	29	Male	Master student	Apple Watch	Aerospace Engineering
G13	G13-1	24	Female	Master student	Apple Watch	Design
	G13-2	24	Female	Master student	Apple Watch	Design
G14	G14-1	28	Female	Master student	Apple Watch	Computer Science
	G14-2	28	Male	PhD candidate	Garmin Watch	Design

we conducted a 15-minute post-hoc interview with each pair of participants. A complete list of questions is in the Appendix in Table 4.

4.4 Data Analysis

4.4.1 Phase 1: Analyze the individual and collaborative visualizations. We reviewed all the images of the data exploration canvas and categorized the developed data representations based on the different uses of the data strips. We reviewed the video recordings and interview transcriptions to ensure the understanding of the developed visualizations and the insights generated from them.

4.4.2 Phase 2: Identify Data-Informed Activities. We analyzed the pair sensemaking activities by following the grounded theory analysis outlined by Glaser et al. [24].

- **Open Coding**: Two coders reviewed video recordings of the initial three groups to identify key interactions with the toolkit at the action level, such as "overlaying data," where participants stacked multiple data strips.
- **Axial Coding**: The coders then categorized these actions into distinct activities based on participants' intentions. For instance, actions like "overlaying data" and "removing data" were grouped under the activity of "reorganizing data," as shown in the activity column of Table 2. This process resulted in a consolidated list of activities that guided the coding of activities of the subsequent groups.
- **Selective Coding**: Finally, the coders discussed and organized the identified activities according to shared goals. For example, activities such as "load data" and "reorganize data" were grouped under the common goal of "develop individual data representations." As illustrated in Table 2, we distinguished individual and collaborative activities based on participant interactions. Collaborative and individual data constructions were identified through physical interactions with the toolkit, while other constructs emerged from verbal communication among participants.

4.4.3 Phase 2: Identify Pair Sensemaking Process. We re-examined the video recordings, coding constructs in the order they occurred. When multiple activities within the same construct (e.g., interpret data, share, and discuss experiences) occurred consecutively, we coded them multiple times using three yellow blocks ( ). Additionally, we incorporated spontaneous activities into the same blocks. For instance, when participants engaged in "developing representation" while simultaneously "explaining data," we represented these overlapping activities as .

4.4.4 Phase 3: Analyze Insight Moments. By reviewing the video recordings, we identified moments when participants explicitly expressed new or interesting personal insights. For instance, one

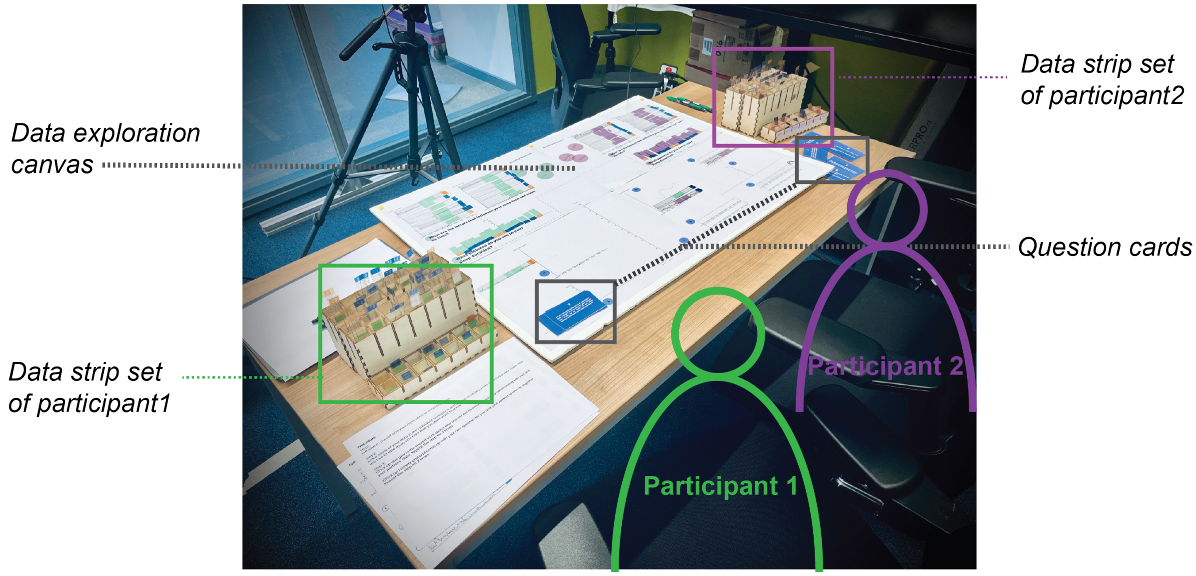


Figure 6: Pair session setup. Participants sit side-by-side in front of the data exploration canvas. Data strips lie on each side, with green strips for participant 1 (left) and purple strips for participant 2 (right). A video camera faces the participants while a second one (out of the picture) captures the scene top-down.

participant remarked, "I didn't notice that the days when I sleep longer, I have more interruptions." We then further analyzed the activities identified during the pair sensemaking process, along with the corresponding data representations, to understand how these insights were generated. We categorized all insight moments according to the leading activities and visualizations, which led to the three types introduced in Section 5.3.

5 Findings

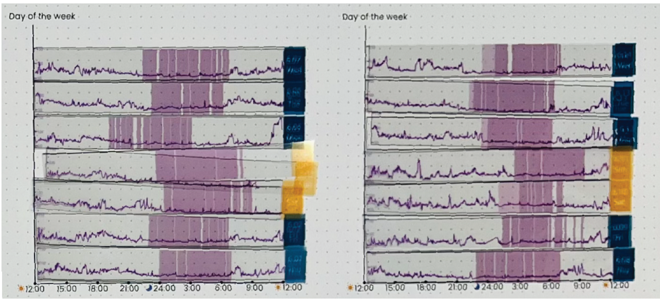
In this section, we report the findings of our study in three parts: (1) Developed data representations, (2) Pair sensemaking process, and (3) Insights moments.

5.1 Developed Data Representations

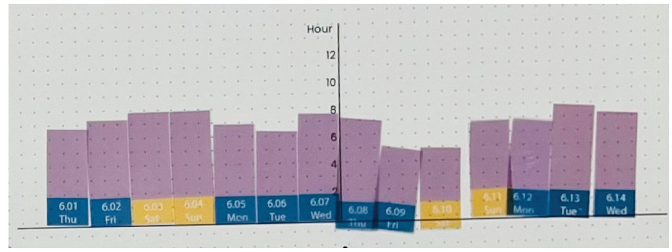
5.1.1 Individual Data Representations. Participants created four types of individual representations using their personal data strips. First, they sought a comprehensive view of all their data over two weeks, leading to stacks of sleep logs and corresponding heart rate strips organized on two exploration grids (see Figure 7a). Second, participants plotted their sleep duration strips for 14 days on side-by-side grids (see Figure 7b). Third, some participants analyzed their behavior weekly; for example, G_{4-1} compared sleep and heart rate across different weeks by plotting her data separately on two grids (see Figure 7c). Lastly, participants conducted in-depth analyses, developing complex representations that revealed data patterns across various time ranges and behavioral aspects, as illustrated by G_{12-1} in Figure 7d.

5.1.2 Collaborative Data Representation. The collaborative data representations consist of data strips of both participants, which we categorized into three types: **sharing**, **blending**, and **mirroring**.

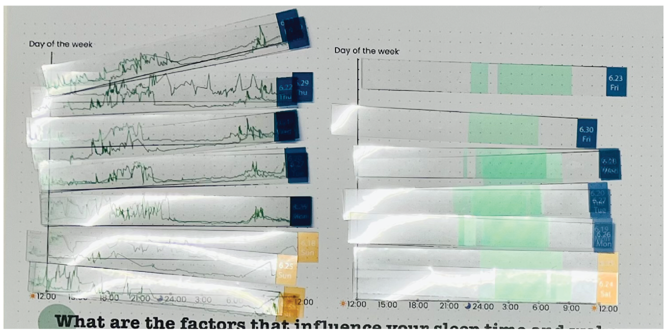
- **Sharing** helped participants compare behavioral trends. This type of data representation consists of stacks placed next to each other, each stack comprising strips of one type of behavior. Figure 8a illustrates this type of comparison with two stacks of seven sleep log strips, the top one from G_{12-2} (purple) and the bottom one from G_{12-1} (green). It shows that G_{12-2} had inconsistent wake-up time, ranging from 08:00 to 10:00 with break-ups, while participant G_{12-1} (green) had more consistent and a somewhat varying wake-up time, ranging from 08:30 to 09:30. Figure 8b provides another example, with two stacks of strips from each participant placed next to each other, each stack containing sleep log and heart rate strips of seven days. It shows that both participants shared the same heart rate pattern, which peaks at a similar time range (18:00 to 21:00, 09:30 to 10:30) and goes down while asleep. While their sleep times were different, G_{11-1} (bottom two, green) slept earlier and woke up at a similar time as participant G_{11-2} (top two, purple).
- **Blending** enabled participants to compare differences in their behaviors on the same day. This collaborative data representation involves multiple stacks of strips, each containing two strips from the two participants, each representing the same behavior on the same day. Figure 9b, for instance, shows that the sleep and wake-up times of G_{4-2} (purple) were always earlier than that of G_{4-1} (green), but with more fragmentation. Figure 9c shows the two participants had surprisingly close sleep and wake-up times with very different



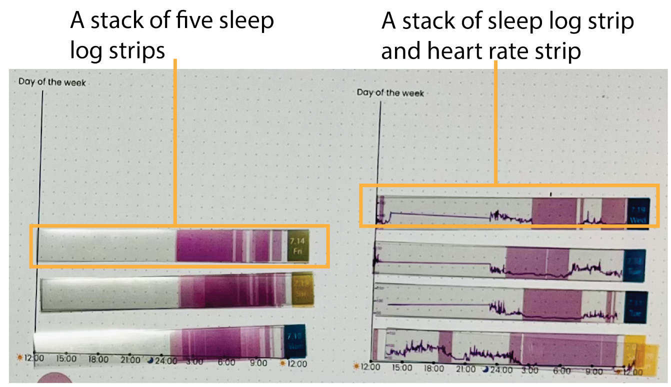
(a) G_{7-1} – Free exploration grids with sleep logs overlaid on heart rate strips, week one (left) and week two (right).



(b) G_{8-1} Side-by-side grid with sleep duration over 14 days.

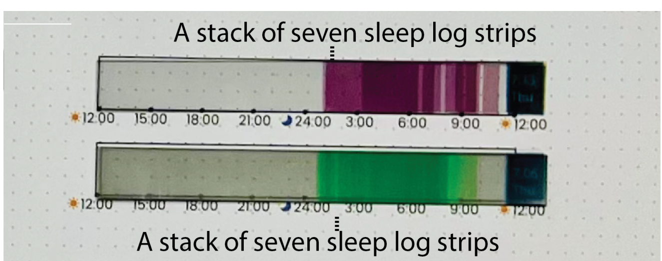


(c) G_{5-1} Free exploration grids with sleep log strips (left) next to heart rate strips (right) over seven days.

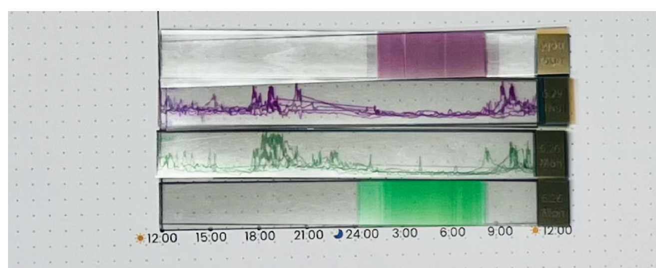


(d) G_{12-1} Free exploration grids with three stacks of five sleep log strips (right) and four stacks of one sleep log strip, and one heart rate strip.

Figure 7: Examples of individual data representations



(a) Overlay grid with two stacks of seven sleep log strips, the top one from G_{12-1} (purple) and the bottom one from G_{12-2} (green).

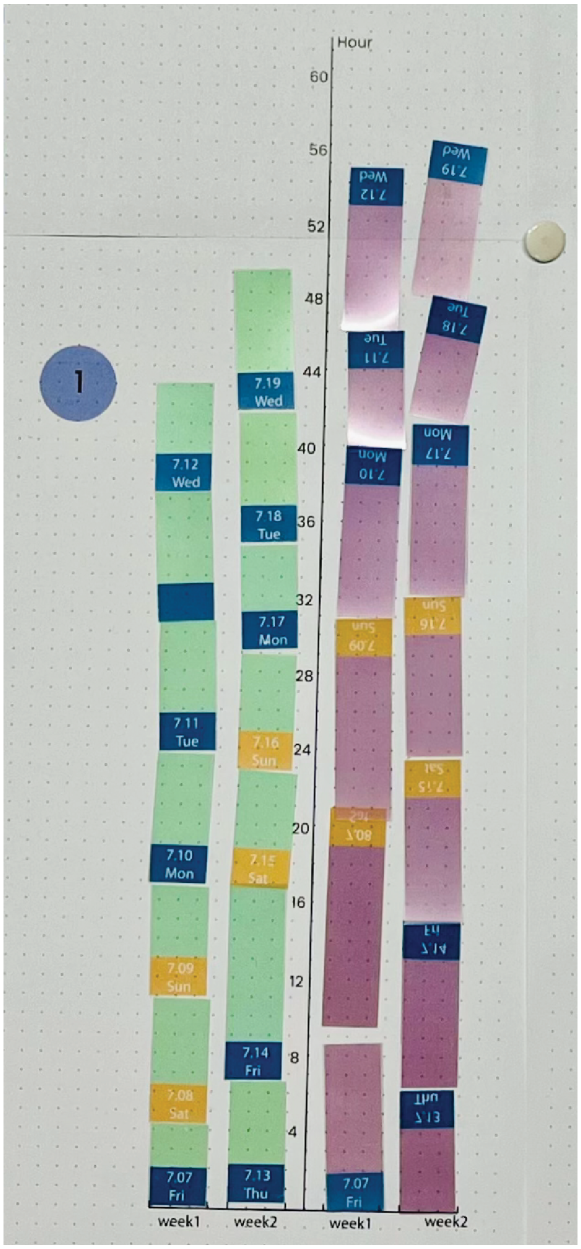


(b) Overlay grid with two stacks from each participant, each stack containing sleep log and heart rate strips of seven days, the top two from G_{11-2} (purple) and the bottom two from G_{11-1} (green).

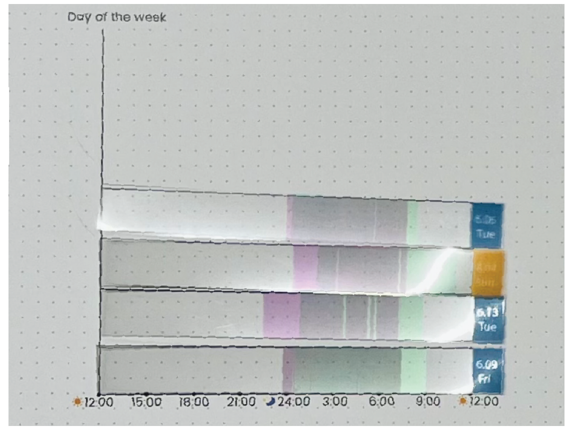
Figure 8: Examples of collaborative data representation supporting *sharing* activities

heart rate patterns. Yet, both sleep patterns correlated with their heart rate patterns. Figure 9d shows the sleep duration of G_{5-1} (green) was almost always longer than G_{5-2} (purple) over two weeks.

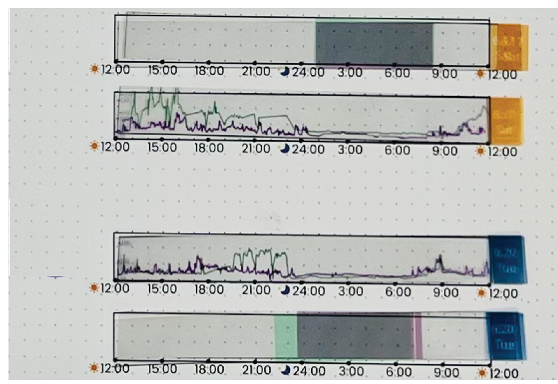
- **Mirroring** aids participants in summing up and comparing the total time of a behavior. This collaborative visualization lines up two sets of strips from two participants side by side on a Sum-Up grid. For example, Figure 9a shows the cummulated sleep of G12-1 (left, green strips) being lower than G12-2 (on the right, purple), grouped per week. Furthermore, we observed that this type of representation generated increased enthusiasm and engagement for most pairs, with a more direct sense of "competition" for the one accumulating the most sleep or exhibiting the most regular sleep duration.



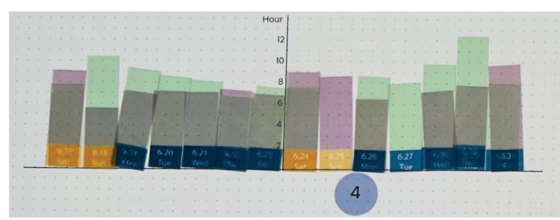
(a) **Sum up grid with weekly cumulated sleep for G_{12-1} (left, green) and G_{12-2} (right, purple)**



(b) **Free exploration grid overlaying the sleep log strips of G_{4-2} (purple) and G_{4-1} (green) across four days.**



(c) **Four overlay grids with stacks of one strip from G_{3-1} and G_{3-2}, sleep log on top and bottom stacks, and heart rate in the middle stacks.**



(d) **Side-by-side grid overlaying sleep duration strips of G_{5-2} (purple) and G_{5-1} (green) across 14 days.**

Figure 9: Examples of collaborative representation supporting *blending and mirroring* activities

5.2 Pair Sensemaking Process

In this section, we introduce the pair sensemaking process, including individual and pair working phases with various activities detailed in Table 2.

5.2.1 Individual working phase. During the individual working phase, participants developed data representations in their individual working workspaces in a loosely-coupled manner. As shown on the left side of Figure 10, this process began with participants individually plotting their data strips ( ) and analyzing patterns by overlaying, grouping, and reordering the strips ( ). Participants occasionally discussed or explained insights from each other's data. These spontaneous exchanges during the development of individual data representations helped participants understand each other's data, facilitating later collaborative visualization and reflection on personal experiences.

Table 2: Pair sensemaking activities. This table presents seven sensemaking constructs, each grouping multiple sensemaking activities according to the same goals when interacting with the PAIRcolator toolkit. Icons on the left of the "Construct" column correspond to the icons in Figure 10.

Construct	Goal	Activity	Description
Individual data representation development	Develop individual data representations	Load data	Select strips from the box, read and plot them on their individual working space to develop a data representation.
		Develop data representation	Develop a new data representation by taking and reorganizing a set of randomly placed strips.
		Reorganize data	Adjust an existing data representation by adding, replacing, or removing strips.
Individual data analysis	Analyze data patterns in own strips	Combine data	Overlay strips representing different behaviors (e.g., heart rate and sleep) of the same day to identify relationships between those behaviors.
		Group data	Organize strips based on criteria (e.g., weekdays and weekends).
		Aggregate data	Overlay strips of the same data type across multiple days to identify a behavior trend.
Collaborative data representation development	Develop collaborative data representations	Extend together	Work in pairs to add more strips to an existing collaborative data representation.
		Develop together	Work in pairs to plot their strips on a shared grid.
		Synchronize data	Work individually or in pairs to adjust a data representation according to that of the others.
Collaborative data analysis	Analyze data patterns across individual and collaborative data representations	Compare data	Work in pairs to read the collaborative data representations and articulate the differences between each other's data.
		Relate data	Work in pairs to identify the pattern in one data representation and relate it to other data representations.
		Explain data patterns	One explains data patterns identified in the data representations to the other.
Collaborative data inquiry	Inquire and explain data meaning in each other's data	Comment on data	Share opinions on the patterns of each other's data representations.
		Inquire data	Identify a data anomaly in each other's data representation and raise questions.
		Contextualize data	Explain data with personal and contextual information.
Collaborative data interpretation	Discuss and interpret behavior and experiences beyond data	Interpret data	Provide explanations and offer interpretation of each other's data.
		Share and discuss experiences	Inquire about each other's experiences and behaviors that are not directly captured in the data, and respond with detailed descriptions of habits, life conditions, and relevant events.
		Summarize insights	Engage in an ongoing exchange of explanations for behaviors not explicitly captured by the data.
Collaborative strategy	Discuss and exchange strategy	Discuss collaboration strategy	Discuss and agree on what data representation to develop to achieve a goal.
		Discuss possibilities	Explain to each other the data patterns they observed and brainstorm potential data representations that could enhance the visibility of these patterns or uncover other related patterns.
		Share data development strategy	Inquire about each other's use of strips and canvas to develop meaningful representations, and explain their approach and rationale.

For example, one participant G_{12-1} explored various overlapping possibilities with their data strips, resulting in the individual data representation shown in Figure 7d. She expressed surprise at the revealed pattern of fragmented sleep, which prompted a discussion with G_{12-2} about sleep quality. This curiosity led to a collaborative investigation of sleep-wake cycles, culminating in the creation of the shared visualization shown in Figure 8a.

> G_{12-1}: "Wow, my sleep was very fragmented... look at all these breaks!" G_{12-2}: "Yeah, that's interesting. Do you think it's linked to something specific, like stress or your schedule?"
> G_{12-1}: "Could be. I've been feeling tired lately. But maybe this is normal? Do you see anything similar in your data Do you have any similar patterns?"
> G_{12-2}: "Not many breaks, but I don't know if overlaying them would reveal some patterns as you. Maybe try it later"

5.2.2 Collaborative working phase. Participants engaged closely-coupled collaboration in developing shared data representations, following a consistent pattern of activities illustrated by the dotted rectangles in Figure 10. The pattern typically began with a discussion on visualization possibilities to address the question card( ), followed by joint development of data representations ( ). Various collaborative activities (, ,) then occurred naturally as participants analyzed and explored the life contexts behind the data. Finally, this pattern process concluded with continuous collaborative data interpretation activities ( ), during which participants delved into experiences beyond immediate data insights.

During the creation of collaborative representations, participants frequently communicated, such as discussing visualization strategies and expressing curiosity about data analysis, to align their exploration interests. At the same time, they actively manipulated each other's data ( ) to experiment with potential patterns in the representations. These exchanges offered contextual insights into each other's personal lifestyles, which subsequently facilitated the interpretation and reflection on the developed representations. The first dotted rectangle of G_9 at the beginning of the collaborative working phase in Figure 10 provides an illustrative example. Participants G_{9-1} initiated the process by individually overlapping their data strips to identify patterns, simultaneously explaining their intention to G_{9-2}. In response, G_{9-2} agreed and mirrored the activity:

Figure 10: Pair sensemaking process. We present the pair sensemaking process by ordering the identified data-informed activities in Table 2. Each row represents the sequence of sensemaking activities of a pair, consisting of an individual working phase (left) and a collaborative working phase (right). Each color block represents a cluster of activities under the same construct described in Table 2. We represented individual activities with two small, separate blocks positioned on the edges of the row (e.g.,), and the collaborative activities with a single central block (e.g.,). The process also allows for two concurrent collaborative activities, such as (e.g.,). On the right side, the legend shows the activity icons in the landscape orientation, while these icons are shown in the portrait orientation in the sequence.

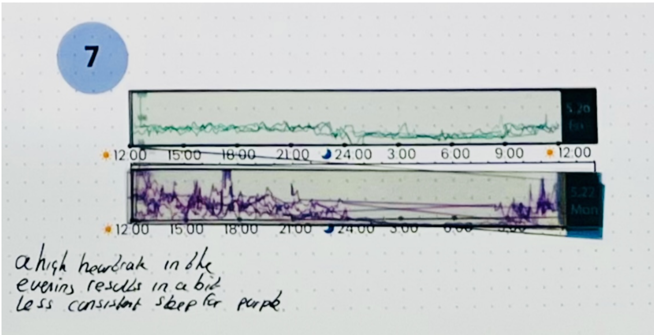
> G_{9-1}: "I am overlapping the heart rate data of a week to see if there is any pattern. I am curious to know how my heart rate changes during the day."
> G_{9-1}: "Oh yes, I am also curious. I think we share similar schedules as we need to go to work during the day."

Building on this shared curiosity, the participants collaboratively placed their overlapped data strips side by side, creating a shared data representation (see Figure 11a). This comparison highlighted a significant variation in G_{9-1}'s heart rate throughout the day (represented in purple), prompting G_{9-2} to inquire about the underlying life contexts:

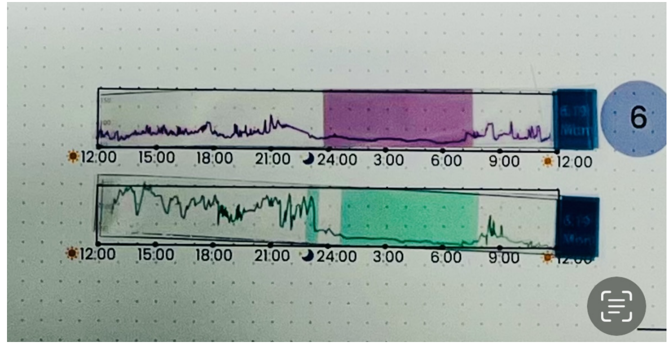
> G_{9-2}: "What did you do during the day? Why does your heart rate vary so much?"
> G_{9-1}: "Haha, I know. This is because I bike a lot from home to campus and back, and I also exercise during the day. However, I didn't predict that it varies this much. Yours looks pretty calm, by the way..."

5.3 Insight Moments

We observed a total of 42 insight moments across the 14 pairs. 17 insight moments arose from participants analyzing data patterns within individual and collaborative data representations, while 25 insights emerged during discussions that interpreted behaviors and experiences beyond the data. Notably, only two pairs (G_1 and G_8)



(a) Two stacks of seven heart rate strips, the top one from G_{9-2} (green) and the bottom one from G_{9-1} (purple).



(b) Two stacks from each participant, each stack containing sleep log and heart rate strips of the same day, the top two from G_{6-2} (purple) and the bottom two from G_{6-1} (green).

Figure 11: Examples of collaborative data representation

did not report any insight moments, whereas pairs like G_{11} and G_{13} experienced eight and six insight moments, respectively.

5.3.1 Comparing data in collaborative data representations. We found that comparing behavioral trends and correlations in collaborative data visualizations (e.g., Sharing and Blending) helped participants identify distinctions among their behavior and experiences. This comparison encouraged inquiry, interpretation, and discussion of the underlying contexts behind data. As a result, participants developed a broader understanding of diverse lifestyles and personal choices, enhancing their self-awareness and prompting them to pay more attention to these behaviors in the future.

For instance, in group G6, participants created a collaborative representation by juxtaposing their heart rate and sleep log strips (see Figure 11b). This comparison revealed an detailed data insights: G_{6-2}'s heart rate increased before sleep, while G_{6-1}'s heart rate remained low. Intrigued, they explored the reasons behind G_{6-2}'s elevated heart rate before bedtime. Ultimately, G_{6-2} expressed fascination with this insight and a commitment to monitor her heart rate before sleep more closely in the future.

> "Ah, I didn't notice. This is very interesting. Your heart rate is low before you sleep. My heart rate is [...] still peaking before I sleep. I need to pay attention to this. I am curious now what I did before sleep." (G_{6-2})

In another example, G_5 developed a collaborative data representation (Blending, see Figure 9d) by overlaying their sleep duration strips one by one over two weeks on a side-by-side grid. After comparing the length of sleep duration strips of each different day, G_{5-2} noticed that his sleep duration was almost always longer than the G_{5-1}:

> "I didn't notice that my sleep duration is always longer than you. It was not obvious in my own data here. You are really different from me!" (G_{5-2})

This difference triggered G_{5-1} to further inquire and discuss G_{5-1}'s working and sleep habits, and the reason behind the choices, which leads to a deeper understanding of diverse PhD life and his personal situation.

> G_{5-2}: " I thought I sleep less than average, but you actually sleep less than me...I don't have problem in falling asleep, the problem is I wake up early naturally."
> G_{5-1}:"I have a problem in falling asleep, and I set 12 alarm clocks to wake me up, in every 5mins... "
> G_{5-2}: "What? hahaha, Literately? 12 alarm clock? What kind of life are we PhD students living? I thought I my sleep quality is less than average, but now I know it can be very diverse... I'm not the only one..."

5.3.2 Relating two data representations through iterative collaborative inquiry and interpretation. We observed that participants formulated hypotheses from one data representation and validated them through iterative comparisons, inquiries, and interpretations of each other's data in the other data representation. This process facilitated the discovery of data pattern that revealed factors influencing their behaviors. The two data representations often consisted of two collaborative representations, though sometimes one was individual.

For example, in group G_{10}, For instance, participants created two collaborative representations, each featuring seven stacks of data strips on the free exploration grid. Each stack combined the sleep log and heart rate data strips from both participants for the same day, with each visualization spanning a total of seven days. In the first representation, G_{10-2} noticed an unusual heart rate peak in G_{5-1}'s data on Monday, prompting a collaborative interpretation dialogue:

> G_{10-2}: "What did you do on this day? Your heart rate in the afternoon is very high compared to the other days."
> G_{10-1}: "Is it on Monday? I was doing prototyping in group work. I don't know why the heart rate goes high."
> G_{10-2}: "Do you like that course?"
> G_{10-1}: "No, I don't. Because one of my group members is a bit aggressive."

> G_{10-2}: "Maybe that's why your heart rate goes high. She gave you a lot of pressure."

Inspired by the discussion, G_{10-1} examined the second data representation and identified a similar high heart rate peak on the Monday of the second week. This consistent pattern across both representations revealed a latent trend in her heart rate, highlighting an environmental factor influencing her anxiety levels.

> G_{10-1}: "You are right, look at this day. I also have group meetings with her, and my heart rate also goes high. I didn't realize that group work induces such anxiety for me. "

5.3.3 Inquiring and discussing experiences beyond data. Beyond confronting data representations, we observed that participants inquired and discussed each other's behavior and related personal contexts. This process helped participants uncover detailed insights into their behaviors. Furthermore, discussing personal contexts and reasons behind their behavior further helped participants uncover new aspects of their self-understanding.

For example, G_{13-2} shared that having early appointments caused anxiety and influenced her sleep:

> G_{13-2}: "This day, I wake up very early. I have an early appointment in the hospital at 06:00. I feel the stress to present that appointment, because it is very hard to make an appointment. I already missed once..."

This information triggered G_{13-1} to remember and share a similar experience:

> G_{13-2}: "Oh yes, I can relate to this. I have had a similar experience that when I have to present an early appointment; I feel the anxiety and couldn't sleep well. My appointment are study related appointment, but the anxiety is similar."

This relatedness in behavior triggered two participants to increase understanding of their personal quality:

> G_{13-2}: "I think both of us are sensitive to feel stressed, even small next day event can cause anxiety and influence your sleep quality. "

6 Discussion

6.1 Pair Collaboration for Making Sense of and Reflect on Personal Data

In this section, we first reflect on the novel approach of pair collaboration in the context of making sense of personal data. Next, we reflect on the proposed design rationales outlined in Section 3.1 and provide insights for future personal visualization design.

6.1.1 Benefits of pair collaboration for making sense of personal data. Our findings indicate that pair collaboration enhances sensemaking and reflection on personal data in two key ways: through data representation and the sensemaking process.

First, dyadic comparisons utilize a partner's data as reference points, allowing participants to focus on smaller data units that reveal detailed data instances for recalling and reflecting on personal experiences. As described in Section 5.1.2, participants created various collaborative representations (e.g., sharing, mirroring, blending) that provided zoomed-in perspectives for comparing data based on behavioral trends and differences. These detailed data patterns served as effective materials for further inquiry and interpretation, ultimately contributing to the emergence of insightful moments (Section 5.3.1).

Second, pair collaboration promotes a reciprocal process where participants engage in structured reflective activities to make sense of each other's data and experiences. Section 5.2.2 highlights a consistent pattern of pair sensemaking, characterized by extensive data communication activities, such as data inquiry and data interpretation, which led to insights. Furthermore, Sections 5.3.2 and 5.3.3 illustrate how one participant scaffolds the reflection process by asking questions and offering speculative explanations about the other's data, which fostered careful reflection and synthesis of personal experiences and beliefs and led to insight moments.

The aforementioned benefits of pair collaboration stand in clear contrast to group collaboration, commonly used in existing research on collaborative personal visualization [21, 60] and data physicalization [28, 64]. While one-to-many group comparisons effectively define norms and situate individuals [21], they often reduce engagement and personal connection to the data [30]. In contrast, pair collaboration uncovers detailed and emotionally resonant data instances revealing nuanced behavior and experiences, which are particularly effective anchors for recalling and re-examining experiences, fostering deeper reflection [12, 23].

In the sensemaking process, group discussions often devolve into monologues dominated by a few voices, limiting balanced participation [19]. Pair collaboration, on the other hand, promotes structured and reciprocal dialogues where both participants actively generate, refine, and evaluate hypotheses based on shared data insights. This balanced interaction fosters mutual understanding, self-awareness, and engagement in reflection. Thus, pair collaboration aligns with the reflective framework [22], widely applied in HCI and personal informatics to advance reflection from surface-level insights to deeper understanding [4, 11]. As fostering self-reflection becomes increasingly central to personal informatics, our findings highlight the pair collaboration's potential to enhance reflective engagement with personal data.

6.1.2 Application of pair collaboration in HCI. Pair collaboration has proven effective in providing detailed data insights through structured dialogues, which is particularly effective in fostering an in-depth understanding of personal behavior and experiences [4, 11]. The strength of this approach holds potential in broader HCI contexts.

One application of pair collaboration is healthcare, where collaboration between peer patients is an effective strategy for self-care and informed decision-making [5, 32, 75]. Patients often face complex, subjective choices about treatments and self-care strategies that require careful consideration of life contexts, economic factors, and personal values [48]. Our toolkit could be utilized in clinical settings, enabling doctors and experts to organize regular meetups where patients engage with peers to share insights, identify subtle symptoms, and assess self-care strategies tailored to their personal circumstances. This process facilitates informed decisions about both self-care and treatment.

Another potential application is in data-enabled design, where personal visualizations are used as reflective materials for users to explain their behaviors and experiences to designers [7, 8]. However, current data-enabled design interviews are often designer-driven [9, 49], which risks overlooking details from the user's perspective. By incorporating pair collaboration, our toolkit allows designers to contribute their perspectives by preparing data strips and question cards while still granting users the freedom to explore and interpret their data in detail. This balance enriches the design process by combining designers' insights with users' perspectives.

6.1.3 Potential Bias in pair collaboration. Pair collaboration can introduce potential biases. First, the insights generated are shaped by the relationship dynamics and shared experiences of the two participants. Pairings such as couples [63], community members with shared interest [13], or colleagues sharing the same working environment [60] may vary in their collaboration nature and levels of information disclosure, particularly in the context of health and intimate data [55]. This variability, in turn, influences the nature and depth of the insights. Second, the limited scale of pair collaboration may affect the reliability of comparisons and interpretations. For example, individuals might feel demotivated when comparing their data with a more successful peer, a phenomenon referred to as "downward comparison bias [17]."

To address biases in pair dynamics, future research could explore participant matching strategies that enhance relevance and mutual engagement, such as aligning pairs based on shared goals or complementary perspectives to foster connectedness [40]. Clear guidance on the purpose of pair collaboration can also mitigate biases from limited-scale comparisons. For instance, framing the toolkit as a tool for uncovering detailed behaviors for self-reflection, rather than performance evaluation, can redirect focus from competition to meaningful reflection, ensuring more constructive engagement with the data.

6.1.4 Privacy concerns in pair collaboration. Pair collaboration introduces privacy concerns, especially regarding the potential disclosure of detailed personal information (see Sec 6.1.1). Such information can include intimate scenarios (e.g., a couple in bed), recognized as sensitive [14, 27]. However, our interviews revealed that most pairs of participants reported that the pair setting reduces their concerns about sharing personal information due to two key factors: equal positioning and the dynamic nature of ongoing conversations.

One participant G_{5-1} noted, *"I like that the people sitting next to me have the exact same setting as I do. I can decide how much and when to share by feeling the atmosphere and considering the information that others have shared."* This sense of equal positioning fosters a balanced dynamic that reduces power imbalances and promotes openness in information exchange. Moreover, ongoing conversations facilitate effective privacy management by enabling participants to reflect on their data, observe their partner's willingness to share, and adjust their privacy boundaries in real-time. Thus, this pair collaboration approach encourages users to engage with their data to better understand its sensitivity and intimacy [26, 56] and aligns with the concepts of privacy as control and boundary management [15], helping to create an environment that supports sharing sensitive information.

Through our recruitment method (Section 4.2), all participants voluntarily agreed to share their data before participating in the experiment and had a clear understanding of their personal data. Notably, no participants withdrew during the study. However, our recruitment approach may have introduced a selection bias, as individuals hesitant to share their data were excluded. This limitation suggests that our findings may not fully capture the perspectives of those with greater privacy concerns. Future research should investigate individuals' apprehensions regarding data sharing in collaborative settings to ensure broader generalizability.

6.2 Design rationales for collaborative personal visualization

6.2.1 Offering guidance (DR2) for dyadic and agential comparison of data (DR1) facilitates aligning subjective perspectives and in-depth data analysis. The example in Section 5.2.2 highlight that entangled physical construction activities with other data-related communications, such as discussions on visualization strategies, facilitate participants create effective data representations, that harmonize their subjective perspectives and offer detailed data insights. In addition, the various shared data representations as detailed in Section 5.1.2 offered detailed insights for the emergence of insight moments in Section 5.3.

These findings suggest that presenting data in smaller, multifaceted segments with predefined guidance rules can effectively support both subjective and (dyadic) comparisons. By shifting the focus to presenting data into smaller and interpretable units, our approach has the potential to transform group-focused visualization tools to be better suited for aligning and leveraging interpersonal perspectives to enhance self-reflection. For example, current personal visualization systems, primarily optimized for group comparisons [16, 21, 59, 60], could be enhanced by integrating more diverse and multi-dimensional rules for data segmentation. These rules might address contextual, temporal, or behavioral dimensions, empowering users to concentrate on data that entails information that is most relevant to their lived experiences.

Our toolkit, while applying guidance-based construction (DP2), offers only limited types of comparisons (see Section 3.2.1). Providing a more effective structure for visualizing data that emphasize diverse comparisons would be beneficial for uncovering meaningful insights. Existing research in personal visualization has explored structures that support subjective data representation [6, 42, 65], these approaches often fall short in enabling comparisons. Future designs in personal visualization can integrate the established comparative methodologies [25] to existing visualization structures to allow more diverse and nuanced comparisons, thereby enhancing individual insights and collaborative understanding.

6.2.2 Prompting inquiry and interpretation of personal experiences (DR4) based on both individual and shared data representations facilitated the co-construction of personal narratives and led to meaningful insights (DR3). Our findings in Section 5.2.1 revealed that developing individual data representations helped participants become familiar with each other's personal data and experiences, which informed the development of collaborative representations. Continuous and close communication during and after the development of shared data representations, especially through inquiry and interpretation of personal data, effectively identified and connected data insights with personal beliefs, thereby fostering deeper reflection (see Section 5.3).

While existing personal visualization toolkits facilitate collaboration, they often prioritize direct comparisons within large groups, neglecting the need to coordinate the sensemaking process [11, 21, 60, 65]. Our findings indicate that combining design rationales DR3 and DR4 effectively coordinates individual and collaborative perspectives, fostering inquiry and interpretation of life experiences, which ultimately enhances reflection. To improve future toolkits—whether tangible or digital—designers could incorporate individual spaces for subjective analysis alongside collaborative environments. This approach balances personal data analysis with insights from others, enriching the interpretation and understanding of personal experiences. Moreover, although co-construction is commonly recognized as beneficial for reflection in data physicalizations [28, 65], our findings emphasize that facilitating ongoing inquiry and interpretation of developed data representations is effective for achieving deeper reflection. On another note, existing personal informatics (PI) tools that utilize conversational interfaces [44] and machine-based interpretation [47, 54] could also benefit from integrating guided visualization tasks to encourage continuous and reflective conversations among users.

We observed that two groups did not experience moments of insight, which may be attributed to the limited possibilities provided for constructing personal and shared narratives. These narratives primarily rely on the developed visualizations, which focus on adjusting time units but do not consider other dimensions, such as marks, layouts, and data content, as highlighted important for storytelling with data [10, 42, 58]. Future work is needed to incorporate more customizable narrative options in collaborative settings, allowing users to create diverse and personalized storylines

6.3 Limitations

6.3.1 Toolkit Design. Our tool faces scalability challenges, primarily due to the labor-intensive process required for its manual creation. Building the toolkit for each pair of participants needed a significant investment of research hours, averaging around 15 hours per pair. This substantial time and effort restrict its broader applicability, particularly in resource-constrained settings. Addressing scalability remains a task for future research.

6.3.2 Method. Participant recruitment for our study involved grouping individuals into pairs primarily based on their education level, without accounting for other demographic factors that could influence collaboration styles and levels of information disclosure. This approach was driven by the challenge of coordinating sufficient participants and their availability. While our primary aim was to qualitatively explore how individuals engage with data in pairs, this limitation may affect the generalizability of our findings. Additionally, despite efforts to diversify the participant pool, our study skewed towards individuals with higher education and data-related backgrounds, likely due to the university's tech-oriented environment. This demographic bias may affect the sensemaking experiences and outcomes, warranting caution in applying our results to broader populations.

7 Conclusion

In conclusion, this research contributes to the field of personal data visualization by addressing the challenge of facilitating communication and coordination within the collaborative sensemaking process of personal data. We explored pair collaboration as a novel approach for personal data sensemaking and proposed a set of design rationals to support this collaborative process. A personal visualization toolkit was developed based on these rationals.

To investigate the pair sensemaking process and toolkit usage, we conducted an observational user study with 24 university students working in 12 pairs, focusing on sleep data. Our findings indicate that pair collaboration offers several advantages: 1) it fosters more detailed comparisons of data, revealing nuanced insights that enhance reflection on personal experiences, and 2) it promotes a reciprocal process where individuals act as each other's "mentor" in inquiring and interpreting data, leading to deeper reflection.

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A Appendix

The appendix contains the pair session instruction, question card design, and the post-hoc interview questions.

A.0.1 pair session instruction. Welcome! In this session, you will use our our toolkit to collaboratively analyze each other's sleep and heart rate data and reflect on your sleep experiences.

Introduction to data strips: You will find a box containing data strips derived from your sleep and heart rate data collected over the past 14 days. We have provided three types of data strips, each presenting the heart rate and sleep data in different formats. These strips can be overlapped in various ways to reveal different data patterns (researcher shows the different possibilities as demonstrated in Figure 2, 3, 4). You are encouraged to explore the relationships and overlaps based on your interests.

Explanation of data exploration canvas and question cards: To explore the various overlaps of the data strips, please use our data exploration canvas. We have designed both individual and collaborative spaces, complete with guiding grids.

In the individual space, you are encouraged to plot your only own data strips based on the provided grids. Take the time to arrange the data strips in this space first to gain an overview of your own data. You may remove any data strips that contain information you prefer not to share; any strips left on the canvas indicate your consent to share that data.

In the collaborative space, you will work together to create visualizations by overlapping each other's data strips. A set of question cards, numbered to correspond with the grids, will guide your exploration. You will create three collaborative visualizations by addressing the questions on the cards. Feel free to personalize the visualizations and explore various methods to answer the questions, provided that your approach is mutually understandable.

A.0.2 Question card deck.

A.0.3 Post-hoc interview questions.

Table 3: The question card deck.

Question Number	Question
Q1	How does your sleep duration differ each day in the recent two weeks?
Q2	Reflecting on sleep data with heart rate data, is there anything that happened during the day that influenced your sleep?
Q3	What is your sleep routine? Please select sleep data and heart rate data from a specific day and explain it.
Q4	How consistent are your sleep durations? What events or factors influence your sleep duration?
Q5	How does your sleep duration vary between weekdays and weekends? What are the factors that lead to this trend?
Q6	How fragmented is your sleep? What factors lead to sleep interruptions?
Q7	Do you usually wake up at a consistent time range? If yes, how do you ensure you wake up on time? If no, what factors influence your wake-up time?
Q8	What is the range of your sleep time? What are the factors that lead you to sleep at this time period?

Table 4: The post hoc interview questions that were asked at the end of the research procedure.

Question Number	Question
Q1	What is your expertise in analyzing data?
Q2	Recall the process and explain what and how you generate insights.
Q3	What interesting insights did you generate?
Q4	Are there any interesting insights you generated by collaborating with your partner? Can you please give me an example?
Q5	Does comparing or relating with your partner's data bring insights to you? Please give me an example. Can you please tell me more details?
Q6	I saw you interpret and guess data. Is it helpful for you to generate insights? Why? Is it also fun?
Q7	In this process, how do you think collaborating with your partner helps you generate insights?
Q8	How does comparing and relating with your partner's data help you generate insights?
Q9	Do you find relatedness with others' data or experiences? How do you feel about it?
Q10	What feature of the toolkit design helps you generate insights?
Q11	What feature of the toolkit design do you like the most?
Q12	How do you feel you engaged in this task? Which part did you engage most, and which does not?
Q13	What makes you feel engaged in the task, and what does not?
Q14	Do you encounter any difficulty/confusion in using the toolkit to generate insights? Such as the individual workspace, collaboration workspace, bars, etc.
Q15	How do you feel about sharing and discussing your data in this pair-wise setting?
Q16	How does this pair collaboration make you feel comfortable and uncomfortable in sharing your data?