Pair Sensemaking of Personal Data
An Approach for Fostering Reflection on Personal Experiences

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Pair Sensemaking of Personal Data

An approach for fostering reflection on personal experiences

Di Yan

Pair Sensemaking of Personal Data:

An Approach for Fostering Reflection on Personal Experiences

Dissertation

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by

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Contents

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Summary

Motivation: In today's increasingly digital world, making sense of personal data has become a valuable approach for individuals to understand their behavior and reflect on lived experiences. Across fields such as personal informatics, data visualization, and design, supporting reflection through sensemaking of personal data is increasingly recognized as a critical for promoting behavior change and cultivating deeper self-understanding. Within the literature on collaborative sensemaking, pair collaboration has emerged as a particularly promising strategy for supporting reflective practices. It offers unique advantages—such as the integration of diverse perspectives, focused dyadic comparison, and rich interaction dynamics—that are especially effective for surfacing tacit knowledge and generating deeper insights. Despite this promise, most existing research in personal informatics and visualization has focused on individual engagement with personal data, with limited exploration of collaborative or group-level interactions. In particular, the distinctive characteristics of pair collaboration remain underexplored in the context of personal data. This reveals a significant gap in understanding how to effectively support pair sensemaking of personal data in order to foster reflection.

Objective: To address this gap, this dissertation introduces and develops the *pair sensemaking of personal data* approach—a novel method for fostering reflection through pair engagement with personal data. This approach emphasizes the integration of both one's own and others' data, dyadic comparison within subjective data representations, and reciprocal, reflective dialogues between pairs to co-construct self-knowledge and deepen personal reflection. To realize this objective, the thesis adopts a progressive, mixed-methods research strategy, unfolding across three empirical studies. Each study incrementally explores and refines how pair sensemaking of personal data can be effectively designed to enhance reflective engagement and foster meaningful insights into lived experiences.

Chapter 1 motivates the need for a new approach, pair sensemaking of personal data, for fostering self-reflection. By synthesizing literature from collaborative sensemaking and personal visualization, the chapter identifies the limitations of existing individual-focused methods and highlights the potential of pair collaboration to support deeper, co-constructed reflection. It defines the key components of the pair sensemaking approach, formulates the research questions, and outlines the methodological strategy guiding the dissertation.

Chapter 2 investigates how different data sources—one's own data and others' data—support reflection outcomes and processes. Through a crowdsourced online experiment, this study reveals distinct mechanisms of reflection and personal insights when making sense of others' data versus one's own data. These findings highlight the value of engaging with others' data and inform the framework's emphasis on integrating multiple perspectives to deepen personal reflection.

Chapter 3 explores and investigates the feasibility of supporting pair collaboration in the context of personal data, with a focus on dyadic comparison in data representations and the interactive dynamics of pair sensemaking. Through an observational study in which pairs of participants engage with a designed tangible visualization toolkit, this study offers empirical insights into how the co-development of shared data representations, along with coordination and role-switching during the sensemaking process, shape reflective

engagement. It also contributes a set of design principles that guide the development of tools for enabling effective pair sensemaking of personal data.

Chapter 4 investigates how the ideas of data humanism can be meaningfully incorporated into pair sensemaking of personal data. Specifically, it explores how personalized data representation, and slower-paced interaction central to data humanism can be balanced with the structured, comparative demands of collaborative sensemaking. To embody this balance, the chapter presents the design of a second tangible visualization toolkit that supports both individual subjectivity and shared interpretation. Through an observational study with pairs using the toolkit, the chapter examines how these design decisions shape the depth and quality of reflective dialogue. The study contributes a set of design principles for integrating subjective expression and collaborative structure, further enriching the thesis framework for pair sensemaking of personal data.

Chapter 5 presents a concluding overview of the research. It synthesizes findings from the three empirical studies to articulate the thesis's central contribution: the framework of pair sensemaking of personal data. By drawing connections across the studies, the chapter distills a set of core concepts and design principles that define this approach. It then situates the framework within existing literature to highlight its conceptual contributions—extending current understandings of reflection, collaboration, and personal informatics by foregrounding the unique dynamics of pair-based sensemaking with personal data. Finally, the chapter discusses the broader empirical implications of this approach across domains and identifies directions for future research.

Samenvatting

Motivatie: In een steeds digitalere wereld is het begrijpen van persoonlijke data een waardevolle benadering geworden voor individuen om hun gedrag te doorgronden en te reflecteren op hun geleefde ervaringen. Binnen vakgebieden zoals persoonlijke informatica, datavisualisatie en design wordt het ondersteunen van reflectie via betekenisgeving aan persoonlijke data steeds meer erkend als cruciaal voor het stimuleren van gedragsverandering en het verdiepen van zelfinzicht. In de literatuur over gezamenlijke betekenisgeving is samenwerking in tweetallen naar voren gekomen als een veelbelovende strategie om reflectieve praktijken te ondersteunen. Deze vorm van samenwerking biedt unieke voordelen—zoals het integreren van verschillende perspectieven, gerichte vergelijkingen in tweetallen, en rijke interactiedynamiek—die bijzonder effectief zijn in het blootleggen van impliciete kennis en het genereren van diepere inzichten. Ondanks deze belofte richt het meeste bestaande onderzoek in persoonlijke informatica en visualisatie zich op individuele interactie met data, en is er weinig aandacht voor samenwerking of groepsinteractie. In het bijzonder zijn de unieke kenmerken van samenwerking in tweetallen nog nauwelijks onderzocht in de context van persoonlijke data. Dit wijst op een belangrijke kennislacune: hoe kan samenwerking in tweetallen effectief worden ondersteund om betekenis te geven aan persoonlijke data en daarmee reflectie te bevorderen?

Doelstelling: Om deze lacune te adresseren introduceert en ontwikkelt dit proefschrift de benadering van *gezamenlijke betekenisgeving in tweetallen van persoonlijke data*—een nieuwe methode om reflectie te bevorderen via samenwerking met persoonlijke data. Deze aanpak legt de nadruk op het integreren van zowel eigen data als die van een ander, het vergelijken van subjectieve datavertegenwoordiging in tweetallen, en wederzijdse reflectieve dialoog om gezamenlijk zelfkennis op te bouwen en persoonlijke reflectie te verdiepen. Om dit doel te realiseren, hanteert het proefschrift een progressieve onderzoeksstrategie met gemengde methoden, verspreid over drie empirische studies. Elke studie onderzoekt en verfijnt stapsgewijs hoe gezamenlijke betekenisgeving in tweetallen effectief ontworpen kan worden om reflectieve betrokkenheid te stimuleren en inzicht in geleefde ervaringen te vergroten.

Hoofdstuk 1 onderbouwt de noodzaak van een nieuwe benadering—gezamenlijke betekenisgeving in tweetallen van persoonlijke data—om zelfreflectie te bevorderen. Door literatuur uit gezamenlijke betekenisgeving en persoonlijke visualisatie te combineren, benoemt het hoofdstuk de beperkingen van bestaande, op het individu gerichte methoden en belicht het de potentie van samenwerking in tweetallen voor diepere, gezamenlijk opgebouwde reflectie. Het hoofdstuk definieert de kerncomponenten van de benadering, formuleert de onderzoeksvragen, en schetst de methodologische strategie van het proefschrift.

Hoofdstuk 2 onderzoekt hoe verschillende databronnen—eigen data versus andermans data—bijdragen aan reflectieprocessen en uitkomsten. Aan de hand van een online crowdsourced experiment laat deze studie zien dat reflectie en persoonlijke inzichten op verschillende manieren tot stand komen afhankelijk van de gebruikte databron. Deze bevindingen onderstrepen de waarde van het werken met andermans data en ondersteunen de nadruk in het raamwerk op het integreren van meerdere perspectieven om persoonlijke reflectie te verdiepen.

Hoofdstuk 3 onderzoekt de haalbaarheid van samenwerking in tweetallen binnen de context van persoonlijke data, met specifieke aandacht voor vergelijkingen in tweetallen en de interactieve dynamiek van gezamenlijke betekenisgeving. In een observatiestudie, waarbij deelnemers in tweetallen werken met een speciaal ontworpen fysieke visualisatietoolkit, levert de studie empirische inzichten op in hoe gezamenlijke datavertegenwoordiging, coördinatie, en rolwisselingen reflectieve betrokkenheid beïnvloeden. Dit hoofdstuk draagt ook een reeks ontwerpprincipes aan voor het ontwikkelen van tools die effectieve samenwerking in tweetallen rondom persoonlijke data mogelijk maken.

Hoofdstuk 4 onderzoekt hoe ideeën uit data humanisme betekenisvol geïntegreerd kunnen worden in samenwerking in tweetallen rond persoonlijke data. Het hoofdstuk verkent hoe gepersonaliseerde datavertegenwoordiging en langzamer, meer beschouwend gebruik—kernaspecten van data humanisme—gebalanceerd kunnen worden met de gestructureerde, vergelijkende eisen van gezamenlijke betekenisgeving. Ter concretisering van deze balans wordt een tweede fysieke visualisatietoolkit ontworpen die zowel individuele subjectiviteit als gedeelde interpretatie ondersteunt. Door middel van een observatiestudie met tweetallen wordt onderzocht hoe deze ontwerpkeuzes de diepte en kwaliteit van reflectieve dialoog beïnvloeden. De studie levert ontwerpprincipes op voor het integreren van subjectieve expressie en samenwerkingsstructuur, wat het raamwerk voor samenwerking in tweetallen verder verrijkt.

Hoofdstuk 5 biedt een afsluitend overzicht van het onderzoek. Het synthetiseert de bevindingen uit de drie empirische studies en formuleert de centrale bijdrage van het proefschrift: het raamwerk voor gezamenlijke betekenisgeving in tweetallen van persoonlijke data. Door verbindingen te leggen tussen de studies, destilleert dit hoofdstuk een set kernconcepten en ontwerpprincipes die deze benadering definiëren. Vervolgens wordt het raamwerk gepositioneerd binnen bestaande literatuur, waarmee het conceptuele bijdragen levert—zoals het uitbreiden van bestaande inzichten in reflectie, samenwerking en persoonlijke informatica door de unieke dynamiek van samenwerking in tweetallen te benadrukken. Tot slot bespreekt het hoofdstuk de bredere empirische implicaties van deze benadering in diverse domeinen en schetst het richtingen voor toekomstig onderzoek.

1

Introduction

1.1 Context and motivation

In today's increasingly digital world, wearable and smart devices seamlessly integrate into our daily lives, continuously collecting vast amounts of personal data that capture our behaviors and activities. Making sense of personal data has served as a valuable approach for individuals to understand their behavior and reflect on live experiences [1, 2]. Through exploring and analyzing personal visualizations, individuals can uncover patterns in their behaviors and habits, enabling them to recall and (re)construct narratives about their lives [3–6]. For example, when reviewing a smartphone screen time visualization, a person might realize they spend several hours each evening on social media, often scrolling late into the night. This insight may prompt reflection on how such habits affect their sleep quality, contributing to daytime fatigue and reduced productivity at work.

Across various domains, there is growing recognition of the value of fostering reflection on lived experiences through the sensemaking of personal data [2, 7]. Personal informatics (PI), systems that help individuals track and analyze their personal data [8], primarily support basic levels of reflection by enabling users to identify insights and recall past experiences [7]. To enhance self-knowledge and drive behavioral change, it is crucial to achieve deeper levels of reflection—such as drawing connections between experiences (dialogical reflection) and developing new self-recognition (transformative reflection) [9, 10]. In data work, the sensemaking of personal data has been utilized to engage product users in articulating their user experiences [2, 11], such as with intelligent systems [12, 13]. As the focus shifts toward a human-centric approach [14–16], intelligent system design increasingly considers users' personal characteristics and contextual needs [17], especially the value users derive from their interactions with AI systems. Encouraging higher levels of reflection where individuals provide varied explanations of multiple experiences and critically examine their personal values [10] becomes increasingly important for systems design.

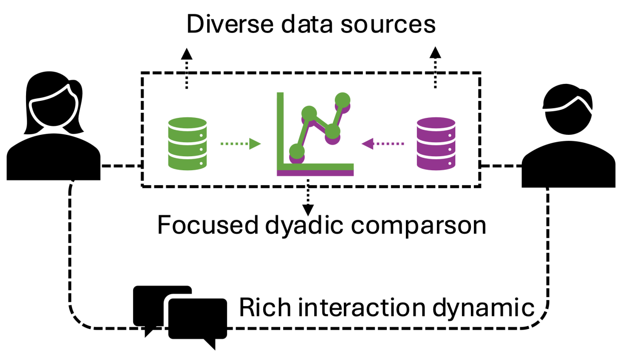

Figure 1.1: Pair collaboration with three characteristics that support self-reflection.

This thesis explores pair collaboration, a form of collaborative sensemaking in which two individuals jointly search for, organize, and interpret information within a shared representation [18, 19], with the aim of deepening reflection on personal experiences. Within the broader landscape of collaborative sensemaking, pair collaboration constitutes a particularly focused and reciprocal mode of joint inquiry, where both participants continuously question, respond to, and adapt to each other's interpretations. This dyadic interaction creates a space in which reasoning unfolds through dialogue—an exchange that is often less sustained in larger group contexts [18–20]. As a result, pair collaboration has been recognized as especially effective in surfacing tacit knowledge embedded in social and cognitive processes, revealing insights that might otherwise remain unspoken [18, 20]. The following outline three characteristics that capture how pair collaboration distinctively supports reflective sensemaking.

- **Inclusion of Diverse Perspectives:** Pair sensemaking integrates data of different sources—one's own data and others' data. Insights derived from different data sources vary in their effectiveness for facilitating reflection [21, 22]. For example, simple observations such as "being happier on weekends" provide limited value in deepening self-knowledge [22]. To achieve a comprehensive self-understanding, it is necessary to consider not only self-images arising from personal experiences spanning the past, present, and future, but also those emanating from others' data [23, 24]. By leveraging diverse data sources, pair sensemaking enhances data insights, facilitating reflection that transcends simplistic observations.

- **Focused Dyadic Comparisons:** Dyadic comparison offers a focused and detailed lens for data analysis by limiting comparisons to two individuals [25]. 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 [26], which serve as effective anchors for triggering the recall of past experiences, as well as for generating and evaluating hypotheses related to personal experiences [3]. Furthermore, dyadic comparison supports personalized visualization, as the reduced scope enables closer attention to specific attributes and the tailoring of visual representations to the characteristics of the individuals involved.

- **Flowing Dialogical Interaction:** Dyadic collaboration in the sensemaking process involves a continuous and reciprocal flow of dialogue through which individuals question, reason, and co-construct understanding [20, 27, 28]. This flowing interaction can manifest in different coupling styles, ranging from tightly-coupled to loosely-coupled collaboration [19, 29]. Loosely-coupled interaction affords individuals the autonomy to explore ideas independently, promoting focused reflection and engagement without excessive mutual influence [19, 30]. In contrast, tightly-coupled interaction fosters continuous, real-time exchange and feedback, creating conditions for the articulation of tacit knowledge that might otherwise remain implicit [20]. For example, studies in pair programming illustrate how such flowing dialogue supports reciprocal roles, where one collaborator takes on a foraging role—questioning hypotheses, seeking information, and maintaining awareness—while the other acts as a sensemaker, synthesizing and interpreting insights to advance collective understanding [31].

However, among personal data technologies, personal visualizations—widely used interactive visual data representations designed for individual contexts [32]—have received limited attention in facilitating pair sensemaking. Existing visualization tools have primarily enabled individual users to manipulate temporal components [33–

35], incorporate contextual information through annotations and algorithmic interpretations [36, 37], and adopt data humanism approaches that promote slow, reflective, and personalized engagement with data [6, 38]. Yet, only limited pieces of research have begun to explore the collaborative sensemaking of personal data [7, 23]. For instance, digital personal visualization tools allow individuals to compare aggregated personal data [36, 39]. Participatory data physicalization supports group comparisons by enabling individuals to collaboratively create shared representations through encoding their data into tangible tokens under predefined rules [40–42]. These approaches primarily focus on group comparisons, which are often limited to establishing norms [39]. Only one recent study by Friske, Wirfs-Brock, and Devendorf explored pair sensemaking, showing that pairs adopt entangled roles as both "makers" and "interpreters" when questioning and reasoning about crafted data representations, aiding in reconstructing personal narratives [26]. There remains a gap in understanding how to effectively facilitate pair collaboration for making sense of personal data, particularly in leveraging the distinctive characteristics of dyadic interaction. This dissertation therefore addresses a fundamental question:

> *How can pair sensemaking of personal data be designed to foster reflection on personal experiences?*

To answer the research question, this thesis introduces and develops the *pair sensemaking of personal data* as a novel approach for fostering self-reflection on personal experiences. In contrast to prior work that briefly explored pair sensemaking, this thesis defines the core elements of this approach by investigating the aforementioned core characteristics of pair collaboration. Specifically, it includes 1) the affect of data sources—one's own data and others' data in supporting reflection, 2) the role of dyadic comparison enabled by shared data representation in generating reflective insights, and 3) the constructive and reciprocal processes of meaning-making through discussion and narrative co-construction.

To investigate and develop this *pair sensemaking of personal data* approach, I employed a mixed-methods research strategy across three studies: a crowdsourcing experiment and two lab-based observational studies. This combination allowed for both breadth and depth in examining reflective practices: quantitatively capturing variation in reflection outcomes resulting from different data sources, and qualitatively uncovering the nuanced interpersonal dynamics and toolkit design that shape pair-based reflection. The insights from those three studies culminate in a conceptual framework of pair sensemaking of framework of pair sensemaking of personal data, along with validated design strategies and empirical insights that inform the creation of future tools for personal informatics and collaborative self-reflection. This thesis thus advances both theoretical understanding and practical applications, offering a socially grounded and relational perspective on how personal data can be used to support deeper, more meaningful reflection.

1.2 Thesis position in research landscape

Building on the recognized need to understand how pair collaboration can enhance personal data sensemaking, this section situates the present study within three interrelated areas of research. First, it reviews how reflection has been conceptualized and assessed within the HCI community, with particular attention to related domains such as personal informatics, data work, and human–data interaction, which emphasize the role of reflection grounded in personal data. Second, it examines the broader literature on collaborative sensemaking and considers how this concept can be applied to the context of personal data interpretation. Finally, it reviews research on personal visualization design, which not only highlights gaps in supporting deeper reflection through pair collaboration but also provides the methodological foundation for operationalizing the ideas developed in this thesis.

1.2.1 Fostering reflection through sensemaking of personal data

Personal data, collected from individuals' interactions with digital systems or physical environments, provides a detailed picture of human behavior [8]. Making sense of this data involves individuals actively exploring and interacting with personal visualizations, through which they identify data insights that representing their past behaviors, and reflect on the underlying experiences, motivation and feelings behind their actions and decisions [3, 43]. As a central goal of the sensemaking of personal data, this thesis regard the concept of reflection as reflection-on-action, which entails retrospective critical thinking aimed at reconstructing past experiences [44]. Following previous work in personal visualization [3], this thesis relies on Fleck and Fitzpatrick's framework and categorize reflection levels.

The sensemaking of personal data has been widely used to encourage individuals to reflect on their personal experiences. Across various domains, there is a growing recognition of the importance of fostering deeper levels of reflection. For instance, in the field of personal informatics, researchers and practitioners have developed systems that collect, analyze, and visualize data, enabling individuals to make sense of their personal data and gain insights into past behavior [8]. A key design objective of PI tools is to promote deeper levels of reflection [1, 7, 45]—particularly dialogical reflection (R2) and transformative reflection (R3), as these processes align with their primary goal of enhancing self-knowledge and driving behavioral change [43, 46, 47]. However, current personal visualization and PI tools primarily support lower levels of reflection (R0, R1), helping individuals recognize data insights and recall past experiences without prompting deeper introspection [7]. A significant gap remains in understanding how to foster reflection [7, 48].

In data work, designers and practitioners have used sensemaking of personal data to engage users in explaining their behaviors, usage contexts, and the underlying experiences that shape their interactions with products and systems [11, 49]. A set of methods and approaches has been developed as part of exploratory design process [2], such as participatory data analysis [50], data-enabled design [11, 51], contextual inquiry [12, 49] and articulation work [52]. For instance, Fahimi *et al.* applied the articulation work to explore Artificial intelligence (AI) fairness, engaging researchers to reflect on their personal and professional experiences with AI through visualizations of publication venues and research sub-areas [13]. As AI design shifts toward a human-centric approach [14–16], it is increasingly vital to understand users' subjective experiences, including personal characteristics and contextual needs [17]. Among these, users' pursued values in recommender systems (e.g., entertainment, well-being) are central to ensuring AI systems align with their preferences [53, 54]. To support more personalized and user-aligned AI systems, it is essential to foster deeper reflection, encouraging users to reinterpret their experiences within context and critically examine their personal values.

The sensemaking of personal data has been recognized as an effective method for promoting self-reflection on individual experiences. Given the growing demand for enhanced self-reflection across various domains, this thesis aims to foster reflection

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by introducing pair sensemaking as a novel approach.

1.2.2 Collaborative sensemaking of personal data

Collaborative sensemaking, involving a process of collaborative searching, schematizing and discussing relevant information [55], has been highlighted beneficial for understanding personal data and reflecting on personal experiences [7, 23, 24]. Comparing data with others, such as cohorts who share related interests and experiences, can reveal data patterns that help recall and relate past behaviors and the contexts underlying the data [24, 39], enriching the material for deeper reflection [10]. This collaborative effort also provides alternative perspectives for individuals to articulate the contextual factors influencing their personal lives and experiences [38, 56], aiding in the reconstruction of personal narratives [26]. Previous research on collaborative sensemaking identifies two key aspects that can be designed to enhance the understanding of personal data and experiences.

- **Shared Representation:** Shared representation serve as the instrument in the collaborative sensemaking process, where individuals re-organize the relevant information and make sense of it. 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 [28, 57]. When presenting personal data, this shared representation should facilitate comparison of both the data as well as personal behaviors [24, 39]. 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.

- **Sensemaking Process:** The sensemaking process incorporating interpersonal perspectives can encourage deeper explanation and interpretation of data. In the context of personal data, collaborative activities such as data explanation, inquiry and interpretation, can help integrate one's subjective perspective with alternative viewpoints from others, thus fostering data analysis and supporting the recall and reconstruction of personal narratives [26]. 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 [10], thus finding the "right sort of experiences" that is particularly reflective [7, 58].

Previous research on collaborative sensemaking has demonstrated its potential to enhance reflection. It also outlines specific design requirements for two critical components: shared representations and sensemaking processes, both essential for realizing the benefits of collaboration.

1.2.3 Personal visualization

Personal visualization involves "the design of interactive visual data representations for use in a personal context" [32]. Existing research has explored both digital and tangible personal visualization formats to offer distinct interactions for people to make sense of their data. Numerous digital platforms integrate diverse interactions with data, including facilitating easy manipulation of time components for visual exploration [33, 35], integrating contextual information through annotation and machine-based interpretation [36, 37], and utilizing storytelling and narrative strategies [4–6]. Another important line of personal data visualization research focuses on data physicalization, which refers to encoding data into physical geometry or material properties [59]. By leveraging the haptic and visual senses provided by tangible materials, tangible visualization enables various forms of interaction, including constructing visualizations by freely arranging building blocks of data [60, 61] or through responsive visualizations that sense and react to user input, such as vibration, temperature, or movement [62, 63].

In addition, recent research in personal visualization has explored the integration of Data Humanism approaches to enhance the understanding of personal data for individuals. Data Humanism is an approach first suggested by Lupi, 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 [64]. 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 [38, 65, 66]. For example, Giorgia Lupi and Stefanie Posavec collected and visualized their personal data through sketching, resulting in various personalized visualizations that reflect their subjective interpretations of personal data and life experiences [38]. Furthermore, there are digital visualization tools designed to help individuals develop personalized and expressive visualizations that convey qualitative personal contexts and information [6, 67]. One example is Dataselfie [6], a web-based interactive system designed to enable individuals to collect their data and decide how to visualize the data.

Despite this progress in individual sensemaking, only a few personal visualization toolkits have explored facilitating collaborative sensemaking of personal data. The most common approaches comprise digital personal visualization tools that offer standard visualizations and design the interaction with data around group comparison [24, 36, 39]. For example, Feustel *et al.* designed a collaborative personal informatics tool for co-workers to compare and annotate each other's data [39]. Similarly, participatory data physicalization [40, 41, 68] supports group comparison by enabling individuals to collaborate in creating shared representations through encoding their data into tangible tokens under predefined rules [41, 42]. For instance, Gourlet and Dassé assembled a large group of participants to craft a personal data physicalization using colorful wooden tokens that depicted their laboratory activities, which encouraged reflection by helping individuals situate themselves within many cohorts [41]. The comparison with aggregated group data is primarily beneficial for defining norms [39]. Only recent research by Friske, Wirfs-Brock, and Devendorf has begun to investigate pair sensemaking, where two individuals knit and interpret personal data representations together [26]. 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, previous research in collaborative sensemaking and reflection theory has highlighted the potential of pair sensemaking of personal data to support self-reflection. However, existing personal visualization tools are largely designed for individual use, with only limited attention given to group-level comparisons or collaborative reflection. A critical gap persists in understanding how to enable and design for pair sensemaking to foster self-reflection. Specifically, there is a need for deeper insight into how to support the distinct characteristics of pair collaboration, including: (1) how one's own data and others' data contribute differently to reflection, (2) how shared data representations can support dyadic comparison and joint interpretation of each other's data, and (3) effectively balance individual and shared perspectives, enabling pairs to co-construct personal narratives through dialogue and mutual feedback.

1.3 Research aim and research questions

The overarching goal of this thesis is to explore how pair collaboration can be leveraged to deepen reflection on personal experiences through the sensemaking of personal data. Specifically, it seeks to understand the unique characteristics of pair collaboration (see section 1.1) and how these can be supported through the design of personal visualization tools. To guide this exploration, the central research question is:

> *How can pair sensemaking of personal data be designed to foster reflection on personal experiences?*

To address this question and the research gap, this thesis introduces *pair sensemaking of personal data* as a novel approach for fostering self-reflection on personal experiences. In contrast to prior work largely focused on individual or group-level sensemaking, this research defines and systematically investigates the unique characteristics of pair collaboration. To develop this approach, I conducted three interconnected studies, each building on the last to deepen our understanding of pair sensemaking and inform the design of visualization tools. Across these studies as illustrated by Figure 1.2, I examine three core dimensions of the approach: (1) the comparative effectiveness of different data sources for reflection, (2) the design of data representations and collaborative processes that enable pair sensemaking, and (3) the integration of data humanism to enhance the reflective collaboration.

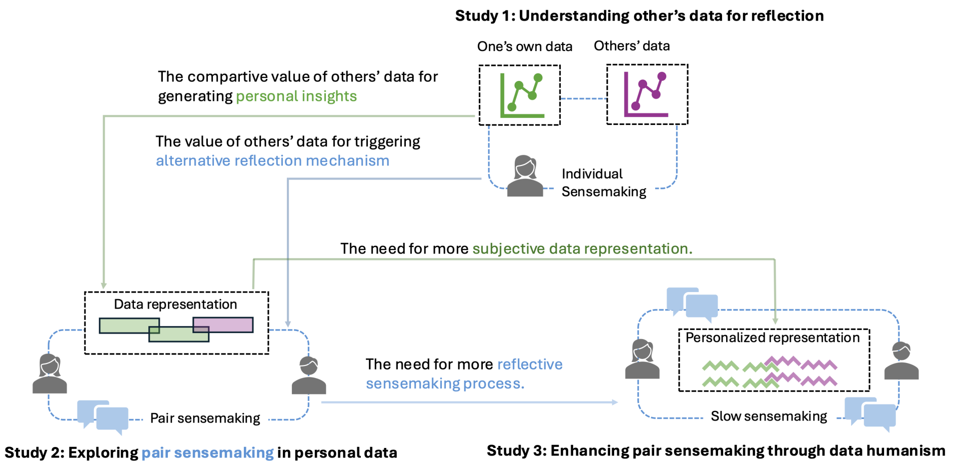

Figure 1.2: Overview of three studies with their goal, synthesis of results, and their relationship. Each chapter in this dissertation describes one study.

1.3.1 Study 1: understanding others' data for reflection

As an initial step in exploring pair sensemaking of personal data, the first study investigates the effectiveness of different data sources in facilitating self-reflection. Specifically, this study focuses on understanding how others' data influence one's own reflection, in comparison to reflecting on one's own data.

Prior research has shown that personal data often function as subjective representations rather than objective records, helping individuals reconstruct memories, analyze experiences, and form personal narratives [26, 69]. From this perspective, the ownership of the data may not be essential—others' data can similarly serve as prompts for reflection, anchoring recall and stimulating interpretation [21, 70]. However, while the reflective potential of personal data has been widely explored, existing work has focused predominantly on how individuals reflect on their own data [3, 71]. There remains limited understanding of how reflective processes and insights may differ when people engage with others' data. This study aims to address that gap by comparing how different data sources influence reflective process and insight generation. It is guided by the following research question:

RQ1: How do the reflective process and insights differ when individuals engage with others' personal data versus their own data?

The findings reveals that others' data can be comparably effective in prompting reflection. Others' data helped participants generate unique personal insights and engage in alternative reflection mechanisms such as guessing others' experiences, which were distinct from those used with their own data.

1.3.2 Study 2: exploring pair sensemaking in personal data

As highlighted in Figure 1.2, the first study's insights into the effectiveness of others' data in generating personal insights and activating distinct reflection mechanisms underscore the potential of incorporating others' data into both data representation (illustrated by the green line) and the sensemaking process (illustrated by the blue line). Building on these findings, the second study takes a step further by exploring the feasibility of the pair sensemaking approach, especially involving others' data in the data representation and pair sensemaking process.

Prior research has highlighted distinctive characteristics of pair sensemaking, such as focused dyadic comparison[25] and reciprocal, co-constructive meaning-making[20, 27], both of which are valuable for fostering self-reflection. However, most existing personal visualization tools have been designed to support either individual exploration[34, 72, 73] or group-level comparison[39, 40]. A critical gap exists in understanding how the defining features of pair collaboration—specifically dyadic comparison and reciprocal meaning-making—can be facilitated in the context of personal data to support deep reflection. In particular, there is limited knowledge about: (1) how to design data representations that enable effective dyadic comparison, and (2) how to support the switching of reciprocal roles and conversations that underpin co-constructive sensemaking. Thus, this study addresses the following research question:

RQ2: How can personal visualizations be designed to support dyadic comparison and facilitate switching between reciprocal roles that characterize the pair sensemaking process?

This study highlights that air sensemaking offers two key benefits in fostering reflection. First, it supports dyadic and agentive comparison, uncovering detailed data insights that are especially useful for recalling past experiences. Second, it fosters

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a structured, reciprocal interaction between participants, enabling deeper reflection through the reinterpretation and re-evaluation of experiences beyond the initial data insights. Additionally, I contribute a set of design principles that emphasize the importance of balancing user agency in developing data representations with providing guidance to effectively coordinate the pair sensemaking process.

1.3.3 Study 3: integrating Data humanism for fostering reflection

Building on the demonstrated feasibility of pair sensemaking of personal data, Study 3 aims to enhance this approach by developing data visualization tools that fulfill its unique requirements for deepening reflection. As illustrated in Figure 1.2, Study 2 highlighted the need to improve user agency in creating data representations and to foster a more reflective sensemaking process through better coordination. Therefore, Study 3 seeks to advance personal visualization design and by incorporating ideas from data humanism.

Data humanism, which emphasizes subjective, interpretive representations and a slower, more thoughtful engagement with data, has been applied in personal visualization research to support meaningful self-reflection and deeper understanding of personal data [6, 38]. While it has shown promise in individual contexts, its effective integration into collaborative visualization processes—especially within pair sensemaking—remains underexplored. Specifically, there exists a tension between the goals of data humanism and the demands of collaborative sensemaking. Collaborative sensemaking typically relies on structured data representations that enable comparison and joint interpretation, whereas data humanism promotes subjective, personalized expression. Additionally, collaboration often involves fluid shifts between individual and shared perspectives, which may conflict with the slower, more deliberate reflection championed by data humanism. In this study, I explore how principles of data humanism can be incorporated into the design of a tangible, collaborative visualization tool to deepen reflection in the context of pair sensemaking. This leads to the following research question:

RQ3: How can pair sensemaking balance the requirements of the data humanism approach with those of collaborative sensemaking to foster reflection on experiences?

This study offers empirical insights into how personalized visualizations and a slower-paced sensemaking process can support collaborative reflection on personal experiences. It also contributes a set of design principles for creating visualizations that integrate data humanism with the dynamics of pair collaboration, helping to guide future tools that promote reflective, co-constructed meaning-making.

1.4 Research methodology

To investigate and develop an approach for pair sensemaking of personal data, this thesis adopts a progressive, mixed-methods research strategy. The approach begins with a broad online experiment examining how different data sources—one's own versus others'—shape reflection, followed by two in-depth, in-person studies that explore the interpersonal dynamics of pair sensemaking. This progression from data source effects to pair dynamics reflects the evolving research focus and ensures both conceptual depth and design relevance. The combination of quantitative breadth and qualitative depth ensures that both conceptual insights and design implications are grounded in empirical observation.

1.4.1 Combining online and lab-based studies

This thesis combines online and lab-based studies to progressively explore pair sensemaking of personal support reflection—first by isolating the role of data sources, then by examining the dynamics of pair sensemaking sensemaking.

Study 1 investigates how different data sources—one's own versus others'—affect self-reflection, without involving interpersonal interactions. To do this, I conducted a crowdsourced online experiment. This crowdsourcing approach enabled access to a large and diverse participant pool, which was critical for the comparative nature of the study. A broad sample allowed for more robust and statistically reliable insights into how each data source shapes reflection. Participants engaged with standardized sleep visualizations generated by smartwatches, typically shared as screenshots. This methodological choices were grounded in the prevalence of digital platforms and smartwatch data in everyday reflective practices [7]. As a result, the findings of this study are more likely to be relevant and applicable to real-world contexts and future research in reflection.

Study 2 and study 3 transitioned to a co-located, observational lab setting to examine the interactive dynamics of pair sensemaking in greater detail. Study 2 explored how to design collaborative visualizations that support dyadic comparison and reciprocal sensemaking. To enable close observation of the interpersonal and interactional aspects of this process, participants used a tangible, physical toolkit in a shared physical space. This setting allowed behaviors such as role-switching, gesture, turn-taking, and narrative co-construction to be made visible, which would have been difficult to capture in a remote or digital context. Study 3 built on the same lab-based setup to investigate how design elements inspired by data humanism, such as personalization and slower-paced interaction, could be integrated into the pair sensemaking process. In doing so, the study also aligns with the perspective of Human–Data Interaction (HDI), emphasizing people's interpretive and situated relationships with data rather than purely analytical engagement. The continuity in study format allowed for a focused examination of how these new elements impacted collaborative reflection.

1.4.2 Mixed Methods

This thesis applies a mixed-methods approach across studies to balance breadth and depth in evaluating reflection practices—quantitatively measuring reflective outcomes and qualitatively unpacking the complex sensemaking processes.

In Study 1, I employed a mixed-methods analysis to examine participants' written reflections, combining quantitative evaluation of reflection levels with qualitative coding of insight types. To assess the depth of reflection, I applied Fleck et al.'s reflection framework [74], which provided a structured rubric for comparing reflection levels across participants. This framework allowed for consistent, quantitative measurement while grounding the analysis in an established conceptual model of reflective practice. To analyze the types of insights generated, I conducted both deductive and inductive coding. The deductive phase drew on existing frameworks from personal informatics research [3, 75], offering a stable foundation for categorizing expected forms of insight. The inductive phase allowed for extension and refinement of these frameworks by capturing emergent insights, particularly those arising uniquely from participants who engaged with others' data rather than their own. This layered approach was adopted to match the comparative and exploratory goals of the study: it enabled both a statistically robust comparison between groups and a nuanced, mechanism-focused interpretation of how participants interacted with different data sources.

Given the exploratory nature of Study 2 and the limited existing understanding of the nuanced interpersonal processes involved in pair sensemaking with personal data, I adopted a qualitative approach to capture and interpret the complexity of real-time collaboration. I collected observational data, including photographs of the co-created visualizations and video recordings of participants' interactions, focusing on how meaning was negotiated through verbal exchanges, role-switching, and joint narrative construction using the designed toolkit. To analyze this data, I employed a grounded theory approach [76], which was well-suited to the study's aims. Grounded theory enabled a bottom-up, iterative analysis that could reveal emergent patterns without imposing predefined categories—an essential methodological fit given the lack of established frameworks for understanding how reflective insights are generated collaboratively in dyadic settings.

Study 3 continued with grounded theory to maintain methodological consistency, while extending the analytical lens to examine how data humanism-inspired design elements—such as personalization and slower-paced interaction—shaped the pair sensemaking process. This consistent analytic strategy allowed for the development of a more nuanced, empirically grounded understanding of how collaborative reflection unfolds in co-located, tangible settings. The resulting insights offer a foundation for designing more relational and human-centered tools that support shared reflection on personal data.

Collectively, these studies exemplify a human-centered, data-oriented methodological approach that aligns with broader HCI theories of triangulation [77] and human-centered design [78]. Triangulation, through the combination of large-scale online experimentation and in-depth lab-based inquiry, strengthens the validity of the findings by integrating quantitative generalizability with qualitative depth. The human-centered design orientation ensures that methodological and design decisions are grounded in participants' experiences, with each iteration of the visualization toolkits informed by direct engagement and reflection. This methodological stance also resonates with the perspective of data humanism, which emphasizes personalization, interpretive engagement, and the creation of meaningful connections between data and lived experience, rather than treating data solely as an analytical artifact.

1.4.3 Iterative literature synthesis and toolkit design

This thesis adopts an iterative approach to literature synthesis to inform both the development of design principles and the creation of collaborative visualization toolkits. Especially in study 2 and study 3, I continuously integrated insights from related fields to guide design decisions across studies.

In Study 2, I synthesized prior research in collaborative and pair sensemaking [19, 25, 28, 55], personal informatics, and personal visualization [23, 24, 39, 41, 42, 79] to develop an initial set of design principles. These principles addressed key challenges in enabling pair sensemaking of personal data, supporting dyadic comparison, and co-construction of meaning between pairs. They were operationalized in the design of a tangible collaborative visualization toolkit, PAIRcolator, which was then evaluated through a lab-based observational study.

In Study 3, I extended this literature synthesis to include perspectives from data humanism [26, 38, 64], which emphasize personalization and slower-paced interaction in data visualization design. These ideas informed a new set of design principles aimed at balancing collaborative insight-making with human-centered values. The revised principles guided the creation of a second collaborative toolkit, Reciportrait, which was again studied in a lab setting. This iterative design process allowed for the exploration of how different design values influence collaborative reflection practices over time.

1.5 Research contributions

Through three interrelated studies, this dissertation introduces the concept of pair sensemaking of personal data and contributes a comprehensive framework, design strategies, and empirical insights to support this novel approach.

The primary contribution is a *conceptual framework* for pair sensemaking of personal data, which defines how two individuals collaboratively develop collaborative visualizations with each others' data and help each other in reflect on personal experiences. This framework identifies and articulates three key characteristics of the approach: (1) the use of complementary data sources, specifically, reflecting on one's own data versus interpreting another's—which shapes the depth and mechanisms of insight; (2) the practice of dyadic comparison, where partners contrast and contextualize each other's data to reveal detailed data insights and scaffold interpretation; and (3) a reciprocal, constructive sensemaking process, driven by interpersonal dialogue based on the revealed data insights. Together, these dimensions characterize a new mode of collaboration that contrasts with the existing group collaboration paradigm in personal visualization and informatics.

This framework extends prior models of reflection and sensemaking in HCI and personal informatics, which have predominantly framed reflection as either an individual cognitive activity or a coordinated group process. Unlike existing frameworks that often emphasize reflection levels or individual cognitive mechanisms [10, 80, 81], it introduce a distinct dyadic mode of collaboration that concretely describes how two individuals engage in and sustain reflective dialogue, what forms of coordination and mutual awareness are required, and how meaning is jointly constructed through shared visualization.

The second major contribution is *a design-oriented contribution*, comprising a set of design principles and tangible toolkits that operationalize the pair sensemaking framework. Through Studies 2 and 3, I translated theoretical insights into actionable design strategies. The first set of principles, derived from Study 2, supports pair sensemaking of personal data by guiding the structuring of data representations and the coordination of the collaborative process. The second set, informed by data humanism, provides guidance for designing personalized and subjective data representations to support slow, reflective sensemaking. These principles were implemented in two tangible toolkits—PAIRcolator and Reciportrait —each developed and evaluated in controlled lab settings.

This design contribution bridges collaborative visualization and personal informatics through the design of tangible, reflective tools and articulated design principles. It advances collaborative visualization by offering humanistic design insights, such as personal meaning, interpretive depth, and emotional resonance—into data representation, expanding the design focus from analytical coordination to reflective and emotionally engaged collaboration. At the same time, it contributes to personal informatics by introducing collaborative design strategies that transform personal reflection from an individual activity into an interpersonal, dialogic process.

The final contribution is an *empirical contribution*, offering a grounded understanding of how pairs engage in reflective sensemaking with personal data. Through qualitative observational studies, I examined how pairs interacted with the toolkits and how design features influenced reflection dynamics, insight generation, and interpersonal coordination. These findings not only validate the framework and design principles but also reveal practical considerations and emergent behaviors that can inform future research and the development of tools for collaborative self-reflection.

This understanding extends existing research on reflection and sensemaking in personal informatics and HCI, which has primarily focused on reflection as an individual cognitive process. It advances this work by showing how reflection emerges through social interaction and continuous dialogue in dyadic settings. The findings offer empirical evidence of co-reflection, role negotiation, and joint meaning-making between partners, deepening understanding of how design mediates interpersonal reflection and enhances personal insight through collaboration.

1.6 Thesis structure

This dissertation follows a paper-based format, with each chapter centered around a peer-reviewed conference publication. The included papers have been published across a variety of venues within the field of Human-Computer Interaction (HCI). At TU Delft, it is standard practice to include published papers in their original form as chapters in a PhD thesis. Accordingly, Chapters 2, 3, and 4 consist of previously published papers that have been included verbatim. This paper-based format allows each chapter to stand alone and be read independently. However, it may also lead to some unavoidable repetition, particularly in the introduction and discussion sections of individual chapters.

Chapter 2 explores the effectiveness of one's own data versus another's in facilitating self-reflection. The findings on the differing sensemaking processes and insights derived from these data sources inform the development of the pair sensemaking of personal data framework. Chapter 3 explores the feasibility of pair sensemaking of personal data. It provides insights into the unique dynamics and benefits of this dyadic collaboration within the personal data context and initiates the design of personal visualization tools. A user study further deepens understanding of the pair sensemaking process and evaluates how the designed visualizations support reflection on personal experiences. Chapter 4 further develops the pair sensemaking of personal data approach by integrating ideas of data humanism into personal visualization design. I propose design principles to facilitate collaborative sensemaking of personal data, balancing the needs of both Data Humanism and collaborative sensemaking. Through a user study, I evaluate the design of toolkit, 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. Finally, Chapter 5 summarizes the key findings of this thesis and consolidates them into a comprehensive framework for pair sensemaking of personal data. This chapter discusses the unique characteristics of the pair sensemaking approach and its implications across relevant domains.

2

Chapter 2: Understanding others' data for self-reflection

This chapter was previously published as: Di Yan, Jacky Bourgeois, and Gerd Kortuem. 2024. Say You, Say Me: Investigating the Personal insights Generated from One's Own data and Other's data. In Proceedings of the 13th Nordic Conference on Human-Computer Interaction (NordiCHI '24). Association for Computing Machinery, New York, NY, USA, Article 12, 1–14. https://doi.org/10.1145/3679318.3685345

This chapter focusing on understanding the effectiveness of one's own data and others' data in facilitating personal insight. The design of collaborative personal informatics (PI) has shifted its focus from using one's own data to integrating others' data to enhance self-understanding. In this trend, understanding the effectiveness of the two data sources in facilitating personal insights becomes essential, as a comprehensive understanding of self knowledge requires insights from both individual and interpersonal perspectives. While recent studies have suggested the potential role of others' data as a reflective medium to generate personal insights, little is understood about its distinctive effectiveness in personal insights generated compared to one's own data.

To address this gap, I conducted a crowdsourced study involving two participant groups (N1=N2=60) in a data-informed reflection task: Data Providers (DP) reflecting on their own data; Non-Data Providers (NDP) reflecting on the data provided by DP. Analyzing the textual responses, I assess the reflection levels, self-disclosure levels, and characteristics of personal insights. The findings uncover that others' data possess a comparable effectiveness in facilitating reflection and self-disclosure of personal thoughts and feelings. Others' data displays a strength in supporting value judgments, while one's own data excels in enhancing behavioral awareness. This research sheds light on the design of collaborative PI, offering insights into how to leverage the benefits while mitigating the disadvantages of both data sources to enhance the self-understanding.

2.1 Introduction

Recent research in HCI has witnessed an increase in the design of collaborative Personal Informatics (PI) systems. In contrast to the common assumption in PI that an individual's knowledge of their personal data facilitates generation of personal insights, recent practices have shifted towards involving others' data to enhance reflection on one's own experiences. This integration of other's data extends to various practices, including incorporating family members' data for providing social and contextual information [82, 83], integrating cohorts' data to compare related behaviors [24, 84, 85], and curating personal data online to stimulate commenting and reflecting on personal experiences [86–89].

Apart from developing practical approaches for making sense of data, it is important to deepen our understanding of the effectiveness of different data sources in facilitating constructing comprehensive self-knowledge [21, 90]. Different data sources possess various effectiveness for generating personal insights [21, 22], which contribute to the description of different self-images [23]. To achieve a comprehensive self-understanding, it is necessary to consider not only self-images arising from personal experiences spanning the past, present, and future, but also those emanating from interpersonal interactions [23, 24]. Understanding the effectiveness of different data sources for personal insights generation is especially relevant in the context of contemporary PI systems that prioritize comprehensive self-understanding through the integration of others' data [7, 85].

However, prior work in PI has primarily focused on understanding the effectiveness of one's data in facilitating personal insights generation. This has led to a concentration on understanding the reflection process and outcomes related to one's own data [3, 52, 71, 91], such as investigating the reflection levels and insight-gaining patterns through visual exploration of one's data [3] and characterizing types of personal insights derived from making sense of personal data individually [3, 71]. In terms of others' data, recent work has suggested that it can serve as digital representations of individuals for subjective analysis [92] and promote the construction of personal narrative through interpretation and remembrances [26, 69], as opposed to providing an objective truth. Thus, engaging with others' data not only aids in analyzing alternative self-images from an interpersonal perspective [10, 23] but also enriches the self-image by introducing intricate personal narratives constructed through (mis)interpreting and (mis)remembering prompted by data [26, 93]. While those insights suggested the potential role of others' data in the reflective process, an understanding of how insights generated from others' data differ from those generated from one's own data is missing. In this study, we pose the following research question:

> *RQ: How do the reflective process and insights differ when individuals engage with others' personal data versus their own data?*

We conducted a study involving a data-informed reflection task wherein participants make sense of sleep data and reflect upon their experiences, via a crowdsourcing platform. We focused on sleep as a context due to the popularity of sleep trackers [94, 95] and prevalent discussions in both online forums [96] and interpersonal Personal Informatics (PI) [82]. We recruited a total of $N = 120$ participants evenly distributed into two groups: Data Providers ($N = 60$) and Non-Data Providers ($N = 60$). Data Providers (DP) comprised participants who were sleep trackers and submitted a screenshot of their sleep data. Non-Data Providers (NDP) were participants who did not submit their sleep data but reported prior experiences in sleep data collection and an interest in understanding their sleep patterns through data. To assess the effectiveness in facilitating personal insights and privacy concerns related to disclosing personal information with data, we systematically evaluated the reflection level, self-disclosure level, and types of insights derived from responses of both DP and NDP.

Our results are threefold. First, others' data possesses comparable efficacy to one's data in facilitating reflective description and dialogic reflection, as well as disclosing personal thoughts, and feelings. Second, others' data demonstrates greater efficacy in assisting individuals in expressing their value judgment by articulating perceptions, attitudes, and opinions. Conversely, one's own data proves more beneficial in enhancing individuals' awareness of their past behavior, particularly in the reconsideration of self-assumptions. Finally, DP tended to generate insights by comparing their self-cognition with data, while NDP tended to compare and interpret other's data to invoke the recall and recognition of their past experiences. These findings underscore the significant role of others' data in fostering reflection, and articulate the distinct effectiveness of others' data versus one's own data in generating personal insights. We provide guidance on leveraging the strengths and mitigating the disadvantages of the two data sources in generating personal insights. We discuss the implications for the design of collaborative PI systems for enhanced insight generation.

2.2 Related Work

2.2.1 Collaboration in Personal Informatics

A growing body of literature in HCI explores the design of collaborative Personal Informatics (PI) [73, 97]. One of the notable shifts is from personal health informatics to family health informatics, where the personal data of family members becomes a valuable resource to provide social and contextual information for understanding the interconnected relationship between each family member's behaviors [82, 83, 98]. Furthermore, several studies have embraced the inclusion of others' data as a comparative tool for participants, facilitating the identification of behavioral differences and thereby enriching reflective insights [24, 85]. There is also a rise in online co-curation of personal data, stimulating sharing and reflection on personal experiences [86, 87, 99]. Making sense of and commenting on others' personal data, especially peers who share related experiences, has proven beneficial in enhancing participants' understanding of their own experiences and in promoting the management of well-being and chronic symptoms [86–89]. In addition, within these collaborative contexts, self-disclosing personal information, thought and feeling upon personal data is a default activity, which benefits a reciprocal process for people to increase self-knowledge and gain emotional support [100]. Prior research has revealed that multiple factors related to data, such as information level [101], post content [100], and presentation style [99], can influence the disclosure of personal data and related experiences.

Apart from exploring the utilization of others' data, it is also crucial to understand the effectiveness of various data sources in facilitating the generation of personal insights [21]. Previous research has emphasized that within a multi-faceted data flow, insights derived from certain data are considered more valuable than others [21, 22]. For example, the more "obvious" insights generated from data, such as "being happier on weekends," provide minimal value in enhancing self-knowledge [22]. Especially for constructing comprehensive self-understanding, it becomes essential to derive personal insights from data that describe multi-faced self-images, including those arise from personal experiences spanning past, present and future, as well as from interpersonal interactions [23]. Thus, it is important to have a deeper understanding of the different effectiveness of others' data and one's data in facilitating personal insights, especially for contemporary PIsystems that prioritize comprehensive self-understanding through the integration of others' data.

2.2.2 Sensemaking and Reflection on Personal Data

In the realm of personal visualization and Personal Informatics, making sense of and reflecting on personal data a pivotal activity that empowers individuals to gain personal insights, thus increasing self-knowledge and potentially enacting behavioral changes [3, 7, 71, 102]. In personal visualization, making sense of personal data through visual exploration is the essential approach to facilitate self-reflection [3, 71]. In line with that, Li et al. [102] proposed a model where reflection is an integral part of a comprehensive five-stage process (Preparation, Collection, Integration, *Reflection*, and Action) where individuals make sense of personal data visualizations to generate insights. While the later models emphasized that reflection happens associated with the lived experiences, making sense of personal data (and visualization) remains a key activity to provide reflective material [47].

Numerous studies in personal visualization and personal informatics have investigated the value of one's own personal data in supporting reflection [7, 94, 103, 104]. Within this domain, researchers have delved into understanding the reflective process and its outcomes. For instance, Choe et al. [3] applied a taxonomy of five reflection levels to investigate how visual exploration on one's own data support reflection. Their study revealed that visual exploration on one's own personal data predominantly facilitates *description* (R0) and *descriptive reflection* - the two low levels of reflection refer to revisiting of past experiences and revisiting with an explanation of past experiences, respectively. Furthermore, they also observed emergence of *dialogical reflection* (R2), which refers to the exploration of relationships among ideas and experiences with the aim of deriving generalizations and attaining. The *transformative reflection* (R3)-characterized by questioning initial self-assumptions and shifts in fundamental self-understanding or behavioral practices and the *critical reflection* (R4) referring to reflecting on aspects that transcend the immediate context (e.g., social and ethical issues) appeared to be rare. In addition, their findings underscore that data serves a dual role in reflection process: recalling past behaviors as well as external contexts and prompting new questions for further exploration. Furthermore, a few studies investigate the type of personal insights. For instance, Choe et al. [71] proposed a framework to examine the characteristics of personal insight as an outcome of self-reflection.

In this study, we extend the exploration of reflective practices to encompass the reflection on others' data. We adopted the reflection taxonomy and characteristics of personal insights from previous works [3, 71] when considering the effects of reflecting upon others' data against one's own data.

2.2.3 The Authority of Data

Personal informatics and other widespread uses of data in society have prompted research inquiries into the authority of data, questioning the unique power of insights derived from data (and visualization) and how they complement other types of insights. One perspective, rooted in the concept of "data doubles" [105], posits that personal data serves as a digital representation of individuals, which is not a source of objective truth but amenable to figurative reconstruction for subjective purposes like personal reflection and interaction. Any attempt to define a meaning from data involves the performance of agential cut, where people separate data into elements or characters from a dataset according to their subjective conceptual boundaries [92]. Furthermore, Rapp and Tirassa suggested that involving alternative perspectives, such as presenting personal data of others, can boost the empathy toward one's own experiences [23]. This, in turn, contributes to the creation of interconnected self-images of oneself that come from the social interactions, as one of the four facets of thyself. We reference these perspectives to suggest that alternative sources of personal data, such as that of others, can be considered as material for constructing self-identity.

Moving beyond exploring the analytic value of personal data, recent studies adopt a different perspective, viewing it as a creative and communicative artifact that facilitates the construction and elicitation of personal narratives through (mis)interpretations. For instance, Gulotta *et al.*'s "Curatorial Agents" reveals differences between human-created and machine-created interpretations of data, and points out that these differences can be productive and that misinterpretations (and mis-remembrances) are important phases in how people create and share the narratives of their lives. In the "Metadating" project, researchers organized a speed dating event where participants crafted and exchanged data profiles containing various types of data, including entirely accurate data collected by tracking devices, estimated data, and fabricated data [69]. It illustrates the concept that data can function as a "creative material" with its unique "social life," departing from its conventional role as a source of objective truth. Similarly, Friske, Wirfs-Brock, and Devendorf's project involves two participants creating and interpreting each other's knitted data representation, revealing that developing one true narrative towards multiple narratives from data equally informs both participants in understanding the data [26].

The above insights suggest that others' data has the potential to facilitate reflection, serving as a medium to provide resources for subjective analysis of past behavior and promoting the construction of personal data narratives through (mis)interpretation. Despite these findings, little is known about the distinctive effectiveness of others' data in generating personal insights. Our work sets out to address this gap, by delving into a comparative study on understanding the differences in the reflection levels, self-disclosure levels, and characteristics of personal insights derived from one's own data and others' data.

2.3 Study

In this study, we aim to understand the different effectiveness of one's own data and others' data in facilitating personal insights generation. We conducted a between-subject study using the crowdsourcing platform Prolific, recruiting two groups of crowd-workers ($N = 120$, $N_{DP} = 60$, $N_{NDP} = 60$). The Data providers (DP) comprised sleep tracker participants who submitted a screenshot of their sleep data, while the Non-Data Providers (NDP) did not provide data, but had experiences in sleep data collection and expressed an interest in understanding their sleep through data. Both groups engaged in a data-informed reflection task (see section 2.3.4) where they provided reflective responses in textual format by making sense of their own data and others' data respectively. Employing a combination of quantitative and qualitative methods, we systematically characterized the mechanisms and outcomes of sensemaking and reflection on both one's own data and others' data.

2.3.1 Study Context

We conducted the study in the context of sleep for two main reasons. Firstly, sleep is a dual-natured activity—partially a bodily process beyond conscious control, and partially a self-conscious activity influenced by daily routines and social family activities [96, 106]. This dichotomy has sparked extensive discussions within online communities [96] and interpersonal PI [82], wherein people share their sleep experiences, offer collaborative support, and gain a deeper understanding of bodily issues. Secondly, sleep data is a common data type that describes direct and simple human behaviors (e.g., asleep, awake) through-

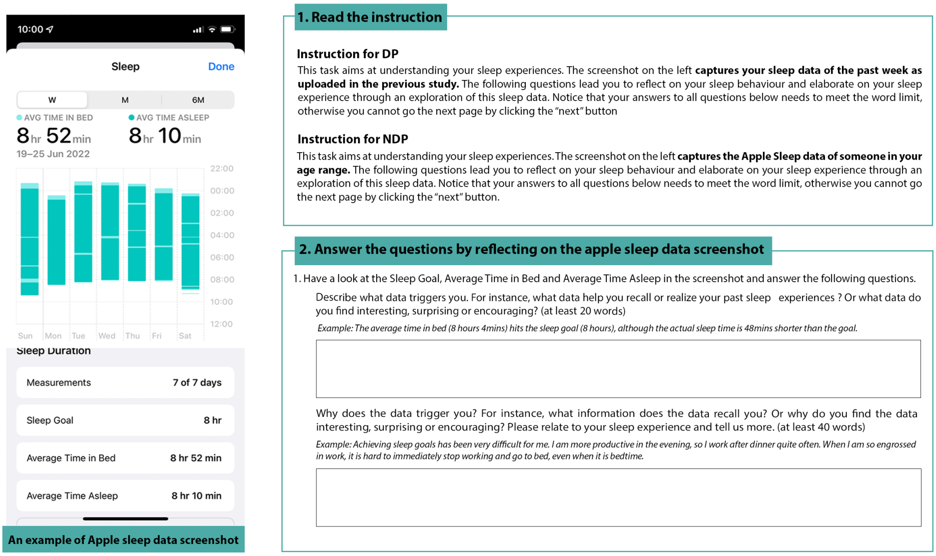

Figure 2.1: Illustration of the data-informed reflection task for DP and NDP. The instructions on the top right slightly differ (bold font) for DP and NDP, while the screenshot and questions are the same.

out the sleep process [95, 107], which is easy to understand for both DP and NDP. Thus, it can serve as equitable material for both DP and NDP to reflect upon their experiences.

We collected screenshots of Apple Health sleep data from DP as reflection material for both DP and NDP (see the example in Figure 2.1 on the left-hand side). According to the informatics design guidance for reflection [104], the Apple sleep data report is considered good reflection material for the following reasons.

- It uses bar charts to represent sleep time with simple statistics (e.g., sleep goal, average sleep time) of the past week, which is easy for both types of participants to understand even at a glance.
- The bar chart of sleep time in the recent week is given in time series, which can help participants notice and reflect on changes in their sleep time that they might not perceive otherwise.
- It includes all types of anchors to support various reflection levels such as average values (e.g., average sleep time), extreme values (e.g., latest sleep time), and patterns and trends (e.g., change of sleep time in one week).
- The Apple sleep data is sufficiently detailed yet rich enough, as it does not record behaviors and experiences about which individuals may have limited knowledge or may even be unaware of themselves. For instance, other apps recording unconscious sleep behaviors (e.g., sleep phases) are overly complex to make sense of, thus not efficient in facilitating self-reflection.

Apple Health: https://www.apple.com/ios/health/

2

2.3.2 Recruitment and Participants

We recruited 120 crowd workers ($N = 120$) through the crowdsourcing platform Prolific , comprising 60 DP and 60 NDP. DP participants were crowd workers who consistently tracked their sleep using a wearable device every day in the week preceding the study. Recognizing the diverse motivations behind (sleep) data collection [95, 107, 108], we welcomed crowd workers who had maintained regular sleep data collection, rather than imposing constraints for specific data collection purposes. NDP participants did not provide their data, and they were individuals who reported prior experience in collecting sleep data and interest in understanding their sleep patterns through data. To further foster reflection, we categorized DP and NDP into three 10-year age brackets (20-29, 30-39, 40-49).

The recruitment criteria and grouping strategy for DP and NDP were chosen to balance the complexity of providing meaningful data for reflection and executing the experiment. Previous literature has emphasized the importance of meaningfulness, which refers to people's interest in data and its relatedness to their lives, rather than merely seeking familiarity between participants [109]. While prior research often involves individuals with close relationships (e.g., family members and colleagues) to encourage reflection [24, 96], given the challenge of recruiting participants in close relationships, we argue that our selection of NDP is also valid. Self-trackers who are not acquainted but share common interests and self-tracking behaviors are considered to share a strong sense of relatedness in PI research [87, 89, 110]. Individuals from the same group can offer alternative perspectives in relating personal experiences and even breaking social norms [23, 89]. As for the grouping strategy, we prioritized the key factor - age - that affects sleep behavior [111–113], considering the challenge of controlling multiple influencing factors (e.g., occupation, gender, and health condition). We specifically grouped participants into 10-year age ranges, as prior sleep literature has considered 10 years a representative period for investigating the influence of age on sleep quality [112, 114]. Thus, grouping participants by 10-year age ranges promotes the establishment of connections and facilitates reflection.

To ensure the recruitment criteria, we utilized two open-ended questions for NDP to elicit explanations regarding 1) their past experiences with data collection and 2) their motivations for reflecting on their sleep patterns. Similarly, we employed an open-ended question to inquire about DP's data collection experiences and objectives. After coding the responses to these questions, we observed that among NDP, 45.3% had previously collected sleep data, while 54.7% reported occasionally or regularly collecting sleep data presently. The main motivations for data collection, identified for both DP and NDP, included sleep management, daily activity management, evening baby care-giving management, and illness management.

To ensure response quality and mitigate spam, participation was restricted to workers with a minimum acceptance rate of 95%. Moreover, we exclusively recruited participants who were native English speakers to ensure that NDP could comprehend the screenshots collected from the DP. Participants were compensated at a rate of 8.00 pounds per hour, which was deemed competitive according to the platform's standards. Our institution's Human Research Ethics Committee and Privacy Team conducted a thorough review and approved these activities.

2.3.3 Procedure

We divided the study into two phases.

Prolific crowdsourcing platform: `https://prolific.co`

- *Phase 1a – Data uploading task, 3 minutes/* ***Data Provider***. We recruited DP and assigned them to capture and upload a screenshot of their Apple sleep data. To guide DP through the process, we provided detailed step-by-step instructions, emphasizing the avoidance of personal identifiers in the screenshots. As an incentive to enhance the likelihood of obtaining valid screenshots, a bonus of 0.5 pounds was offered. This phase produced over 80 screenshots from DP, including over 20 for each of the three age ranges. The first author manually verified the validity of each data screenshot.

- *Phase 1b – Data-informed reflection task, 15 minutes/* ***Data Provider***. We extended invitations to DP who had successfully provided valid screenshots in the previous phase 1a. They were prompted to engage in a 15-minute data-informed reflection task (see details in Section 2.3.4). First, they were asked to explain their motivation for collecting sleep data by answering an open-ended question. Then, they were prompted to make sense of their Apple sleep data (screenshot provided in Phase 1a) and disclose their sleep experiences by answering the open-ended reflective questions. The response rate was generally high, with only a small fraction of DPs not responding to our invitation. Upon collecting 60 responses from DPs, we concluded this task. This phase yielded a total of 60 responses from DP, consisting of 20 responses in each of the three age ranges.

- *Phase 2 – Data-informed reflection task, 15 minutes/* ***Non-Data Provider***. In this phase, we called for NDP to execute the data-informed reflection task (see details in Section 2.3.4). To ensure that NDPs met the study requirements, we first asked them to report their past experiences in collecting sleep data and their motivation for reflecting on their sleep via two open-ended questions. Subsequently, presented with a randomly selected data screenshot from a DP (Phase 1) within the same age range, NDP were encouraged to utilize this screenshot to reflect on and share their own past sleep experiences by responding to the reflective questions. The quality of responses was assessed manually by the first author. Three responses were excluded from participants who reported no prior data collection experiences and lacked interest in understanding sleep, while two responses were discarded due to low-quality input in the reflective questions (primarily consisting of short answers with only 5 words in all questions). After recruiting 5 more participants to execute the task, this phase yielded 60 responses from NDP.

Participants completed all tasks via a web platform we developed in Python Django and hosted on [Author's University]'s servers. Before each task, we provided participants with a consent form describing the task in detail, the expected completion time, and the appropriate data-sharing policies. For DP, we specifically included a clause for sharing their anonymized data screenshot with other crowd workers. Finally, we scrutinized data submissions at each phase to ensure the anonymity of provided screenshots and written text.

2.3.4 Data-informed Reflection Task Design

The data-informed reflection task involves participants making sense of and reflecting upon sleep data by responding to open-ended reflective questions (see Figure 2.2). Recognizing that establishing a rationale for reflection is crucial for directing reflection toward the intended outcome [10], distinct instructions with two different purposes were provided to DP and NDP participants, accompanied by a screenshot of sleep data (see top right of Figure 2.1). DP were instructed to reflect on their *own* sleep data and disclose their *own* sleep experiences. In contrast, NDP were prompted to make sense of *someone else's* sleep data but disclose and reflect on their *own* sleep experiences.

2

A. Have a look at the Sleep Goal, Average Time in Bed and Average Time Asleep in the screenshot and answer the following questions.

- *Describe what data triggers you. For instance, what data helps you recall or realize your past sleep experiences? Or what data do you find interesting, surprising or encouraging? (at least 20 words)*
- *Why does the data trigger you? For instance, what information does the data recall you? Or why do you find the data interesting, surprising or encouraging? Please relate to your sleep experience and tell us more. (at least 40 words)*

B. Have a look at the sleep trend and pattern in the bar chart and answer the following questions.

- *Describe what data triggers you. For instance, what data helps you recall or realize your past sleep experiences? Or what data do you find interesting, surprising or encouraging? (at least 20 words)*
- *Why does the data trigger you? For instance, what information does the data recall you? Or why do you find the data interesting, surprising or encouraging? Please relate to your sleep experience and tell us more. (at least 40 words)*

C. Have a look at the latest sleep time and earliest wake-up time in the bar chart and answer the following questions.

- *Over the recent month, do you usually sleep at the latest sleep time or earliest wake-up time in the screenshot? If you did, what were the reasons for going late to bed or waking up early on that day(s)? If you didn't, please tell us why you do not sleep or wake up at these times? Please mention yes or no at the beginning of your answer(at least 40 words).*

Figure 2.2: The reflective question list for DP and NDP

Both DP and NDP were presented with the same open-ended questions (Figure 2.2) to reflect on and disclose their feelings and experiences of sleep. We carefully designed these reflective questions by striking a balance between providing guidance and allowing freedom to facilitate reflection. This decision is informed by prior literature emphasizing that reflection often requires explicit guidance rather than occurring naturally [10, 115].

First, we chose open-ended questions to support data sensemaking and reflection. Open-ended questions provide a standard and flexible way to explicitly guide and structure reflection [10, 104]. They prompt participants to specifically consider issues relevant to achieving the intended purpose of reflection while allowing for dynamic levels of reflection. Furthermore, we intentionally divided the reflection questions into sub-questions to guide participants from lower levels to higher levels of reflection. Specifically, the first sub-questions are designed for participants to identify data patterns from the visualization, responding to reflection levels from lower (R0, R1). The second sub-questions are designed to prompt people to relate the identified data patterns with their personal experiences, responding to higher reflection levels (R2, R3). This decision is informed by prior literature highlighting higher levels of reflection are usually supported and prepared by the lower levels of reflection [10]. In addition, we avoided incorporating reflection level R4 (the highest), as it tends to be excessively abstract and detached from real-life scenarios [10]. Figure 2.2 provides detailed information on our list of three reflective questions in the data-informed reflection task.

- **Question A:** This question started by prompting users to identify patterns in their overall sleep data (e.g., sleep goal, average time in bed, and average time asleep), providing an overview of their sleep experiences. The first sub-question aims to guide participants in identifying and explaining triggering data points that capture their behaviors, corresponding to description(R0) and descriptive reflection(R1). Sample questions are provided to further specify our intention. The second sub-question is designed to elicit the reasons behind participants' identified or recalled behaviors. By encompassing the overall data, this question investigates people's goals and plans, which can encourage reflection not only on the relationship between experiences but also on behavioral change [116], responding to the levels of dialogic reflection (R2) and transformative reflection (R3). Sample questions are also provided to give further detailed instructions.

- **Question B:** This question began by inquiring about detailed sleep data (e.g., sleep trends and patterns) that represented a more concrete picture of sleep behaviors. Similar to Question A, the first sub-question was designed to guide participants in identifying and explaining data patterns that drew their attention, while the second sub-question prompted participants to provide reasons behind the identified or recalled behaviors. Considering the use of sleep data patterns and trends as anchors, the second sub-question can encourage participants to reason about the relationships within multiple experiences [22], responding to dialogic reflection (R2).

- **Question C:** This question utilized outlier data (e.g., latest sleep time and earliest sleep time) as an anchor to guide reflection. The first sub-question ("Over the recent month, do you usually sleep at the latest sleep time or earliest wake-up time in the screenshot?") prompted participants to identify extreme data points and recall their past experiences beyond the presented data, addressing description (R0) and descriptive reflection (R1). Inquiring about the reasons behind these extreme behaviors, the follow-up questions encouraged participants to delve into detailed context and information in interpreting and relating the data [22], fostering dialogic Reflection (R2).

2.3.5 Data Analysis

Table 2.1: Example Quotes Categorized by Reflection Level

Reflection Level	Example Quote
Reflective Description (R1)	"No, I usually sleep very late. Mainly past midnight. I find myself very busy during the day with my children, housework, and jobs. By the time I got chilled time to myself, it is quite late already." NDP22(30-39)
Dialogic Reflection (R2)	"My bedtime is inconsistent and a lot of nights I have broken sleep. I carry out most of my work in the evenings and I need some time to wind down before bed. I also have a young child who doesn't always sleep well. I need to be up by 7am to get him ready for school." DP3(40-49)
Transformative Reflection (R3)	"I'm in bed for an average of 8 hours 42 minutes. I think I should not be on my phone before I go to bed and wake up at 9. Or I need to change my alarm to wake me up at 9." DP7(30-39)

We collected textual responses from the data-informed reflections on sleep provided by DP and NDP. By employing a combination of quantitative and qualitative methods, we analyze reflection levels, self-disclosure levels to understand the effectiveness of two data

Table 2.2: Example Quotes Categorized by Self-Disclosure Level

Self-Disclosure Level	Information	Thoughts	Feelings
No self-disclosure	"Within a short time, the person falls asleep and then wakes up. They get out of bed straightforwardly." NDP60(40-49)	"This person got less sleep on Sunday, potentially because they do not have a strict schedule on weekdays." NDP11(20-29)	"I keep a consistent rhythm with sleep. The graph really shows that. I don't know what else to say." DP37(30-39)
Little self-disclosure	"I think the difference between my time in bed and my sleep time is a lot bigger than this data shows." NDP29(30-39)	"I know I sleep badly. This data just proves it." DP24(30-39)	"It is frustrating to see tangibly the effect of commuting and being in the office on my sleep and life." DP35(30-39)
High self-disclosure	"I take medicine at night, and I have to eat something before taking it. This can sometimes push my bedtime too late." DP13(30-39)	"I think I need to adjust my bedtime to 11 p.m., or maybe stay active until around 10 p.m." DP33(30-39)	"I wake up frequently during the night because I have a young child waking throughout the night. It is depressing to see the actual gaps in my sleep." DP31(30-39)

sources as reflective medium. In addition, we analyzed the self-disclosure level to gain insights into the influence of different data sources on people's disclosure of personal information, thoughts, and feelings.

In the first round of analysis, we aimed to gain an overview of the difference in reflection and self-disclosure levels between DP and NDP. The first two authors coded the collected annotation by applying the frameworks of reflection [10] and [117] to identify reflection and self-disclosure levels. We specifically applied this self-disclosure framework proposed, as it is designed and widely adopted for analyzing self-disclosure in the online environment. For each participant, we rated the reflection and self-disclosure level three times, corresponding to the answers to the three questions. The first two authors coded 30% of the reflections separately and then resolved disagreements through discussions. After agreeing on the first 30% of the codes, they independently coded the remaining reflections, compared their codes, and discussed possible revisions. This process resulted in final inter-rater reliability of 98%. Notice that we did not evaluate R0, due to the fact that R0 involves the recall of past experiences without further explanation, a subtlety that can be challenging to observe and distinguish from the text responses. We also excluded the evaluation of R4, as it refer to the reflection on social and ethical aspects that is rare. Table 2.1 and 2.2 provides examples quotes for reflection and self-disclosure levels. Finally, we compared the distribution of reflection and disclosure levels of the two participant groups, and calculated the p-values using a Mann-Whitney-U test.

In the second round of analysis, we combined inductive and deductive coding based on the data-driven personal insights categories [3, 75], to understand the types of personal insights participants gained from data-informed reflection. For example, we extracted the following piece of annotation from DP2:"I have been sleeping a little less than the recommended 8 hours and it mentally shows. I would like to get at least 8 hours and not." This quote involves two types of insights: *confirmation* ("...it mentally shows...") and *against external data* ("less than the recommended 8 hours"). The two first authors separately coded the first 30% of the reflections. Then, they discussed discrepancies, revised and expanded the existing categories until they reached an agreement of 90%, thereby creating a new coding scheme of personal insight categories. After this step, the first author applied the coding theme to the rest of the annotations, generated the final coding theme of personal insight categories after several iterations.

2.4 Results

This section presents our results, mapping differences and similitudes between Data Providers (DP) who reflect on their data from Non-Data Providers (NDP) who reflect on others' data.

2.4.1 Reflection Levels

	Reflective Description (R1)	Dialogic Reflection (R2)	Transformative Reflection (R3)
DP	44.44%	27.78%	27.78%
NDP	31.67%	60.00%	8.33%

Table 2.3: Distribution of reflection levels

	Information			Thoughts			Feelings		
	No	Little	High	No	Little	High	No	Little	High
DP	0.00%	17.28%	82.72%	44.44%	29.01%	26.54%	67.90%	30.86%	1.23%
NDP	2.47%	28.40%	69.14%	43.21%	30.86%	25.93%	75.31%	24.07%	0.62%

Table 2.4: Distribution of disclosure degrees of information, thoughts, and feelings.

We observed no significant difference in the average reflection levels between the answers from the two participant groups (Mann-Whitney $U = 15945$, $N_{DP} = N_{NDP} = 60$, $p\text{-}value > .05$, two-tailed). To further compare the distribution of reflection levels between the two groups, Table 2.3 shows the proportion of answers provided by DP and NDP at each reflection level. We observed that the answers of DP are relatively balanced across all three reflection levels, with more answers given at the R1 level than those at the R2 and R3 levels. On the other hand, NDP answers show a more skewed distribution: answers at the R2 level ($NDP_{R2} = 60\%$) are significantly more than the others, very few answers are found at the R3 level ($NDP_{R3} = 8.33\%$). These results indicate that

- DP can reflect at all three levels, describing and explaining past behaviors and experiences, reconsidering self-assumptions, and new insights. In contrast, NDP can only reflect at the levels of R1 and R2, lacking consideration of personal assumption and intention to change behavior (R3).
- DP provide more direct descriptions and explanations of experience without exploring alternate explanations (R1), whereas NDP tend to explain the relationships between experiences and other points of view (R2).

2.4.2 Disclosure Level

We now compare the types (information, thoughts and feelings) and the degree (no, little or high) of disclosure of answers by DP and NDP. Overall, DP shows a significantly higher degree of information disclosure than NDP (Mann-Whitney $U = 13962.5$, $N_{DP} = N_{NDP} = 60$, $p\text{-}value < .05$, two-tailed), but no significant difference in the degrees of thoughts (Mann-Whitney $U = 16044$, $N_{DP} = N_{NDP} = 60$, $p\text{-}value > .05$, two-tailed) or feelings (Mann-Whitney $U = 15282.5$, $N_{DP} = N_{NDP} = 60$, $p\text{-}value > .05$, two-tailed) disclosure. Table 2.4 shows the degree distribution of answers given by DP and NDP across all three disclosure types. We observed similar degree distribution of DP and NDP answers for all three disclosure types, except for a slightly higher degree of DP in disclosing information.

These results suggest that DP and NDP have a comparable tendency to disclose personal thoughts and feelings. The only difference is that DP has a slightly stronger tendency to provide detailed personal information such as past behaviors and personal context.

2.4.3 Different Insight Types

To classify insights by types in the directed content analysis, we enriched the classification of Choe et al.'s framework [3] to include the different insight types for DP and NDP, summarized in Table 2.5. We start by enriching the insight type of *recall*, which covers insights generated by recalling past behaviors and events not captured by data. Next, we refined the previous sub-insight type *external data* from the framework of Choe. et al. [3] with **behavioral description**, **reasoning**, and **life events** and **justification with external data** which both DP and NDP share. Then specifically to NDP, we identified the sub-types **difference** and **similitude** while reserving the original *confirmation* and *contradiction* for DP. We refined the *value judgment* type by distinguishing between the judgment over subjects, namely **data judgment** and **behavioral judgment**. Finally, we added **Behavioral awareness** as a new insight type for both DP and NDP.

With this extended classification, we identified close numbers of insights for both DP (720 insights, average=12/person) and NDP (600 insights, average=10/person). We characterize nuances in the following.

Different composition of recall

Recall is the most frequent insight type and its amount is similar for both DP and NDP. DP generated 242 recall insights while NDP generated 253 insights, accounting respectively for 37.6% and 43.5% of the total amount of insights. Despite this similar amount of recall insights, sub-insights compositions differ between DP and NDP. Only DP generate the sub-insight of *life events*, *contradiction* and *confirmation*, and they also create more sub-insights of *behavioral description* (105 insights for DP, 80 insights for NDP). NDP generated a fair amount of sub-insight *difference* (87 insights for NDP) and *similitude* (50 insights for NDP). As shown below, NDP7 explain their early wake-up time by comparing it to the late sleep time of the DP.

> **Difference:** *"I find the data surprising that someone is going to bed so late and waking up late in the day. I have to wake at 6 am every day to get ready for the day and do household chores."* NDP7 (20-39)
>
> **Similitude:** *"The average time in bed and average time asleep triggers me as I am very similar in that it will take me a while to fall asleep, despite actually being in bed. However, it is encouraging to know I am not alone in this."* NDP17 (20-29)

It indicates that both DP and NDP can use data as an anchor to recall their past behaviors. DP recall their memory of past events, behavior, and experiences directly triggered by data. In contrast, NDP recall their past behaviors by comparing with the behavior represented by data through the identification of differences and similitude.

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Table 2.5: Personal insight types for DP and NDP. Note that '(DP)' represent the insights only generated by data providers, and '(NDP)' represent the insights only generated by non-data providers.

Type	Subtype	Description	Example quotes
Recall	Behavioral description	Remind and describe past behavior not captured by data but reminded by data	"I notice that I have a hard time staying asleep all night. I am often waking up and rolling over back and forth during the night." – DP31 (30-39)
	Reasoning	Explain the reasons behind the behaviors, such as habits, life condition, routines	"I usually always wake up at the same time every day because I work every day and have to get up at that time." – DP9 (20-29)
	Difference (NDP)	Describe own behavior contrasting with the observed data	"The similar bedtime on the weekends surprises me as I often go to sleep several hours later on those days compared to the weekend." – NDP2 (20-29)
	Similitude (NDP)	Describe own behavior similar with or related to observed data	"It appears as if towards the weekend, the time that they went to sleep was later which is similar to my sleep routine as I have to get up earlier on the weekdays." – NDP11 (20-29)
	Life events	Explain data points by recalling and elaborating on past events	"For the late sleep time on the Saturday I was very restless and could not get to sleep, thinking back I had a few drinks with caffeine in them which may have been a factor." – DP43 (40-49)
	Justification with external data	Bring external data to justify behavior or opinions	"I have my alarm at 8:55 but will always snooze till 9 AM or a little past 9 AM to start my day." – DP35 (30-39)
	Confirmation (DP)	Collected data confirms existing knowledge	"This isn't surprising as the weather has been very warm which has had a negative impact on my sleep." – DP11 (20-29)
	Contradiction (DP)	Collected data contradicts existing knowledge	"I am fairly diligent in terms of going to bed at a similar time, the varying state of the time that I rise is surprising to me." – NDP2 (20-29)
Value Judgment	Data judgment	Convey positive or negative connotations about the measured data	"I feel like this information is helpful in knowing how well I slept." – DP4 (20-29)
	Behavioral judgment	Convey positive or negative connotation about the behavior represented by the data	"5 am seems a horribly early time to wake up!" – NDP23 (30-39)
Behavioral Awareness	Behavioral wish	Describing behavior that the person would like to have	"I really wish I could have more consistent sleep but sometimes I stay up too late to hang out with friends." – DP5 (20-29)
	Intention to change	Express the intention and the motivation to change behavior	"As it shows how bad my sleep schedule is. It makes me want to change my habits." – DP9 (20-29)
	Changed self-assumption	Adjust or change the understanding of themselves	"I was also surprised by the fact that I am waking up in the night. I thought I consistently slept through the night with no problems." – DP28 (30-39)

NDP express stronger judgment

We identified two distinct sub-insights under Value Judgment: *behavioral judgment* and *data judgment*. These two sub-insights delineate between the subjects of judgments, with *Behavioral judgment* conveying positive and negative perceptions, attitudes or opinions about the behavior represented by data, and *data judgment* expressing a perception on the value of the data itself. Our analysis reveals that DP tended to comment on their own data and share opinions directly.

> **Data judgment:** *"Analyzing the data is always helpful when you look at it in the big picture. The data helps to understand sleep patterns and helps to show how I can improve my sleep."* DP47 (40-49)

NDP express their own perceptions, understanding and opinions on sleep behavior by commenting on other's data or the behavior represented by data.

> **Behavioral judgment:** *"I find the data surprising that someone is going to bed so late and waking up late in the day. I have to wake at 6am every day to get ready for the day and do household chores. I also find it surprising that the person falls asleep so quickly after getting into bed."* DP12(40-49)

2

Figure 2.3 highlights that, overall, NDP generate substantially more value judgment insights than DP. In particular, DP generate twice as many behavioral judgment insights as NDP (47 insights for DP, 89 insights for NDP), and the amount of data judgment insight is similar for both crowds. It indicates that NDP have a stronger ability to express their perception, attitudes and opinions by reflecting on others' data. It also stresses the critical role of others' data in helping NDP disclose their perception of bad, average, and good behaviors.

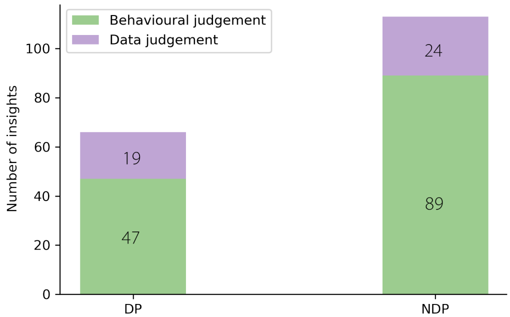

Figure 2.3: The number of sub-insights of Value Judgment from DP and NDP. This stack chart shows that NDP gains more insights into behavioral judgment than DP, but the number of data judgment are similar.

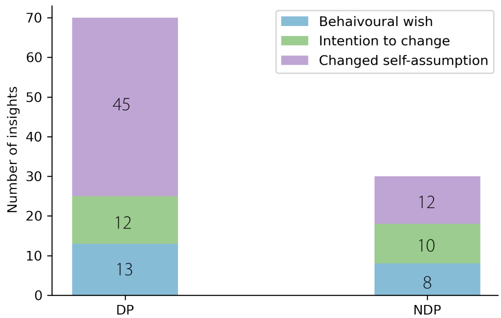

Figure 2.4: The number of sub-insights of Behavioral awareness from DP and NDP. This stack chart shows that DP gains more insight into behavioral awareness than NDP, with a big advantage in the number of changed self-assumption.

DP gain more behavioral awareness from their data

We augmented the insight types from Choe et al's framework [3] with *Behavioral awareness* insights, which include three sub-insights: *behavioral wish, changed self-assumption* and *intention to change*. Figure 2.4 highlights that DP gain more insights into behavioral awareness than NDP (70 insights for DP, 30 insights for NDP). Specifically, DP discloses almost 3 times more *change self-assumption* insights than NDP (45 insights for DP, 12 insights for NDP), while the number of *intention to change* insights are similar (12 insights for DP, 10 insights for NDP).

> **Changed self-assumption:** *"I'm fairly pleasantly surprised by my averages as I thought they would be much worse, this hasn't been my greatest week for constant sleep."* DP3 (20-29)

These results indicate that data support DP gain more behavioral awareness, and it exerts influence on DP primarily by making them re-considerate their self-assumption rather than directly initiate behavior change.

2.4.4 Additional Insights from NDP

Except for the extended classification, we identified two types of additional insights generated only by NDP: **behavioral identification** and **speculation**. Behavioral identification involves NDP identifying purely behavior of DP from their data, without any personal information, thoughts, or feelings of DP. These insights usually prepare a context for NDP to relate to their experiences, opinions and attitudes that are different from or similar to DP.

> **Behavioral identification:** *"This individual's regular waking time of approximately 6 am, and the brief intervals of waking in the middle of the night, for example on Tuesday and Friday nights."* NDP39 (30-39)

The second type of insight is speculation, containing speculation and interpretation of DP's behaviors. Through these speculations, we can still discern the lifestyle or past behaviors of the NDP. For example, in the following quote, NDP5 speculates that the time the DP spent in bed before falling asleep was on the phone, implying that they might have the habit of using a phone in bed themselves.

> **Speculation:** *"From the chart I can see from Monday, Wednesday and Thursday there is time spent on the bed which would indicate the person is awake but on their phone. The days the person is not on their phone after waking up are Saturday and Sunday."* NDP5 (20-29)

These two additional insights suggest that NDP convey their experiences and behaviors by relating to and interpreting others' data, diverging from the comparison mechanism outlined in Section 2.4.3.

2.5 Discussion

In this section, we discuss the differences and similarities between reflection levels, self-disclosure levels and types of personal insights derived from others' data and one's own data. We also discuss the implications of these insights for the design of collaborative personal informatics systems.

2.5.1 Comparable Value in Facilitating Reflection

In Section 2.4.1, our findings reveal that there is no significant difference in average reflection levels between DP and NDP. DP participants tended to reflect across all three levels, while NDP participants primarily engaged in reflective description (R1) (60%) and dialogic reflection (R2) (31.67%). This suggests that others' personal data holds comparable value to one's own data in facilitating self-reflection. Specifically, others' data proves valuable in aiding individuals in recalling and explaining experiences (reflective description R1) and in reasoning about the relationship between underlying expectations, needs, and feelings (dialogic reflection R2). Furthermore, in Section 2.4.3, the close numbers of insights for DP (720 insights, average=12/person) and NDP (600 insights, average=10/person) also suggest echoing this finding of the comparative ability of others' data to one's own data in facilitating insights generation.

Our findings indicate that other's data can serve as a protagonistic material for people to recall and reflect upon experiences, even in the absence of one's own data. This insight contrasts with numerous existing PI tools that focus on the use of one's own data as reflective material [7, 23, 118]. Traditionally, the process of data collection has been considered a crucial step in PI tools, often posing barriers to reflection [9]. Future research could explore innovative ways to incorporate others' data into PI tools, thereby extending the scope of reflection to a broader range of individuals who may not engage in self-tracking. For example, future collaborative PI tools could involve the collection of a small dataset and subsequently share this data with users who share similar interests and experiences within a group setting (e.g., a workplace or educational institution [84]). Moreover, the inclusion of others' data can enrich the reflective process by providing users with a wider range of perspectives and experiences to draw upon. Machine-assisted reflection systems, which excel in providing explanations and interpretations of personal data [1, 119], could leverage others' data as input to offer users a detailed portrayal of different lifestyles and contexts. By providing users with a comprehensive understanding of others' lives, these systems can facilitate deeper reflection and insight generation.

Beyond the realm of PI, our findings also suggest the potential for scaling out data work, such as articulation work [52] and data-enabled design methods [51], by leveraging others' data as material for users to reflect and disclose their past experiences. Involving product users in making sense of personal data has been recognized as a key activity in these fields to reveal underlying expectations, feelings, and experiences [52, 120, 121]. However, current methods often entail significant design and setup efforts for data collection and participant recruitment, limiting their scalability and reach [122]. Our findings suggest that future work in articulation work and data-enabled design could leverage a smaller number of pre-collected data to engage a larger number of participants, thus enabling a deeper understanding of users on a broader scale.

2.5.2 Differences in Behavioral Awareness and Value Judgment

Our findings in Section 2.4.3 reveal the proficiency of DP in generating insights into "Behavioral awareness," while NDP exhibit a tendency to generate insights related to "Value judgment." These results suggest the different strengths of one's own data and others' data in facilitating insight generation:

One's own data holds greater strength in aiding individuals to enhance their awareness of past behaviors. This insight aligns with a substantial body of prior research in Personal Informatics (PI), rooted in the ego-centric perspective derived from behavioral change theories, which consistently emphasize the pivotal role of one's own personal data in facilitating reflective processes and promoting self-awareness [7, 23]. Therefore, our findings confirm prior PI design principles and underscore the importance of prioritizing the inclusion of individuals' own data when designing PI tools aimed at fostering self-awareness and behavioral changes. PI tools that focus on self-experiments [33, 94] and machine-assisted reflection [1] should prioritize the use of personal data to facilitate the (re)construction of detailed self-images, rather than relying on others' data, which primarily serves to define norms.

Others' data is proficient in assisting individuals in expressing and justifying their perceptions, attitudes, and opinions on behaviors. This finding extends prior research emphasizing the reference value of others' data in establishing norms [85]. Combined with the finding that NDP is comparable in disclosing thoughts and feelings except for more personal information (Section 2.4.2), others' data is indicated to be valuable in fostering community engagement and enriching online discourse. For example, within online platforms aiming to promote discussion and knowledge-sharing [87, 96], prioritizing the inclusion of data from multiple sources can amplify the richness of conversations and encourage active participation from members. Furthermore, PI systems geared towards facilitating decision-making processes can also benefit substantially from the integration of others' data. For instance, making medical decisions, such as cancer treatment, which often hinges on individuals' perceptions, attitudes, and opinions about specific aspects [123], can be informed by incorporating others' data. The involvement of other's data can help participants reflect on and justify their perceptions of specific situations and treatments, thereby empowering them to make decisions that align with their values and preferences.

2.5.3 Different mechanism in facilitating reflection

Our findings in Section 2.4.3 reveal that insights of **confirmation** and **contradiction** within the Recall type were generated exclusively by DP, while insights of **difference** and **similitude** were generated only by NDP. This result suggests a different mechanism of the two data sources in facilitating reflection. DP participants tended to generate insights by comparing their self-cognition with data, thereby recalling their past behaviors and evoking external contexts. In contrast, NDP participants tended to identify others' behaviors captured by data to recall their different or related experiences through comparison. Additionally, our findings in section 2.4.4 demonstrate insight of **speculation** solely for NDP, indicating an alternative way of making sense of data—interpretation, where individuals use their own experiences to provide plausible explanations for others' data.

Our findings extend the understanding of the anchoring role of one's own data in facilitating reflection [3] and suggest that others' data also serves an anchoring function, albeit through a distinct mechanism—comparison. One's own data enables people to discern conflicts between the "past me" and the "self-recognized me," ultimately fostering a shift in self-understanding. Others' data facilitate reflection by providing a picture of either the "similar me," sharing similar behaviors, or the "different me," displaying different personal lifestyles. Prior literature has emphasized the importance of providing the "right sort of experiences" to foster reflection [124], but many PI tool designs have fallen short in this regard [125]. Our findings indicate that both one's own data challenging self-assumptions and others' data offering relatedness, whether through differences or similarities, serve as effective materials to evoke the "right sort of experiences." However, our data reflection task design only involve simple interaction where people review one single screenshot, which can limit deeper understanding and reflection on personal data. Especially when interpreting others' data, it necessitates an explanation of the underlying contexts [26]. Thus, future research could explore alternative interactions with data, such as speculative methods [70], to enhance individuals' connection to others' data and facilitate the identification of the "similar self."

Moving beyond the conventional one-vs-many comparisons used to define norms [85], our findings also highlight an alternative approach—one-vs-one comparison. This detailed perspective of analyzing data through one-vs-one interactions allows individuals to identify patterns through direct comparison within smaller data sets. Future collaborative PI tools could explore methods to facilitate pair collaboration [26, 31], which is effective in supporting deeper and more spontaneous feedback between individuals.

2.5.4 Limitation and future work

To size the impact and validity of our study, we identify limitations around three aspects.

First, we recognize that various factors such as occupation, gender, and life conditions can co-influence the relatedness between DP and NDP, thereby potentially affecting reflection and insight generation. Prior research has highlighted that building relatedness is a complex technique that extends beyond merely finding similarities or differences [109]. While our study attempted to facilitate relatedness between participants, we acknowledge the limitations of recruitment due to the feasibility of experiment execution. Future studies can explore identifying key characteristics that better match participants to facilitate building relatedness for collaborative reflection.

Second, the design of the data-reflection task, which involved participants answering reflective questions based on screenshots with word limits (20 and 40 minimum words), may pose limitations in facilitating reflection. Specifically, communication around data—such as inquiry, explanation, and interpretation of underlying contexts—is crucial for fostering reflection but is constrained by presenting only a single screenshot to participants. Additionally, restricting the length of responses could impact the depth of reflection and self-disclosure. Research suggests that longer answers are associated with higher levels of reflection and self-disclosure [10, 126]. Although pilot studies were conducted to balance freedom and constraints in facilitating reflection, there remains a risk that the depth of reflection and self-disclosure could be affected.

Third, we minimised the factors influencing self-disclosure (e.g., personal traits, language, culture [127]) by screening crowd-workers who are English native speakers and grouping them in three age ranges. However, other factors, such as the difference in the enjoyment and the social effect caused by reflecting on one's data and others' data can still influence the degree of self-disclosure [128, 129]. It is challenging to measure and explain reflection and self-exposure separately because of the entangled nature of those factors influencing them. In addition, the frameworks we used to evaluate the level of reflection and self-disclosure are sometimes too subjective and abstract to assess the participants', especially for the disclosure of feelings. We followed a procedure with two coders working independently before aligning to reach a high inter-rater reliability. However, the results remain under the influence of subjective judgments.

2.6 Conclusion

This paper investigates the different effectiveness of one's own data and others' data in facilitating self-reflection and generating personal insights. Through a crowdsourced approach, we recruited two groups of participants - DP and NDP - to make sense of their own data and others' data through answering opening ended questions in textual format. We evaluate the reflection level, disclosure level, and types of insights derived from the responses of DP and NDP. Our analysis shows that others' data and one's own data have comparable effectiveness in facilitating reflective description (R1), dialogic reflection (R2), and self-disclosure of personal thoughts and feelings. Specifically, we found that one's own data are efficient in supporting the gain of behavioral awareness, while others' data are efficient in helping people express their perceptions, attitudes, and opinions. Furthermore, others' data can serve as an anchor for individuals to recall their own past experiences and trigger the expression of their perceptions, attitudes, and opinions. These results highlight the comparable effectiveness of others' data as protagonistic material in data-informed self-reflection and provide insights into exploiting the advantages while compensating for the shortcomings of the two data sources in collaborative PI for enhancing self-knowledge.

3

Chapter3: Exploring pair sensemaking in personal data

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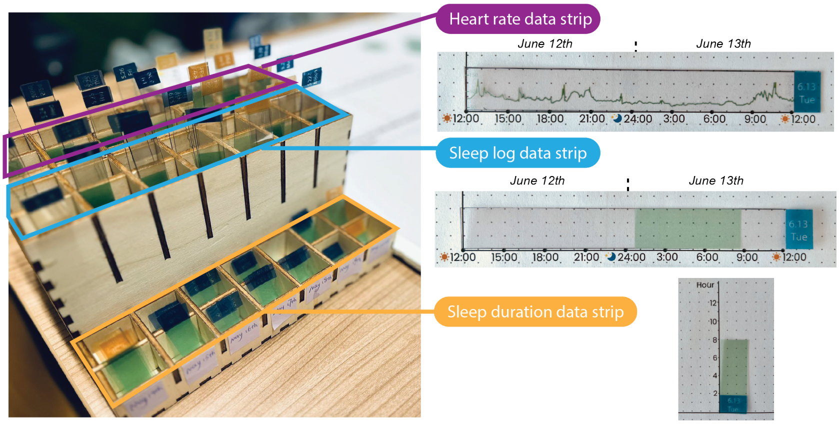

Figure 3.1: **A set of transparent data strips in a wooden holder (left), core component of the data PAIRcolator toolkit.** The toolkit took its name from the "percolator", brewing coffee and connecting people. The PAIRcolator bring people in pairs to *brew* insights from their data. In this example, the strip holder hosts 14 days of personal data to combine heart rate, sleep log and sleep duration data strips.

This chapter 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 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, I propose a set of design rationales supporting subjective data analysis through dyadic comparison and mixed-focus collaboration styles for co-constructing personal narratives. I operationalize these principles in a tangible visualization toolkit, PAIRcolator. The 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. These 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.

3.1 Introduction

Personal visualization [33, 34] and Personal Informatics (PI) [8, 35], play a crucial role in helping individuals make sense of their personal data, enabling them to understand past behaviors and reflect on underlying experiences [4, 7, 130, 131]. 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 [38, 56], and engage in analysis and interpretation according to their subjective conceptual boundaries [92, 132]. Personal visualization, focusing on the design of interactive data representations of personal data [32], 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 [36, 37], and enabling subjective analysis through agentive manipulation of time components [33–35]. Tangible toolkits further enhance sensemaking by fostering direct and haptic interaction, promoting intuitive exploration and deeper reflection [45, 133].

Recent work by Friske, Wirfs-Brock, and Devendorf has highlighted the benefits of pair collaboration in facilitating subjective analysis and interpretation of personal data, fostering reflection on personal experiences [26]. 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 [20, 27]. Through dyadic comparisons, this approach can uncover detailed patterns that might remain hidden during group comparison [25], providing effective anchors for recalling and reflecting on underlying personal experiences [3]. Additionally, the flexibility of dyadic interaction—ranging from closely coupled to loosely coupled collaboration [19]—allows participants to naturally adopt and switch roles, assisting each other in questioning and reasoning about relevant information [27]. Despite these advantages, current collaborative personal visualization tools predominantly focus on designing data representation for group comparisons [24, 40, 41], which are often limited to establishing norms [39] and lack the coordination to integrate individual and collaborative perspectives [7, 10].

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 [33, 92], 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 [19], facilitating individual perspectives for subjective data analysis and interpretation [5] while encouraging communication to interpret, enrich, and reconstruct each other's personal narratives [26]. To address these challenges, our research focuses on the following question:

> *How can personal visualizations be designed to support dyadic comparison and facilitate switching between reciprocal roles that characterize the pair sensemaking process?*

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.

3.2 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.

3.2.1 Collaborative personal visualization

Personal visualization is defined as "the design of interactive visual data representations for use in a personal context" [32]. In personal visualization [33, 34] and Personal Informatics [8, 35], sensemaking of personal data is a vital activity for people to understand their past behaviors and experiences, and to support self-reflection [4, 130, 131] and behavioral change [7]. Collaborative sensemaking, involving individuals who collaborate in searching and externalizing relevant information, creating shared representations, and generating and evaluating hypotheses [28, 55], has been considered beneficial for understanding and reflection on personal data [7, 23]. The data representations that incorporate comparisons between one's data and others' can uncover patterns that might remain hidden in individual analyses [24, 39, 79]. Furthermore, the sensemaking process can benefit from incorporating interpersonal perspectives to encourage the explanation and interpretation of personal experiences underlying personal data [24, 134].

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 [24, 39, 79]. Similarly, participatory data physicalization [40, 41, 68] supports group comparison by enabling individuals to collaborate in creating shared representations through encoding their data into tangible tokens under predefined rules [41, 42]. The comparison with aggregated group data is primarily beneficial for defining norms [39]. Only recent research by Friske, Wirfs-Brock, and

Devendorf has begun to investigate pair sensemaking [26]. 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.

3.2.2 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 [92]. 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 [33–35]. For instance, tangible visualization has introduced tangible data tokens that allow users to construct, organize, and manipulate blocks of data freely [60, 61], fostering more intuitive and engaging interactions with data [59]. 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 [115].

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 [5, 38, 56]. To address this, existing visualization approaches have employed storytelling techniques, such as crafting narratives along timelines [4], reconstructing personal experiences into personalized visualizations [6, 38], and incorporating (machine-driven) annotations and interpretations [36, 37]. 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.

3.2.3 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 [20, 27]. 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 [25]. 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 [26], which serve as effective anchors for triggering the recall of past experiences, as well as for generating and evaluating hypotheses related to personal experiences [3].

2. **Sensemaking process:** Dyadic interactions within the sensemaking process can take various forms, ranging from tightly-coupled to loosely-coupled collaboration [19, 29]. Through these different collaboration styles, individuals adopt reciprocal roles in questioning and reasoning, facilitating knowledge construction [20, 27, 28]. 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 [19, 30]. 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 [20].

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.

3.3 The PAIRcolator Toolkit

To address the challenge highlighted in Section 3.2.3, we introduce the four Design Rationales (DR) and the PAIRcolator toolkit operationalizing these design rationales.

3.3.1 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 [24, 39, 41, 42, 79] and the sensemaking process [23, 26, 28, 55].

- *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 [19, 25, 26] and enabling mixed-focus collaboration styles [19, 30].

- *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 [33–35, 60, 115] and narrative reconstruction [4, 5, 38, 56].

- *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 [33, 92]. These units also support dyadic comparison, which focuses on detailed data insights [25], aiding in the recall of past experiences [3]. 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 [6]. Combining it with dyadic comparison introduces additional challenges, particularly in integrating the perspectives of both individuals [25]. 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 [115].

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 [5]. Through mixed-focus collaboration, pair collaboration can balance the need for individual sensemaking with the benefits of information exchange in pairs, enhancing knowledge construction [19, 27]. 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 [55]. In the context of personal data, dialogue—encompassing data inquiry, explanation, and interpretation—is crucial for reconstructing personal narratives [26]. 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.

3.3.2 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.

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 3.1 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 3.2, 3.3, 3.4.

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 3.5, 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.

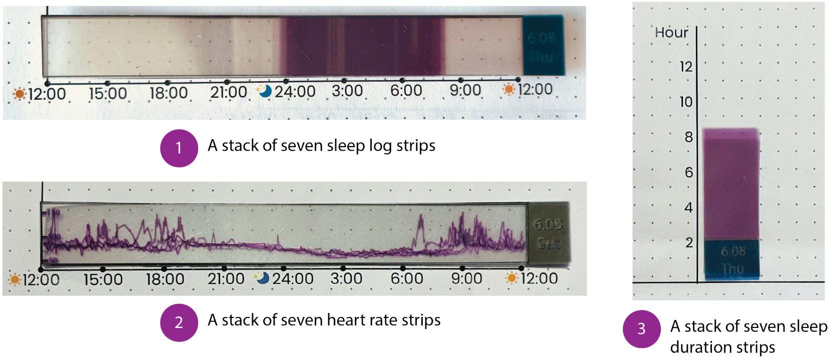

Figure 3.2: **Stacking the same type of data strips**: This type of stack contains several data strips of the same type, which allows users to discover data patterns over a customized time range.

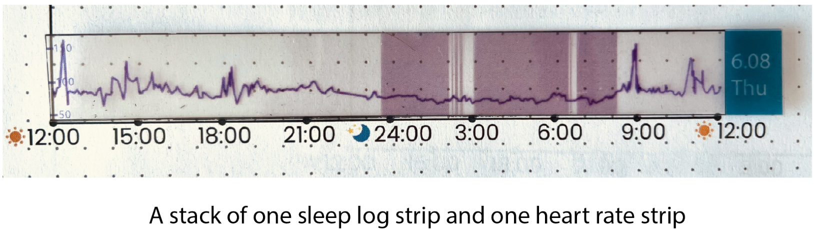

Figure 3.3: **Stacking different types of data strips**: This stack includes two data strips of different types, allowing users to explore patterns of various sleeping behaviors.

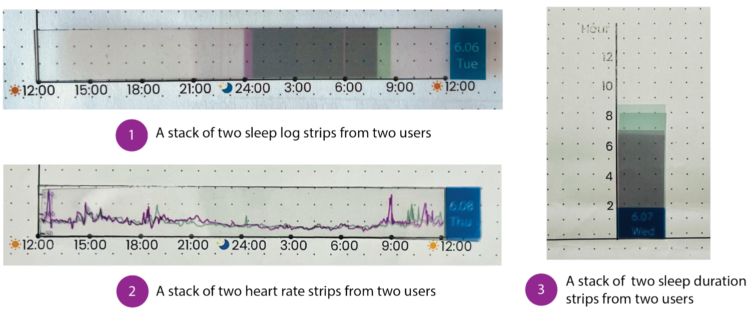

Figure 3.4: **Stacking data strips from two persons**: This type of stack contains data strips from two different users, helping users identify and discuss the differences and similarities in their behaviors.

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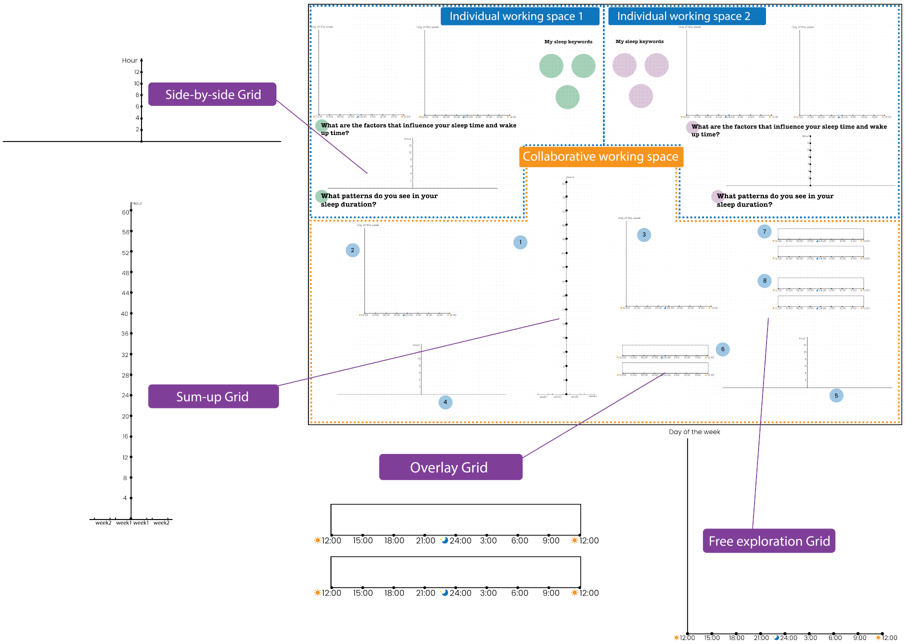


Figure 3.5: The data exploration canvas features four grid types—Free Exploration, Side-by-Side, Overlay, and Sum-Up—designed for both individual and collaborative analysis. The **Free Exploration Grid** allows users to freely distribute or overlay multiple data strips, providing only an x-axis (time unit) while leaving the y-axis open. The **Side-by-Side Grid** encourages grouping data by custom principles for comparison, using time units on the y-axis and an open x-axis. The **Overlay Grid** prompts users to consolidate multiple data stripes into one view, using two blocks with a 24-hour x-axis. The **Sum-Up Grid** enables comparison by distributing two users' data on either side, using time as the y-axis while keeping the x-axis open for alignment and total calculation.

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 [135, 136], while also facilitating agential privacy control [137].

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 3.3 in the Appendix.

3.4 Method

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

3.4.1 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 [138–140]. Second, sleep is influenced by social dynamics and the living environment, in addition to individual physical conditions [96, 138, 141]. Collaborative reflection on sleep data has been shown to enhance self-awareness of sleep patterns and related experiences [107]. 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.

3.4.2 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 3.1), 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 [80, 87, 142]. Second, comparison serves as a means to trigger self-reflection, making any potential comparison bias less critical.

3.4.3 Study Setup and Procedure

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 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

Table 3.1: **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.

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

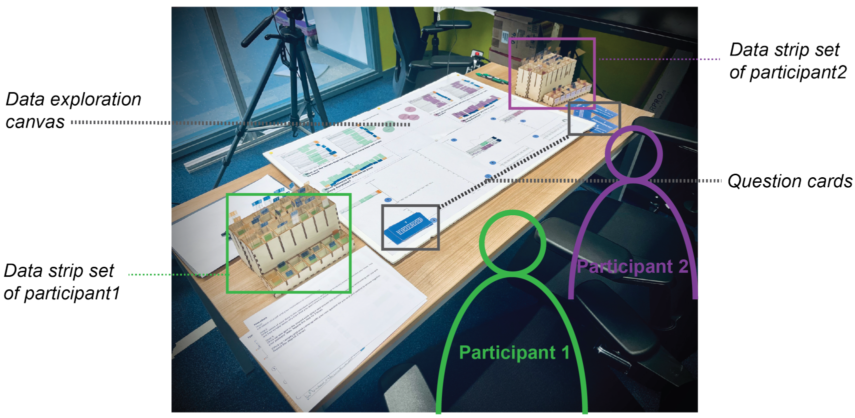


Figure 3.6: **Pair session setup.** Participants sit side-by-side in front of the data exploration canvas. Data strips lie on each side, with green strips for participant 1 (left) and purple strips for participant 2 (right). A video camera faces the participants while a second one (out of the picture) captures the scene top-down.

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.

Setup and Procedure of the Pair Session

As shown in Figure 3.6, 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 3.4.3), 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 3.7). Then, participants are asked to use the toolkit collaboratively, without seeking further assistance from the research team. After the pair session, we conducted a 15-minute post-hoc interview with each pair of participants. A complete list of questions is in the Appendix in Table 3.4.

3.4.4 Data Analysis

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.

Phase 2: Identify Data-Informed Activities.

We analyzed the pair sensemaking activities by following the grounded theory analysis outlined by Glaser, Strauss, and Strutzel [76].

- **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 3.2. 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 3.2, 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 between participants.

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 .

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 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 3.5.3.

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.

3.5.1 Developed Data Representations

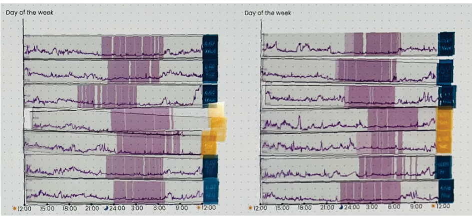
Individual Data Representations

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 3.7a). Second, participants plotted their sleep duration strips for 14 days on side-by-side grids (see Figure 3.7b). 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 3.7c). 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 3.7d.

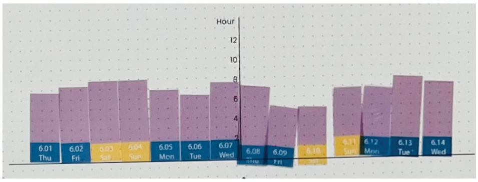
Collaborative Data Representation

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

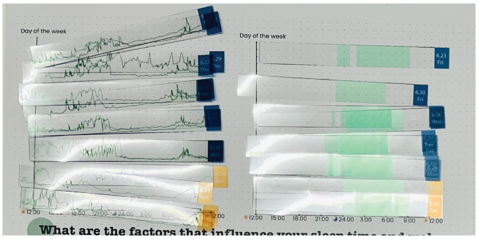
- **Sharing** helped participants compare behavioral trends. This type of data representation consists of stacks placed next to each other, each stack comprising strips of one type of behavior. Figure 3.8a illustrates this type of comparison with two stacks of seven sleep log strips, the top one from 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 3.8b 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



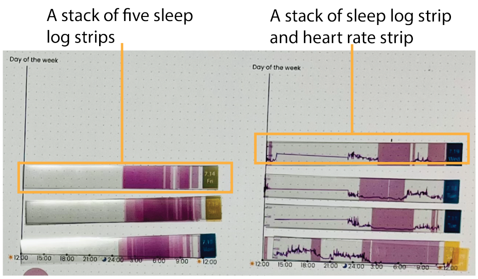
(a) G_{7-1} – Free exploration grids with sleep logs overlaid on heart rate strips, week one (left) and week two (right).



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

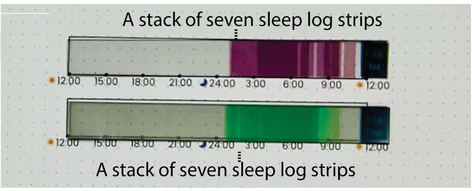


(c) G_{5-1} Free exploration grids with sleep log strips (left) next to heart rate strips (right) over seven days.

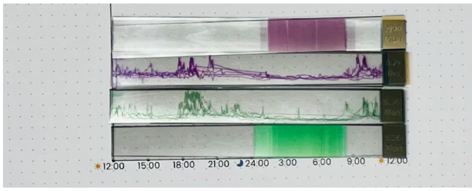


(d) G_{12-1} Free exploration grids with three stacks of five sleep log strips (right) and four stacks of one sleep log strip, and one heart rate strip.

Figure 3.7: **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 3.8: **Examples of collaborative data representation supporting *sharing* activities**

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 3.9b, 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

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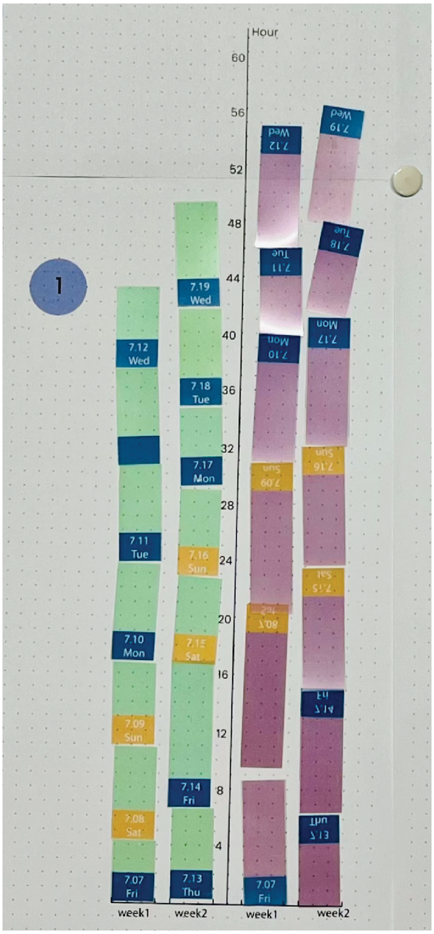
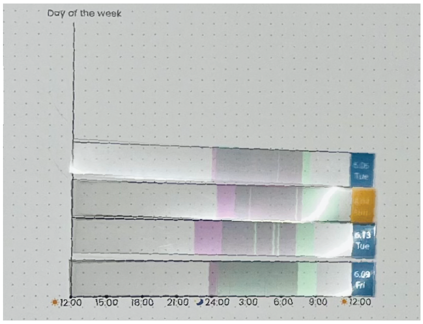
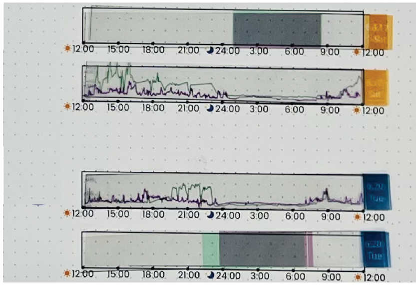


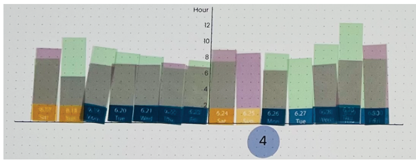
(a) Sum up grid with weekly cumulated sleep for G_{12-1} (left, green) and G_{12-2} (right, purple)



(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 3.9: **Examples of collaborative representation supporting *blending and mirroring* activities**

fragmentation. Figure 3.9c shows the two participants had surprisingly close sleep and wake-up times with very different heart rate patterns. Yet, both sleep patterns correlated with their heart rate patterns. Figure 3.9d 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 3.9a 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.

Table 3.2: **Pair sensemaking activities.** This table presents seven sensemaking constructs, each grouping multiple sensemaking activities according to the goals when interacting with the PAIRcolator. Icons on the left of the “Construct” column correspond to the icons in Figure 3.10.

Construct	Goal	Activity	Description
Individual Vis. development	Develop individual data Vis.	Load data	Select strips from the box, read and plot them on their individual working space to develop a data Vis.
		Develop Vis.	Develop a new data Vis by taking and reorganizing a set of randomly placed strips.
		Reorganize data	Adjust an existing data Vis by adding, replacing, or removing strips.
Individual data analysis	Analyze data patterns in own strips	Combine data	Overlay strips of different behaviors (e.g., heart rate and sleep) in the same day to identify relationships between.
		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 Vis. development	Develop collaborative data Vis.	Extend Vis.	Work in pairs to add more strips to an existing collaborative data Vis.
		Develop Vis.	Work in pairs to plot their strips on a shared grid.
		Synchronize data	Work individually or in pairs to adjust a data Vis according to that of the others.
Collaborative data analysis	Analyze data across individual and collaborative data Vis.	Compare data	Work in pairs to read the collaborative data Vis and articulate the differences between each other’s data.
		Relate data	Work in pairs to identify the pattern in one data Vis and relate it to other data Vis.
		Explain data	One explains data patterns identified in the data Vis 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 Vis.
		Inquire data	Identify a data anomaly in each other’s data Vis 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 Vis to develop to achieve a goal.
		Discuss possibilities	Explain to each other the data patterns they observed and brainstorm potential data Viss 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 Viss, and explain their approach and rationale.

3.5.2 Pair Sensemaking Process

In this section, we introduce the pair sensemaking process, including individual and pair working phases with various activities detailed in Table 3.2.

Individual working phase

During the individual working phase, participants developed data Visualizations in their individual working workspaces in a loosely-coupled manner. As shown on the left side

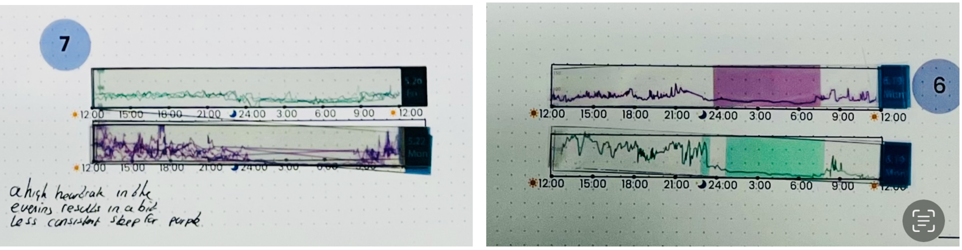
Figure 3.10: **Pair sensemaking process.** We present the pair sensemaking process by ordering the identified data-informed activities in Table 3.2. Each row represents the sequence of sensemaking activities of a pair, consisting of an individual working phase (left) and a collaborative working phase (right). Each color block represents a cluster of activities under the same construct described in Table 3.2. 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.

of Figure 3.10, 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 Visualizations helped participants understand each other's data, facilitating later collaborative visualization and reflection on personal experiences.

For example, one participant G_{12-1} explored various overlapping possibilities with their data strips, resulting in the individual data Visualization shown in Figure 3.7d. 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 3.8a.

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"



(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 3.11: **Examples of collaborative data Visualization**

Collaborative working phase

Participants engaged closely-coupled collaboration in developing shared data visualizations, following a consistent pattern of activities illustrated by the dotted rectangles in Figure 3.10. 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 3.10 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:

> 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 3.11a). 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..."

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

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 3.11b). 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 3.9d) 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..."

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. "

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. "

3.6 Discussion

3.6.1 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 3.3.1 and provide insights for future personal visualization design.

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 3.5.1, 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 3.5.3).

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 3.5.2 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 3.5.3 and 3.5.3 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 [24, 39] and data physicalization [41, 143]. While one-to-many group comparisons effectively define norms and situate individuals [39], they often reduce engagement and personal connection to the data [144]. 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 [3, 26].

In the sensemaking process, group discussions often devolve into monologues dominated by a few voices, limiting balanced participation [145]. 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 [10], widely applied in HCI and personal informatics to advance reflection from surface-level insights to deeper understanding [7, 146]. 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.

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 [7, 146]. 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 [147–149]. Patients often face complex, subjective choices about treatments and self-care strategies that require careful consideration of life contexts, economic factors, and personal values [150]. 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 [11, 51]. However, current data-enabled design interviews are often designer-driven [50, 151], 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.

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 [152], community members with shared interest [87], or colleagues sharing the same working environment [24] may vary in their collaboration nature and levels of information disclosure, particularly in the context of health and intimate data [134]. 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 [153]."

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 [80]. 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.

Privacy concerns in pair collaboration.

Pair collaboration introduces privacy concerns, especially regarding the potential disclosure of detailed personal information (see Sec 3.6.1). Such information can include intimate scenarios (e.g., a couple in bed), recognized as sensitive [154, 155]. 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 [135, 136] and aligns with the concepts of privacy as control and boundary management [137], helping to create an environment that supports sharing sensitive information.

Through our recruitment method (Section 3.4.2), 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.

3.6.2 Design rationales for collaborative personal visualization

Offering guidance (DR2) for dyadic and agential comparison of data (DR1) facilitates aligning subjective perspectives and in-depth data analysis.

The example in Section 3.5.2 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 3.5.1 offered detailed insights for the emergence of insight moments in Section 3.5.3.

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 [24, 39, 68, 79], 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 3.3.2). 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, 115], these approaches often fall short in enabling comparisons. Future designs in personal visualization can integrate the established comparative methodologies [156] to existing visualization structures to allow more diverse and nuanced comparisons, thereby enhancing individual insights and collaborative understanding.

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 3.5.2 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 3.5.3).

While existing personal visualization toolkits facilitate collaboration, they often prioritize direct comparisons within large groups, neglecting the need to coordinate the sensemaking process [7, 24, 39, 42]. 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 [41, 42], 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 [157] and machine-based interpretation [36, 37] 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 [5, 6, 158]. Future work is needed to incorporate more customizable narrative options in collaborative settings, allowing users to create diverse and personalized storylines.

3.6.3 Limitations

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.

3

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.

3.7 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.

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

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 3.2, 3.3, 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.

Question card deck

Table 3.3: 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?

Post-hoc interview questions

3

Table 3.4: 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 pairwise setting?
Q16	How does this pair collaboration make you feel comfortable and uncomfortable in sharing your data?

4

Chapter 4: Integrating Data humanism for reflection

This chapter is previously published as: Di Yan, Chenge Tang, Senthil Chandrasegaran, and Gerd Kortuem. 2025. Reciportrait: a Data Humanism Approach for Collaborative Sensemaking of Personal Data. In Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25). Association for Computing Machinery, New York, NY, USA, Article 827, 1–21. https://doi.org/10.1145/3706598.3713300

Figure 4.1: **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.

This chapter examines how the principles of Data Humanism can be integrated into collaborative personal visualizations to support meaningful engagement with personal data. 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, I propose design principles for creating both subjective and effective collaborative visualizations, while coordinating the slow sensemaking process and promoting data awareness and communication. I 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. The 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.

4.1 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 [56, 159, 160]. 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 [3, 4, 130]. Existing personal data visualizations that apply Data Humanism have involved digital platforms [e.g., 67], or analog approaches such as sketching [e.g., 66] and the use of tangible tokens [e.g., 61]. These applications of Data Humanism emphasis understanding personal data through imperfect and personalized data representations for subjective data analysis and interpretation [6], and a slow and thoughtful sensemaking process for in-depth engagement and comprehension of personal data [64].

While Data Humanism advocates for a subjective and deliberate exploration of personal data, recent work by Friske et al. [26] 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 [55], and these benefits also hold in the context of personal data [7, 23, 133]. Encouraging collaboration on personal data provides alternative perspectives for comparison, which can reveal previously invisible data patterns during individual analysis [7, 24]. The social communication can engage individuals in explaining and interpreting personal experiences [23] 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 [24, 26, 39], 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 [55], while Data Humanism requires personalised representations that might be distinct for each individual for affording subjective analysis and interpretation [6]. 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 et al. [64] calls "personal engagement". The pace at which different individuals engage with the data or visualizations may thus be different. However, collaborative personal visualization requires an element of coordination between creators [7, 10]. 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.

4.2 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.

4.2.1 Data Humanism and Personal Data

Data Humanism is an approach first suggested by Lupi, 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 [56, 64, 159]. 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 [6, 26]. 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 [6, 64]. 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 [5, 159]. Additionally, incorporating context during the collection, analysis, and display of data is essential, as the underlying contexts contribute to constructing personal narratives [26, 45]. 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 [67].

2. **Sensemaking process.** Data Humanism acknowledges that making sense of and gaining a deep understanding of data requires deeper engagement. As Lupi 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 [38]. This approach also aligns with the concept of slow technology [161], 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 [38, 65, 66]. Second, constructive visualization offers non-actuated token-based physical data representations for people to construct and manipulate data representations [60, 61, 162]. Third, there are digital visualization tools designed to help individuals develop personalized and expressive visualizations that convey qualitative personal contexts and information [6, 67].

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.

4.2.2 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, 55]. In personal data visualization and personal informatics, there exists a consistent theme underscoring the need for incorporating collaborative sensemaking of personal data [7, 23, 133, 142]. 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 [23].

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.

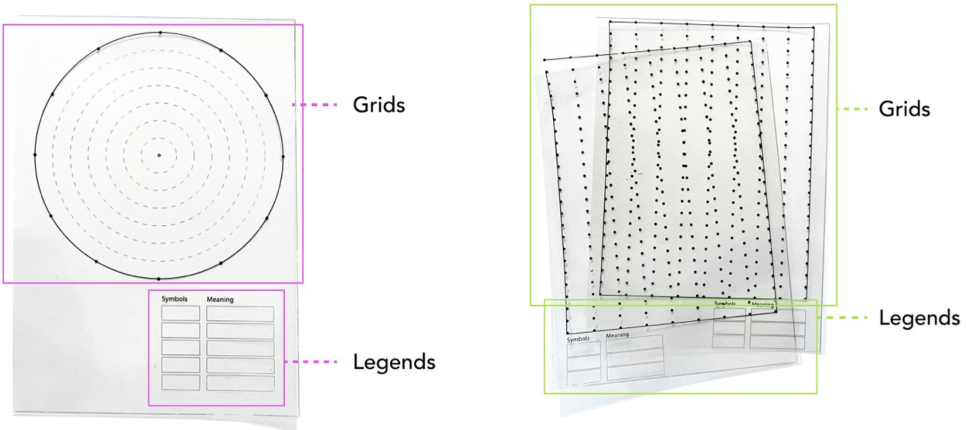
1. **Data Representation.** Shared representations—in the context of this paper, visualizations that are created and interpreted together by individuals working together—serve as the key instrument to present relevant information. A shared representation requires effective structure to illustrate data in a format that is not only understandable to one individual but also relatable and accessible to others [28, 57]. When presenting personal data, this shared representation should facilitate comparison of both the data as well as personal behaviors [24, 39]. 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 [163, 164]. 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 [26]. 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 [165–167]. 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 [10], thus finding the "right sort of experiences" that is particularly reflective [7, 58].

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 [7, 133]. The most common approaches comprise personal visualization tools that offer standard visualizations and design the interaction with data around comparison [24, 39]. For instance, Puussaar, Clear, and Wright designed a collaborative personal informatics tool for co-workers to compare and annotate each other's data. One notable direction is Participatory data physicalization [40–42, 68], 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, Dragicevic, and Jansen 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, Wirfs-Brock, and Devendorf 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.

4.3 Toolkit Design



(a) An example of circular visualization grid

(b) Two overlapped rectangular visualization grids

Figure 4.2: The transparent visualization grids

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

4.3.1 Design Principles

We employed a structured, multi-phase process to propose the design principles. First, we reviewed literature on Data Humanism [5, 6, 26, 38, 45, 64, 92, 159, 161, 169] and collaborative sensemaking of personal data [7, 23, 24, 26, 39, 55, 163, 165] 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, 38, 40–42, 60, 65, 66, 68, 69, 115, 162, 170] 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

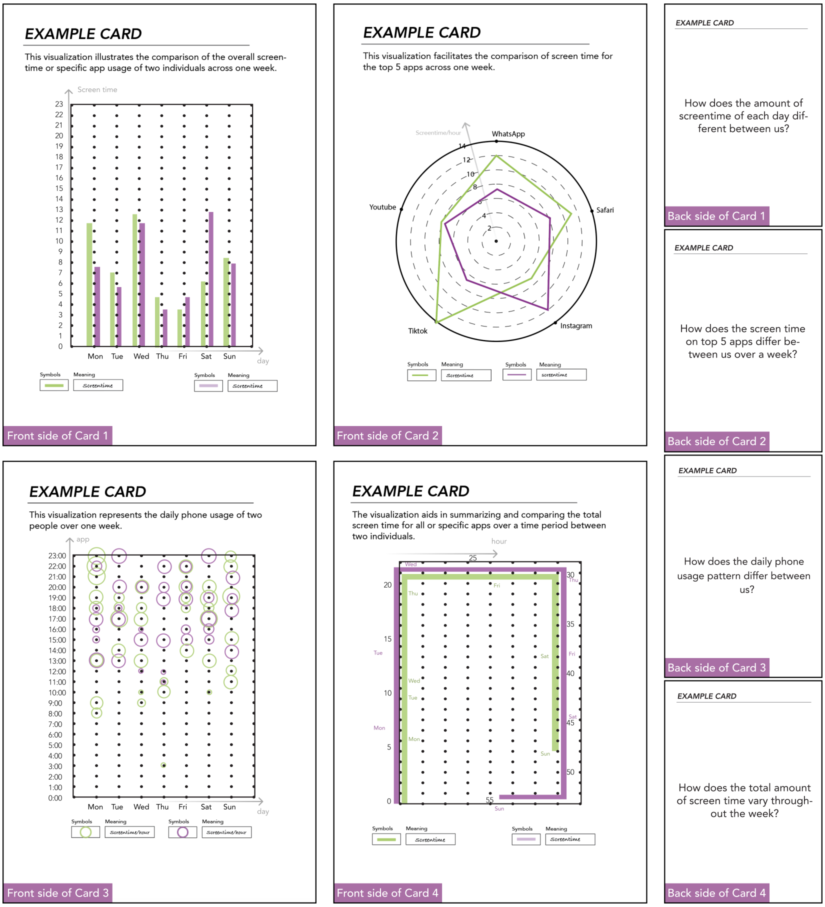


Figure 4.3: **Example cards provided to participants.** The data represented in these cards all relate to smartphone screen time. The example cards represent a diverse set of visualizations such as grouped bar chart, radar chart, bubble chart, and a type of grouped bar chart wrapped around a rectangular spiral for compactness, reminiscent of W.E.B. du Bois' design [168]. These examples are meant to encourage participants to explore diverse representations of their own data.

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 [169]. Understanding data requires a localized resolution, where individuals segment it based on personal boundaries and connect it to broader organizational structures while incorporat-

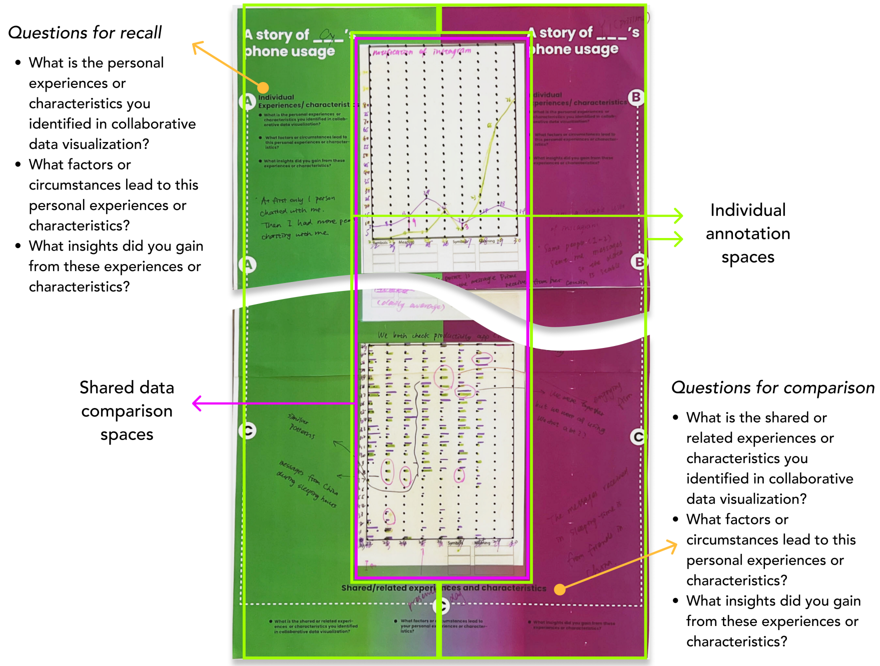


Figure 4.4: **The data reflection canvas.** This canvas includes individual annotation spaces and shared data comparison spaces. Reflective questions at the top and bottom of the canvas guide users through three levels of reflection: recalling past experiences and comparing behaviors, relating these patterns to contextual factors, and summarizing insights in relation to self-identity [10].

ing personal contexts related to the captured data [92, 169]. 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 [65, 66], while also connecting data to life activities and broader contexts [6, 26].

- **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 [5, 66]. Offering structure is essential to guide users in developing effective visualizations that clearly illustrate data patterns while ensuring the system's usability [170]. 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 [24, 39].

- **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 [161]. 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 [7]. Bentvelzen *et al.* highlight that offering instructions is helpful for preventing aimless data exploration, and save more cognitive space necessary to foster reflection [115].

- **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 requires not only collaborative efforts but also careful coordination between individual and joint analysis, questioning, and relating personal experiences [10]. On one hand, facilitating data-related communication—such as inquiry, explanation, and interpretation—is crucial for uncovering the context behind the data [69] and engaging in a reciprocal process of data analysis to foster reflection [26]. On the other hand, it is essential for individuals to engage deeply with their own data, recalling past experiences and generating and evaluating hypotheses [3]. 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 [163].

4.3.2 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.

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 4.2b). We chose two types of grids—circular (Figure 4.2a) and rectangular (Figure 4.2b), 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 [171] and externalizing thoughts [172]. 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 4.2b).

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 4.4.1. 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 [4, 34, 173].

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. 4.4), consists of two elements: shared data comparison spaces and individual annotation spaces. The shared data comparison space features three 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.

4.4 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.

4.4.1 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 [174, 175], screen time data offers a meaningful and engaging way for users to explore and manage their digital behaviors [176, 177]. Despite the widespread use of screen time data in PI tools, most of these tools offer only standard and simplified visualizations [178, 179], which contrasts with the richer and more subjective approach advocated by Data Humanism. Second, screen time data is a form of time series data [178], making it particularly effective for tracking behavioral patterns, identifying trends, and observing fluctuations over time [4, 34]. The temporal nature of this data allows users to recall past behaviors and reflect on their experiences more easily.

4.4.2 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 [87, 176]. 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

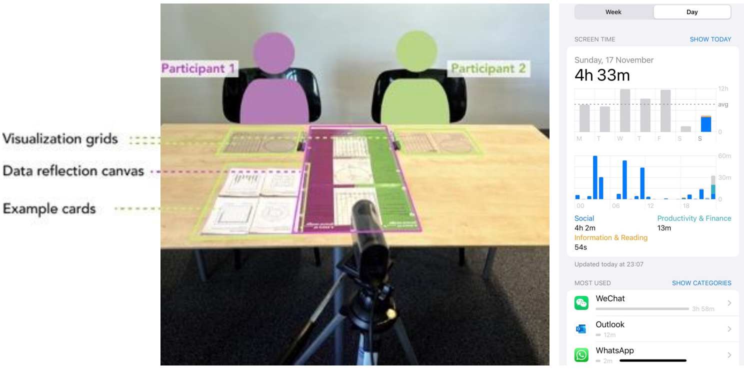


Figure 4.5: **Study setup and example of screen time visualization.** The left image illustrates the study setup, where participants sit side-by-side in front of the data reflection canvas, with a video camera capturing their interactions with the Reciportrait toolkit. The right image shows a screenshot of participants' screen time visualization from an iPhone.

provided in Table 4.1. Our institution's Human Research Ethics Committee and Privacy Team reviewed and approved our study.

Table 4.1: **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

4.4.3 Study set up and procedure

The observational user study with the toolkit was conducted in a dedicated user study room. As shown in Figure 4.5, the data reflection 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 4.5, 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 4.8.1, 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.

4.4.4 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.

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 [180]. We used the interview data to understand data patterns participants identified from these visualizations.

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, we applied the grounded theory analysis method as outlined by Glaser, Strauss, and Strutzel, following three steps.

- **Open Coding:** Two coders independently analyzed video recordings from the first three groups to identify sub-activities in the second column of Table 4.2. For example, participants scrolling through each other's phones to read data was labeled "review data."

- **Axial Coding:** The coders grouped sub-activities into broader categories based on shared goals (see the first column of Table 4.2). 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.
- **Selective Coding:** The collaborative sensemaking sub-processes (see Figure 4.8) 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.

Phase 3: Analyze Insight Moments

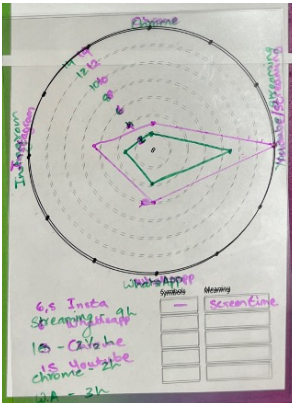
In this phase, we identified and analyzed "insight moments" where participants reported gaining new personal insights, following a three-step process. First, two coders independently reviewed the video recordings to pinpoint moments where participants explicitly expressed that they had generated new 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 [3, 10], 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.

4.5 Findings

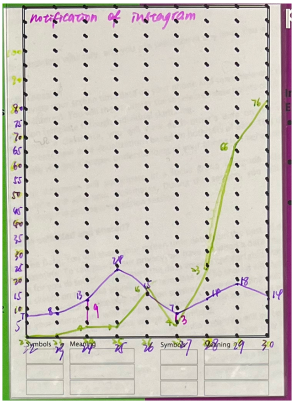
We present our observations of (1) the collaborative sensemaking process enabled by Reciportrait, by reporting the developed collaborative visualizations in Section 4.5.1 and the collaborative sensemaking activities and sub-processes in Section 4.5.2, and (2) the outcomes of this process by demonstrating the gained personal insights in Section 4.5.3.

4.5.1 Developed Collaborative Visualizations

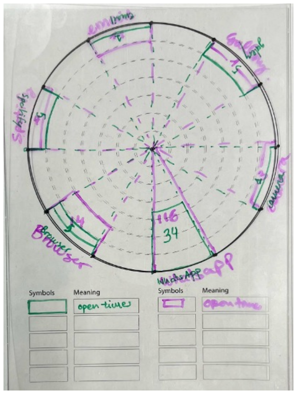
All eight groups successfully authored the required three collaborative visualizations, each representing an overlap of two sketched individual visualization grids (as described in Section 4.3.2). These collaborative visualizations demonstrated a variety of modifications based on the provided examples (as described in Section 4.3.2), 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.



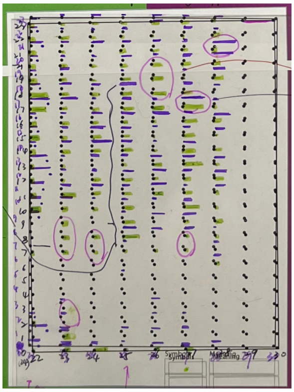
(a) An example of visualization with modified data categories (Participants G8)



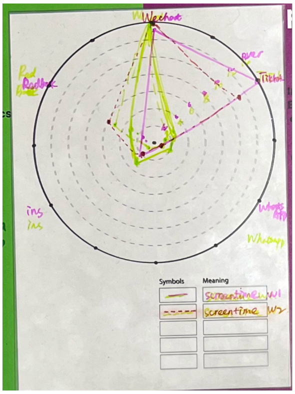
(b) An example of visualization with modified data attributes (Participants G2)



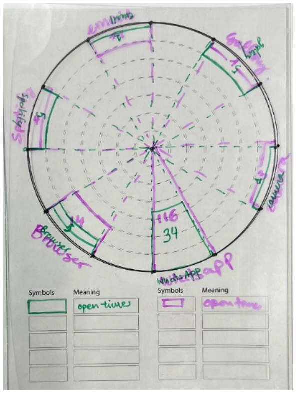
(c) An example of visualization incorporate reprocessed data (Participants G3)



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



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



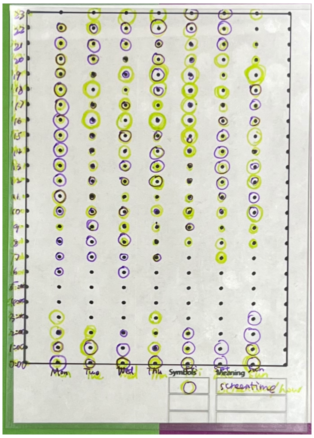
(f) An example of visualization with changed channels (Participant G7)

Figure 4.6: Example Visualizations with Modifications in Data Types, Scales, Marks, and Channels

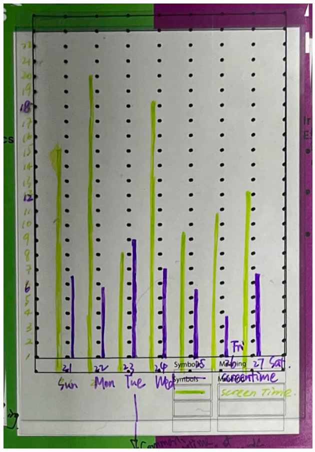
Modifying Data Types, Scales and Marks

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.

- *Modifying Data Categories:* In visualizations altering data granularity, participants adjusted the axis to include different types of apps according to their shared interests.



(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 4.7: Visualizations that emulating example design.

For instance, Figure 4.6a 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.

- *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 instance, in Figure 4.6b, 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.

- *Incorporating Reprocessed Data*: We observed one group reprocessed data provided by their phones and incorporated them into the visualization. As shown in Figure 4.6c, 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).

- *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 types and channels. As illustrated by the bar chart in Figure 4.6d, participants maintained the design from example card 3 (Figure 4.3) 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.

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.

- *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 4.6e, 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.

- *Change of Channels:* In some cases, participants changed the channels used to represent the data. For instance, Figure 4.6f 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. 4.6f), but they reported that the process of creating the visualization helped them engage with and think about the data.

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 4.7a illustrates a visualization that follows the design from card 3 (see Figure 4.3). 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 4.7b replicates the design in card 1 (Figure 4.3), 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.

4.5.2 Collaborative Sensemaking Activities and Sub-processes

We outline the collaborative sensemaking activities during the use of Reciportrait in Table 4.2, categorized based on participants' objectives in the creation of collaborative visualizations. Table 4.3 describes the sub-process of the collaborative sensemaking process, with the usage of both individual and shared working spaces of Reciportrait. In this section, we present our observations of the collaborative sensemaking process enabled by

4

Table 4.2: **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 4.5.

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.

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 4.8, 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

Table 4.3: **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 4.3.2, and the collaborative working space is referred to as the "Data Reflection Canvas" in Section 4.3.2.

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.

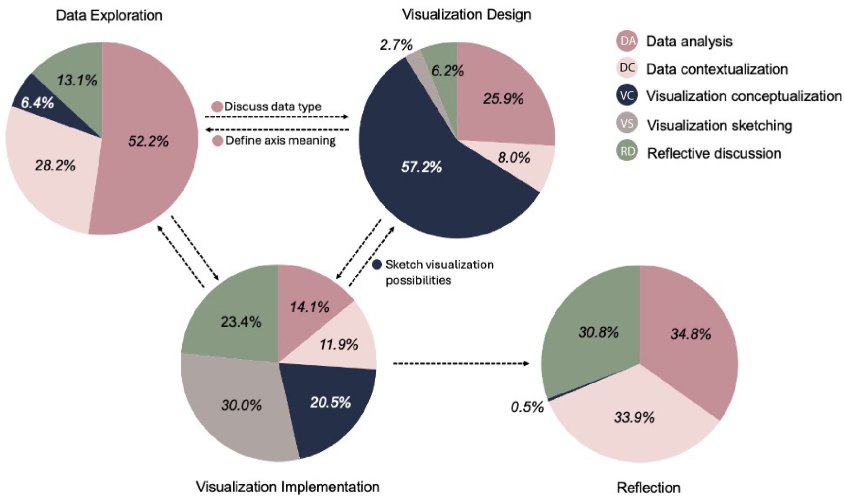


Figure 4.8: **The overall collaborative sensemaking process, highlighting the distribution of activities across four distinct sub-processes.** The four pie charts represent the frequency of sensemaking activities outlined in Table 4.2, within each sub-process. Activities that frequently cause transitions between sub-processes are highlighted between the bar charts.

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 4.8, 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 4.6c, 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.”

Table 4.4: 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."

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 4.8, 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 (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 4.8).

4.5.3 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 4.4. Additionally, we provide a detailed account of how these insights emerged through a sequence of activities, outlined in Table 4.5. In this section, we explain the observed insights and how the execution of activities contributes to different types of insights in detail.

Table 4.5: **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,"...

		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	Data	DA					Compare data	Reflection
5	G5		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	Behavior	VS	DC	RD			Visualization Sketch + Explain data + Reasoning behavior	Vis Impl.
12	G4		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	Experiences	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		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-	RD	RD	RD			Non-data inquiry + Explain behavioral pattern	Reflection
28	G2	recognition	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

Gaining insights into data through visualization sketching and data analysis.

As shown in Table 4.5, 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 4.5, row 1, participant G3-2 sketched her screen time using purple circles, as depicted in Figure 4.6d. 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 4.6b). 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)

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 4.4, 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 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."

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 4.4). 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).

4

> 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!"

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 4.5, 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)"

4.6 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.

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

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 4.2.1). Our findings in section 4.5.1 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 4.5.1 example 1), verify beliefs (section 4.5.1 example 2), and observe similarities (section 4.5.1 example 3) and differences (section 4.5.1 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 4.5.1—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. 4.5.1 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 [5, 38]. Going beyond the benefit of engaging people deeply with their data, this self-authoring process also introduced an "IKEA effect" [181, 182]—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 [24, 39], 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 4.5.1), enhancing the collaborative sensemaking process.

Addressing the tension of coordinating individual and collaborative perspectives in the sensemaking process while maintaining engagement.

Our findings in Section 4.5.2 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. 4.8), 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 [161]—*"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 4.5.2 and table 4.2), 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" [161]—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 4.5.2), 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" [161], 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 [165, 167] 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 [183, 184] 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 [60, 162, 185] 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 [40, 41], 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.

4.6.2 Personal Insights Enabled by Balancing Data Humanism and Collaborative Sensemaking

Insights into Data and Behavioral Patterns

Our findings in section 4.5.3 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 4.6.1, extending beyond traditional patterns of insight generation—flexible data manipulation [33, 34, 186].

As detailed in section 4.5.3, 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 [10] 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 [4, 187]. Existing methods have achieved this by presenting personal data chronologically [4, 7], utilizing machine-driven explanations [1, 93, 188], and only a few cases involving collaborative data communication [26, 69]. 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.

Insights into experiences and self-recognition

As shown in Table 4.5, participants experienced self-recognition and insights into experiences, corresponding to Fleck and Fitzpatrick’s[10] definitions of Dialogic Reflection and Transformative Reflection.

As detailed in section 4.5.3 and section 4.5.3, 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 4.5). 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 4.8. 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 [7, 10]. They also align with existing research on collaborative sensemaking [163] and personal data insights [3], 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 [7]. 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.

4.6.3 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 4.6.1). Second, the collaboration aspect provides a reciprocal approach that actively engages users in exploring and reflecting on their personal data in detail (see Section 4.6.1). 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 [189, 190]. 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 viusalization 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 [176]. 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.

4.6.4 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 [38, 72]. 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" [191] 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.

4.7 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.

4.8 Appendix

4.8.1 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.

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.

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.

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.

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.

5

Discussion and conclusion

In this concluding chapter, I revisit the aims of this thesis and summarize the key research questions and contributions. I then discuss the *pair sensemaking of personal data* framework, highlighting its significance and distinguishing characteristics in relation to existing work. This is followed by a reflection on the implications of the pair sensemaking approach for the design of personal visualizations, as well as its potential application as a user research method to inform product and system design. Finally, I acknowledge the limitations of the pair sensemaking approach and propose directions for future research.

5.1 Summary of answers to research questions

In this section, I re-capture the aim of each study in Figure 5.1 and provide a summary of the research questions.

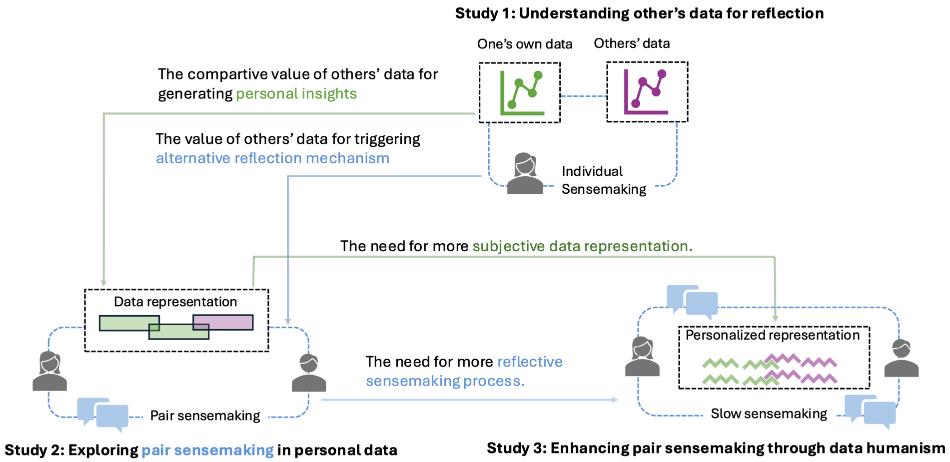


Figure 5.1: The exploration of various characteristics of pair sensemaking of personal data approach across three separate studies.

5.1.1 Study 1: understanding others' data for reflection

Prior research suggests the potential of others' data in the reflective process [26, 69]. Like one's own data, it also serve as digital representations of individuals that trigger subjective analysis and the recall of personal narratives rather than offering objective truth. However, different data sources can vary in their effectiveness for generating personal insights [21, 22]. To explore this, the first study investigated: **RQ1: How do the reflective process and insights differ when individuals engage with others' personal data versus their own data?** This research question aims to compare the reflective value of self- versus other-generated data in fostering personal insight. I conducted a crowdsourced study with two participant groups: data providers (n=60), who submitted screenshots of their own sleep data and reflected on it, and non-data providers (n=60), who reviewed someone else's data and reflected on their own sleep patterns. I analyzed participants' textual reflections to evaluate the types of insights produced and their corresponding levels of reflection. As discussed in Chapter 2, the findings reveal three distinct ways in which self- and other-generated data contribute uniquely to reflective processes.

First, others' data holds comparable value to one's own data in facilitating recall and reinterpretation of personal experiences. Participants generated a similar number of insights when reflecting on others' data as they did with their own. In particular, others' data served as a reflective prompt, helping participants recall past events, reinterpret personal experiences, and articulate internal states. This contrasts with the typical focus of personal informatics tools on self-data as the primary reflective material [7, 23, 118], and suggests that others' data can serve as a protagonistic material, even in the absence of one's own data.

Second, others' data is especially effective in eliciting value judgments and externalized reasoning. Participants frequently used others' data to express and justify opinions, beliefs, and social attitudes about behaviors, particularly when interpreting unfamiliar patterns or making comparisons to themselves. In contrast, self-data is more likely to elicit introspection and behavioral awareness, which extends prior research emphasizing the reference value of others' data in establishing norms [85]. This finding also suggests that others' data functions as a kind of social mirror, encouraging users to articulate their own values in response to observed patterns.

Third, others' data supports self-reflection through interpretation and comparison, while one's own data supports it through memory and context recall. When engaging with others' data, participants often constructed plausible narratives by drawing on personal experience or by comparing the data to their own. One's own data, by contrast, tended to trigger direct recollections and situational context. This finding extends prior research on the anchoring role of self-data [3] and introduces interpretation as a distinct mechanism through which others' data facilitates reflection.

Together, these findings highlight that others' personal data is not merely a reference point for comparison, but an active source of reflection that can support memory, interpretation, and judgment. This expands current understandings of data-driven self-reflection in personal informatics and underscores the importance of designing tools that incorporate both self and other perspectives [7, 23].

5.1.2 Study 2: exploring pair sensemaking in personal data

As highlighted in Study 1, others' data can serve as an effective source for supporting self-reflection, albeit through different mechanisms and with varying effects. The next step is to explore how such reflective data sources can be leveraged within a collaborative context to further foster self-reflection. Prior research in collaborative sensemaking has shown that pair sensemaking can be beneficial for reflection due to its dynamic and interactive nature. However, there is still limited understanding of how this form of collaboration can be effectively applied to personal data. To address this gap, the second study investigated: **RQ2: How can personal visualizations be designed to support dyadic comparison and facilitate switching between reciprocal roles that characterize the pair sensemaking process?** In particular, this study explores two key aspects: (1) the ways in which pair collaboration facilitates sensemaking of personal data and fosters reflection on personal experiences, and (2) the design of personal visualizations that support pair sensemaking. To understand how to effectively support pair sensemaking, I reviewed and synthesized relevant literature on pair sensemaking and personal visualization, proposing a set of design principles (DPs) that facilitate the sensemaking of personal data. I then designed a tangible visualization toolkit that implements these proposed design principles. To evaluate the effectiveness of pair sensemaking and the design toolkit, I conducted an observational user study, detailed in Chapter 3.

Among the findings, the most significant insight was the two key mechanisms through which pair collaboration enhances personal data reflection: the structure of the data representation and the interactional dynamics of the sensemaking process itself.

First, I found that the use of a second person's data as a reference point leads to deeper, more focused engagement. Unlike one-to-many group comparisons, which typically aim to establish behavioral norms [39], the one-to-one structure of pair collaboration allowed participants to zoom into smaller data units. This granularity enabled individuals to uncover subtle patterns, recall detailed experiences, and make richer interpretations of their own behaviors. This finding highlights the value of dyadic comparison as a mechanism that not only fosters recall but also drives personal insight in a way that group-level data cannot.

Second, the reciprocal roles established through the pair sensemaking process enabled participants to scaffold each other's reflection. I observed that participants naturally adopted reciprocal roles: one would often ask clarifying questions, while the other provided speculative interpretations. This mutual scaffolding led to deeper, more sustained reflection than is typically seen in group discussions. Unlike group settings which frequently suffer from imbalanced participation or conversational drift, the structured interaction between two participants fostered balanced, focused engagement. This finding highlights that pair sensemaking offers a more equitable and reflective dialogue format than group discussions, which often devolve into monologues dominated by a few voices [145].

To support the two mechanisms at play, I propose a set of design principles as the second major contribution of this work, which facilitate self-reflection from two complementary perspectives: data representation and the sensemaking process.

With regard to data representation, the findings indicate that effective toolkits should offer **structured guidance for both dyadic and subjective data comparisons.** Participants engaged deeply with each other's data when it was presented in smaller, multifaceted segments that could be selectively manipulated and compared. Those data representations enabled alignment between individual perspectives and supported more nuanced exploration of behaviors, expectations, and motivations. These insights informed two key design principles: one focused on enabling granular data segmentation to support personalized exploration **(DP1)**, and another on providing scaffolding to guide users through the reflective process **(DP2)**.

Equally critical was the sensemaking process, which necessitates the integration of both individual and shared data representations. Beyond offering subjective and comparable data representations, the sensemaking process is especially effective when participants are encouraged to actively question, explain, and reinterpret their experiences not only individually, but in collaboration with their partner. This led to the articulation of two additional principles: one emphasizing the importance of supporting both individual and shared views of the data **(DP3)**, and the other focusing on fostering reflective dialogue through inquiry and interpretation **(DP4)**.

These insights into pair sensemaking reveal two critical limitations in existing personal data tools. First, while current personal visualization designs support collaborative sensemaking of data, they often lack the ability to represent personal data in subjective and comparative formats that align with users' lived experiences, thereby limiting the depth of individual reflection (as highlighted by DP1, DP2, and the dyadic comparison mechanism). Second, existing research falls short in supporting and facilitating the reciprocal, dialogical nature of pair sensemaking (as revealed through the sensemaking mechanism and encapsulated in DP3 and DP4). These limitations point to a pressing need to move beyond conventional analytical or normative visualization designs and toward approaches that support subjective interpretation and the collaborative construction of personal narratives.

5.1.3 Study 3: integrating Data humanism for fostering reflection

In response to this need, Study 3 explores how the idea of data humanism can be integrated into pair collaboration to support pair sensemaking of personal data. Data humanism advocates for subjective, personalized representations and slow, thoughtful sensemaking. While it has informed the design of personal visualization for individual reflection, it remains unclear how it can be operationalized within collaborative contexts. Specifically, a key tension lies in balancing the inherently personal and interpretive nature of data humanism with the shared, structured processes required for collaborative reflection. I therefore ask: **RQ3: How can pair sensemaking balance the requirements of the data humanism approach with those of collaborative sensemaking to foster reflection on experiences?** To explore this, I reviewed the literature on data humanism and collaborative sensemaking and developed a set of design guidelines that extend the principles outlined in Chapter 3. These guidelines informed the creation of Reciportrait, a tangible visualization toolkit designed to support expressive and co-constructed sensemaking. I conducted an observational user study to examine how this design enabled collaborative reflection.

The findings of this study reveal the proposed design principles, integrating the ideas of subjectiveness and slowness from Data Humanism, inform the design of personal visualization tools, for fostering reflection across levels: the importance of **subjective and shared data representation**, and the **slow and structured sensemaking process** to support reflective and reciprocal dialogue.

In terms of data representation, I found that enabling users to personalize their visual encoding methods(DP1) while offering structured design guidance (DP2) empowered them to co-author visualizations that reflected both shared and subjective perspectives. This balance proved essential in aligning individual interests, fostering a deeper engagement with data and uncovering personally meaningful insights. Furthermore, creating these personalized visualizations, informed by DP1 and DP2, requires less effort in managing the complexity in defining visuals, thus enhancing people's willingness to personalize the visuals and and analyze data insights. The co-creation of collaborative visualizations that capture both shared and individual perspectives (supported by DP1 and DP2) helps participants reveal personally meaningful data insights that represent their personal experiences. These insights align with the reflection level R1-description outlined by Fleck and Fitzpatrick, which emphasizes the articulation and identification of experiences without further explanation.

As for the slow and collaborative sensemaking process, my findings demonstrated DP3 (coordinate slowness in collaborative sensemaking) and DP4 (providing both individual and shared working spaces), which supported a reciprocal and structured the visualization process for reflecting on each others' experiences. Reciportrait's design facilitated three distinct modes of slowness in reflection, mapped to Hallnäs and Redström's framework that were made possible by its paired layout of identical, individual working spaces. First, by allowing one participant to lead while the other observed and commented, users engaged in a thoughtful articulation of their visual thinking ("how it works"). Second, real-time co-construction of visuals through these parallel spaces enabled spontaneous communication and mutual insight as participants uncovered personal data patterns together ("see what it is"). Third, the layering of these individual visualizations onto a shared canvas led to surprising "aha" moments ("find out the consequences of using it"), deepening the collaborative interpretation of data and experience. The three different types of slowness supported by DP3 and DP4 help individuals identify and contextualize data patterns, leading to insights into their past behaviors. These insights align with Fleck and Fitzpatrick's concept of "descriptive reflection"—recalling, justifying, and explaining actions—which can be enhanced through social interaction that encourages users to articulate the reasons behind their behaviors.

5.2 The pair sensemaking of personal data framework

Supporting self-reflection through the sensemaking of personal data has long been recognized as a central goal in the fields of personal informatics and personal visualization. In these fields, the framework proposed by Fleck and Fitzpatrick has been widely adopted, outlining five levels of reflection—from descriptive and explanatory to the more advanced dialogical and transformative reflection [10]. However, a recent review has shown that most existing tools primarily facilitate the lower levels of reflection, focusing on describing or explaining past behaviors, while providing limited support for deeper, critical, or transformative engagement with data [7].

Broader research in HCI has proposed strategies for enabling richer forms of reflection. For instance, the Reflective Practicum by Slovák, Frauenberger, and Fitzpatrick emphasizes the importance of identifying the "right kind of experience" to trigger deeper reflection [58]. Similarly, the concept of slow technology has highlighted the potential of designing systems that encourage mindfulness and reflective engagement in situ [161]. Yet, how these theoretical insights can be effectively operationalized in the context of personal visualization remains an open question. Among these emerging strategies, collaboration stands out as a particularly promising yet underexplored approach. Insights from both Personal informatics and broader HCI research have increasingly pointed to the potential of collaborative sensemaking to deepen self-understanding [23, 83, 85]. Working with others can bring in alternative perspectives, help users notice overlooked patterns in their data, and elicit interpretations that might not surface in isolation. Despite this potential, most collaborative systems in personal informatics have focused on group-based comparisons [40, 85], which are effective for exposing social norms but are less suitable for supporting the personal, situated, and interpretive nature of individual reflection [85]. There remains a critical gap: the need for approaches that move beyond normative comparison and instead support dialogical, co-constructive engagement with personal data through interactive and reflective collaboration.

To address this gap, this thesis introduces *pair sensemaking of personal data* as a novel approach to foster reflection on personal experiences. As conceptualized in the Pair Sensemaking of Personal Data framework (Figure 5.2), the approach centers around two key components: a pair of individuals and a shared data representation generated from both individual's personal data. The pair of individuals collaboratively develop shared visualizations that integrate both personal and collective perspectives. Through this process of co-development, they engage in pair dialogues where they they inquiry, explanation, and interpretation of each other's data and personal experiences. These dialogues enabling them not only gaining deeper insights into data, but also the relational and contextual dimensions of both their own and others' lived experiences. As illustrated by Figure 5.2, the *Pair Sensemaking of Personal Data framework* is defined by three core conceptual characteristics, each highlighting how this approach uniquely shapes reflection and distinguishes itself from other forms of collaborative sensemaking that typically involve larger groups with aggregated personal data [39–41].

The Pair Sensemaking of Personal Data framework is intended to serve both *explana-*

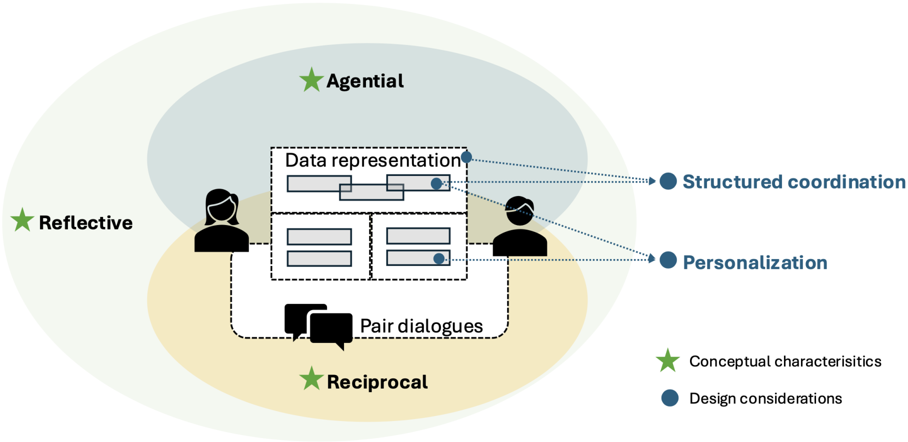


Figure 5.2: Pair Sensemaking of Personal Data Framework

tory and *prescriptive* purposes. As an explanatory framework, it provides a structured lens for analyzing how reflective collaboration unfolds, capturing the agency, reciprocity, and reflective nature of pair sensemaking.

The **Agential** dimension (illustrated by the blue circle covering primarily data representation in Figure 5.2) emphasizes participants' autonomy in controlling *what* and *how* data is represented and interpreted, especially in the process of developing data representations. With the designed toolkit, participants actively design the (collaborative) visualizations based on their own subjective interpretations and conceptual interests [5, 38]. This hands-on manipulation of data representations enables them to navigate both their own data and others' data in personally meaningful ways, tailoring the process to their own questions, interests, and narrative boundaries. Building on this foundational control, participants also exercise agency over *how much* to share, navigating data privacy within the collaborative process. Through the gradual and reflective manipulation of data representations, the two individuals develop a deeper understanding of both their own and their partner's data. Agential control further extends into the dialogue itself, as participants choose which themes to explore, what questions to pose, and how deeply to reflect. This evolving awareness enables them to thoughtfully manage personal boundaries and determine how open or vulnerable they wish to be throughout the collaboration. Altogether, this autonomy supports a self-directed sensemaking process, enriching both engagement and personal ownership of insights.

The **Reciprocal** nature (illustrated by the yellow circle covering primarily data representation in Figure 5.2) is another core strength of the pair sensemaking approach, particularly evident in the pair dialogues. The two individuals fluidly shift between roles—forager (exploring data, posing questions, noticing patterns) and sensemaker (interpreting findings, synthesizing insights, and shaping narratives)—aligning with prior work in pair analytics [19, 27]. This dynamic exchange creates opportunities for mutual scaffolding [192], where each partner not only learns from the other's perspective but also helps deepen the other's reflection. Reciprocity is further enriched by the integration of two distinct data sources, which offer contrasting yet complementary views that catalyze more nuanced comparisons and collective interpretations. The interaction is inherently co-constructive:

participants challenge assumptions, validate interpretations, and extend one another's thinking in real time. This reciprocity fosters a relational mode of reflection—one that is dialogic, evolving, and ultimately richer than what either person could achieve independently.

The **Reflective** dimension, represented by the green circle in Figure 5.2 and encompassing both data representation and pair dialogue, captures the framework's capacity to support deep and evolving reflection on personal experiences. The development and manipulation of data representations facilitate subjective analysis and interpretation, allowing participants to externalize personal experiences and engage with their data in ways that align with their own conceptual boundaries. Simultaneously, pair dialogues enable collaborative inquiry and sensemaking, as individuals pose questions, offer explanations, and build on each other's insights. Grounded in constructivist learning theories [60, 193, 194], this integration of visual and dialogic processes supports iterative meaning-making. By combining individual exploration with mutual scaffolding [58], pair sensemaking turns reflection into a co-constructed, layered process that enhances both engagement and depth of insight.

As a prescriptive framework, the Pair Sensemaking of Personal Data framework translates the conceptual dynamics outlined above into actionable design considerations that guide the development of tools, methods, and studies supporting interpersonal reflection. In particular, it incorporates design principles for the data visualization toolkits that enable pair sensemaking, emphasizing a balance between personalization—to maintain individual agency and interpretive freedom—and structured coordination—to scaffold collaborative engagement without constraining it. These considerations operationalize the framework's core dimensions by showing how design can mediate both personal and relational aspects of reflection

Personalization aligns with the agential dimension by ensuring that individuals can tailor visualizations and interactions according to their own interpretive needs and conceptual interests. The toolkit supports flexible representation, allowing participants to select which aspects of their data to visualize, how to structure them, and how to interpret them. This supports not only subjective sensemaking but also privacy-aware collaboration, as individuals can decide what and how much to share. Drawing on ideas from data humanism [38] and constructive visualization [61], the design encourages users to maintain ownership over the meaning-making process, ensuring that each visualization remains personally resonant.

Structured coordination, in turn, supports the reciprocal dimension by embedding mechanisms that guide the collaborative flow without overconstraining it. For example, features such as mirrored visualizations, annotation tools, and synchronous interactions help pairs align their attention, coordinate their actions, and co-develop shared insights. These design elements are grounded in collaborative sensemaking literature, offering just enough scaffolding to support fluid role-switching, mutual awareness, and iterative exploration. Rather than enforcing linear tasks or rigid structures, the toolkit facilitates open-ended dialogue and co-reflection.

Together, these design considerations also reinforce the reflective dimension of the framework. The development and manipulation of shared data representations externalize thought processes, while pair dialogues provide a space for mutual inquiry, prompting reinterpretation and synthesis. The viualization toolkit is thus conceived not only as a medium for interaction, but as a "thinking space" where reflection is made visible, social, and iterative—an idea rooted in constructivist approaches to learning and design [58, 60, 193].

By integrating explanatory insights with prescriptive guidance, the framework transforms the thesis findings into a practical model that can inform both the study and design of systems for collaborative reflection.

5.3 Implications for Personal Informatics and Visualization

Reflecting on the **reciprocal** and **reflective** nature of pair sensemaking approaches to personal data, we discuss their implications for the fields of personal informatics and personal visualization, particularly in supporting personal experience understanding and informed decision-making.

Facilitating informed decisions for patients: One application of pair sensemaking of personal data is in healthcare, where collaboration between peer patients has proven to be an effective strategy for self-care and informed decision-making[147–149]. Patients often navigate complex, subjective choices regarding treatments and self-care strategies, requiring them to weigh factors such as life context, financial constraints, and personal values[150]. However, making these decisions in isolation can be challenging, as patients may struggle to fully contextualize their experiences or identify patterns in their health data.

Through pair sensemaking, patients could meet regularly, either in clinics or online, to collaboratively explore their personal health data, such as sleep, mood, or medication adherence records. Using a toolkit designed for shared visualization, each patient could select aspects of their data they wish to discuss and construct visual representations that make their experiences visible to their peer partner. Together, they might compare fluctuations in symptoms, discuss coping strategies, and identify contextual factors (e.g., stress, diet, exercise) influencing their health outcomes. Clinicians could facilitate these peer sessions by providing reflective prompts or by helping participants interpret patterns without directing the discussion. Such structured yet participant-led collaboration decentralizes authority, allowing patients to generate insights grounded in lived experience while maintaining clinical oversight. This process not only supports personalized and informed decision-making but also strengthens patients' confidence, empathy, and sense of agency in managing their health.

Encouraging self-reflection for students: In educational contexts, reflection is a critical component of learning, enabling students to deepen their understanding, develop self-awareness, and make informed decisions about their behaviors and goals. While Personal Informatics (PI) tools have been designed to support student reflection, they often fall short in sustaining engagement and fostering deeper, meaningful reflection, which requires introspective activities, discussion, and active engagement with one's experiences [176].

Applying pair sensemaking of personal data could reframe reflection in learning environments as a shared, socially grounded process. For example, students could periodically pair up to review their learning analytics data, such as study patterns, class participation, or stress and focus levels, using an interactive toolkit that supports collaborative visualization. During these sessions, each student could explain their data choices and interpretations to their partner, compare differences in learning approaches, and co-develop strategies for improvement. Such dialogues transform abstract metrics into meaningful stories about learning habits, challenges, and achievements. Teachers could introduce guided prompts (e.g., "What patterns surprised you?" or "How does this reflect your goals?") to facilitate the discussion without dominating it. By embedding reflection in peer dialogue, this approach encourages mutual accountability, motivation, and emotional support, making reflection less performative and more personally meaningful. Over time, students not only learn to analyze their own data critically but also to empathize with others' learning processes, cultivating metacognitive and interpersonal skills essential for lifelong learning.

5.4 Implications for understanding user experiences

Sensemaking of personal data has long been employed as a valuable method for understanding users' experiences with products, systems, and services across domains [2, 49, 51]. In light of the **agential** and **reflective** nature of pair sensemaking with personal data, we explore its implications in two contexts: data work and the understanding of AI user experiences, respectively.

5.4.1 Data work

In data work, methods such as articulation work [52], participatory data analysis [195], and data-enabled design [11, 51] actively engage users in analyzing visualizations of their personal data, facilitating them in recalling and articulating their experiences, expectations, and emotions when interacting with products and services. However, many of these approaches remain designer-driven [50, 151], with designers constructing visualizations and framing questions to elicit user feedback. This dynamic can limit the emergence of user-led insights, overlooking subtle meanings that arise from users' own interpretive processes.

In contrast, pair sensemaking extends and enriches this body of work by shifting reflection from a designer-led activity to a peer-driven, dialogic process. It gives users greater agency to interpret personal experiences and negotiate their meanings collaboratively, while still providing designers with structured entry points for guiding reflection through visualization toolkits and prompts. This approach enhances data work in a specific way: it decentralizes control from designers to participants. Rather than relying on designers to define analytical goals, determine relevant data views, or frame interview questions, participants themselves take ownership of what to explore, how to visualize their experiences, and when to share or withhold information. This redistribution of interpretive power allows reflection to emerge organically through dialogue, situating insight generation within participants' lived experiences rather than designers' predefined perspectives. The resulting synergy between user autonomy and designer facilitation enables richer, more contextualized understandings of user needs and experiences, thereby extending the methodological repertoire of data work toward more participatory and relational forms of inquiry.

5.4.2 Understanding user experiences in AI

In the design of AI systems, such as recommender system, user experience is crucial for fostering effective interactions, building trust, and ensuring users derive meaningful value from the system [17, 196]. Prior research has emphasized that user experience should account for both user characteristics (e.g., demographics, prior knowledge, values) and contextual factors (e.g., choice goals, trust in the system). More recently, the role of user values has gained attention as a fundamental yet underexplored aspect of AI system design [53]. However, capturing such nuanced aspects of user experience remains a challenge, as traditional evaluation approaches, such as user ratings, behavioral data (e.g., clicks, watch time), and surveys [197, 198], tend to focus on surface-level preferences rather than deeper motivations and values.

To tackle this challenge, pair sensemaking provides a promising reflective approach that complements existing evaluation methods. For instance, online evaluations, which typically collect user ratings [197, 198] or behavior signals [199] through built-in mechanisms, could integrate a pair sensemaking task both immediately after and at a later stage following system use. Users could be paired based on shared or overlapping experiences with the system to trigger more meaningful self reflection [109], aligning with existing recommender approaches such as collaborative filtering [200]. By engaging in structured discussions centered on their personal data, participants can articulate their experiences in ways that go beyond traditional self-reporting, uncovering subtle motivations and values that shape their interactions. For example, two users who frequently watch the same videos may do so for different reasons—one seeking content that matches a particular mood, the other revisiting familiar content for comfort or habit. Pair sensemaking of personal data enables them to compare their experiences, articulate their motivations, and reflect on their personal values shaping their interactions.

Additionally, user studies—typically structured around predefined tasks followed by post-hoc surveys [199, 201]—could greatly benefit from integrating pair sensemaking tasks into their workflows. By incorporating reflective discussions, pair sensemaking fosters a comprehensive understanding of user interactions, particularly in uncovering negative experiences and subtle frustrations that often go unnoticed in behavioral data [202]. For instance, participants may struggle to find satisfying content but might not express this frustration through ratings alone. Engaging in reflective dialogue with a peer allows them to articulate their goals for seeking videos, such as the desire for entertainment, education, or emotional support, while also considering how their personal values and life contexts influence their viewing choices.

By integrating pair sensemaking with existing RS evaluation approaches, researchers can move beyond traditional system centric metrics to develop a more user-centered understanding of recommender systems. This approach not only enhances the evaluation of user experiences but also informs the design of systems that more effectively align with users' diverse values and needs. Future work can explore how pair sensemaking can be systematically incorporated into large-scale evaluations, such as crowdsourced studies, or embedded within real-world RS interfaces to continuously capture user reflections over time.

5.5 Limitation and future work

5.5.1 Findings and methods

One limitation of this thesis lies in the composition of participant pairs. Due to the challenge of recruiting a sufficient number of self-volunteering participants, this research focused on pairs that were either strangers who collect sleep data, stranger university students from the same university, or university friends with shared experiences. While this strategy enabled the study to proceed within feasible logistical constraints, it did not allow for a systematic exploration of how different types of interpersonal relationships may influence the pair sensemaking process.

As emphasized in the Pair Sensemaking of Personal Data framework, the two individuals engaged in the process are foundational to its success. Prior research has highlighted that the degree of relatedness between participants can significantly influence the depth, openness, and quality of reflective dialogue [80]. However, this relational dimension was not systematically examined in this thesis. Future research should investigate how different interpersonal dynamics—such as familial relationships, romantic partnerships, or professional collaborations—shape trust, emotional safety, and the interpretive depth of pair-based reflection.

Moreover, it would be valuable to explore the criteria by which participant pairs are matched, particularly how these criteria affect the relevance and meaningfulness of data comparison. As discussed in Study 2, comparative dynamics such as upward or downward social comparisons may influence participants' engagement or emotional responses. For instance, individuals may feel demotivated when comparing their data with that of a more successful peer, a phenomenon commonly referred to as downward comparison bias [153]. To address such biases and foster more constructive pair dynamics, future work could explore matching strategies that emphasize shared goals, complementary perspectives, or similar life contexts. These strategies could enhance perceived relevance and mutual empathy, thereby improving the conditions for reflective collaboration. Additionally, providing clear guidance on the purpose and scope of pair collaboration may help participants navigate comparisons constructively, reducing the potential for negative effects stemming from mismatched expectations or perceived inequities.

Beyond participant composition, it is also important to acknowledge how the methodological design shaped the findings of this thesis. The reliance on short-term reflection tasks and toolkit-based studies foregrounded close observation of interactional dynamics but limited understanding of how pair sensemaking evolves over longer periods or in everyday contexts. Similarly, the use of structured visualization toolkits directed attention toward co-construction and dialogue, potentially constraining more spontaneous or naturally emerging forms of collaboration. Recognizing these methodological boundaries clarifies that the findings primarily capture in-situ reflection behaviors within designed settings rather than longitudinal transformation. Future research could extend this work through longitudinal or in-the-wild studies to examine how pair reflection practices develop and stabilize over time

5.5.2 Ethical and social implications

Another important limitation of this research concerns the privacy within the *pair sensemaking of personal data* approach. This approach inherently involves sharing personal even intimate data to support interpersonal reflection, where privacy becomes a critical design and ethical consideration. While findings from Study 2 suggest that the reciprocal nature of pair collaboration—where both individuals occupy equal positions and mutually benefit from shared experiences—can mitigate some privacy concerns, the privacy concerns was not comprehensively investigated in the current work.

Existing literature highlights that privacy is perceived in diverse and dynamic ways, such as the ability to control the flow of personal information ("privacy as control") and the selective disclosure of information based on contextual cues and personal intentions ("privacy as boundary regulation") [137, 203]. These perspectives emphasize that privacy is not a static condition but an ongoing process of negotiation, shaped by factors such as perceived autonomy, trust, and situational dynamics. In the context of the *pair sensemaking of personal data* approach, personal disclosure is central to enabling reflection. Rather than being incidental, sharing is deliberately encouraged to foster deeper self-understanding and mutual insight. Accordingly, future research should examine how individuals perceive and manage privacy within dyadic data-sharing settings. This includes exploring what types of personal data individuals feel comfortable sharing, how disclosure boundaries evolve throughout the interaction, and what design mechanisms can support a sustained sense of agency, trust, and emotional safety. Such investigations could inform the development of systems that more thoughtfully balance openness and discretion—facilitating meaningful reflection while respecting individual privacy boundaries. Beyond privacy, these dynamics also intersect with broader socio-technical questions around identity, interpretation, and collective memory. As participants co-construct narratives around their data, they negotiate self-presentation and shared meaning, linking pair sensemaking to theories of narrative identity and social reflection. Future studies could therefore explore how design can support this narrative co-construction while maintaining ethical sensitivity to consent, ownership, and emotional well-being.

Last but not least, this thesis primarily explores the *pair sensemaking of personal data* approach through the use of tangible visualizations. While Study 1 involved a crowd-sourced study in which participants interacted with screenshots of visualizations, subsequent studies emphasized hands-on engagement with physical artifacts. As discussed in the implications for understanding AI systems and user experiences, there is a clear opportunity and need to operationalize this approach within digital platforms to enable broader accessibility and scalability. Future work should explore how the core principles of pair sensemaking, particularly co-construction, dialogue, and deep reflection, can be meaningfully translated into interactive online environments. For example, it remains an open challenge to adapt the inherently slow and subjective process of collaborative sensemaking to the often fast-paced and small nature of crowdsourcing platforms [204, 205]. Investigating how to scaffold reflective, interpersonal engagement within such constrained contexts could expand the applicability of this approach while maintaining its core values.

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Curriculum Vitæ

Di Yan is a passionate Human Computer Interaction researcher. Her work focuses on reflective sensemaking of personal data, engaging people in exploring visualizations of their own data and reflecting on the underlying reasons behind their behaviors and experiences. Drawing on her design background, she develops visualization and collaborative sensemaking systems that support collective interpretations of personal data, revealing latent insights into how people perceive and value products and systems in everyday life. She also extends this approach to examine how AI systems embody human values in lived contexts, with the aim of advancing value aligned AI design and contributing to critical discussions on AI governance and policy.

Education

2013–2017 B.Eng, Zhejiang Agriculture and Forest University Interior and furniture design
2017–2020 MFA, Jiangnan University & Environmental design
2018–2019 Msc., Queen Mary University of London & Media and Art Technology by Research
2020-2025 PhD., Delft University of Technology

List of Publications

- **Di Yan,** Jacky Bourgeois, Gerd Kortuem, Say You, Say Me: Investigating the Personal insights Generated from One's Own data and Other's data. In NordiCHI 2024: Proceedings of the 13th Nordic Conference on Human-Computer Interaction.
- **Di Yan,** Jacky Bourgeois, Yen-Chia Hsu, Gerd Kortuem, PAIRcolator: Pair Collaboration for Sensemaking and Reflection on Personal Data. In CHI 2025: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems.
- **Di Yan,** Chenge Tang, Senthil Chandrasegaran, Gerd Kortuem, Reciportrait: A Data Humanism Approach for Collaborative Sensemaking of Personal Data. In CHI 2025: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems.
- **Di Yan,** Yizhen Zhang, Gerd Kortuem, Jie Yang, "It Reminds Me of My Old High School Days": Integrating Personal Data Reflection into Crowdsourcing for Recommender System Evaluation (Under review by CHI 2026).
- Xun Zhang, Stephen Jia Wang, Maaike Kleinsmann, **Di Yan**, Ziyu Wei, Pan Wang, Human-AI Co-Creativity: Integrating Brain Decoding and Image Editing via EEG in a Human-AI Collaborative Design proces (Under review by Journal of Engineering Design).