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SURVEY ARTICLE

Data Sensemaking in Self-Tracking: Towards a New Generation of Self-Tracking Tools

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ABSTRACT
Human-Computer Interaction (HCI) researchers have been increasingly interested in investigating self-trackers' experience with self-tracking tools (STT) to get meaningful insights from their data. However, the literature lacks a coherent, integrated and dedicated source on designing tools that support self-trackers' sensemaking practices. To address this, we carried out a systematic literature review by synthesizing the findings of 91 articles published before 2021 in HCI literature. We identified four data sensemaking modes that self-trackers go through (i.e., self-calibration, data augmentation, data handling, and realization). We also identified four design implications for designing self-tracking tools that support self-trackers' data sensemaking practices (i.e., customized tracking experience, guided sensemaking, collaborative sensemaking, and learning sensemaking through self-experimentation). We provide a research agenda with nine directions for advancing HCI studies on data sensemaking practices. With these contributions, we created an analytical information source that could guide designers and researchers in understanding, studying, and designing for self-trackers' data sensemaking practices.

1. Introduction

Over the centuries, people used diaries and personal logs for self-reporting (Crawford et al., 2015; Lupton, 2016; Neff & Nafus, 2016). With the recent advancements in technology, activity trackers, smartwatches, and other wearable technologies have emerged as new products used for self-reporting, namely self-tracking tools (STT). While both personal informatics and self-tracking tools have been used to refer to technologies designed to support self-tracking practices, we use the term Self-Tracking Tools (STT) for simplicity. Equipped with sensors, these tools help self-trackers collect a range of personal data from simple health metrics like step counts to more complex ones like sleep quality, blood glucose level, heart rate, and calories. STT enables self-trackers to make informed decisions about their health and well-being by providing such data.

In parallel with the proliferation of STT, Human-Computer Interaction (HCI) researchers have been exploring digital self-tracking practices from different facets. So far, researchers have investigated how users monitor their behavior with the help of STT (e.g., Li et al., 2010; Lupton, 2014), identified the qualities of STT that support self-tracking practices (e.g., Jin et al., 2020), proposed guidelines and implications to inspire new STT designs (e.g., Elsden et al., 2016; Rapp & Cena, 2016), and identified challenges and opportunities to advance the personal informatics field (e.g., E. T. Kersten-van Dijk et al., 2017; Khovanskaya et al., 2013).

More recently, researchers have challenged the classical view of STT as devices that quantify behavior. They question the essence of quantifying and recording every aspect of human life by arguing that the tendency towards "over-quantification" and "over-digitalization" damages the intrinsic values of human experience (Coskun, 2019; Lupton, 2017). Furthermore, they promoted an alternative view of STT that prioritizes *qualitative* (Epstein et al., 2016; E. Kersten-van Dijk & IJsselsteijn, 2016; Ohlin & Olsson, 2015; Puussaar et al., 2017; Rapp et al., 2016; Rapp & Tirassa, 2017), *subjective* (Ohlin & Olsson, 2015; Rapp & Tirassa, 2017) and *social* aspects of tracking (Epstein et al., 2014; Feustel et al., 2018; Lupton, 2014; Murnane et al., 2018; Pina et al., 2017; Puussaar et al., 2017). This view posits that STT should go beyond the numerical representation of behavior, and support self-trackers in gathering meaningful insights from data, insights that facilitate a more subjective and holistic understanding of the self and actionable behavioral decisions about one's life (Karyda et al., 2020; Li et al., 2010; Rapp & Tirabeni, 2018).

The shift from quantification to gathering insights from data has led HCI researchers to explore self-trackers' data sensemaking practices and how they make sense of digital data collected by STT (e.g., Jones & Kelly, 2016; Puussaar et al., 2017; Rapp & Tirabeni, 2018). Data-centric sensemaking requires people's cognitive involvement and engagement

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with information providers (Koesten et al., 2021), which brings many challenges for self-trackers. For instance, they may misinterpret their data (Hollis et al., 2018) as different data types can present conflicting results based on the contexts and use cases (Victorelli et al., 2020). One might simply interpret a fluctuation in heart rate during sleep as an indicator of a problem in health. However, this fluctuation might be due to daily stress, low hydration, intense physical activity, or even minor changes in one's sleeping room.

Furthermore, self-trackers may feel frustrated when the meaning derived from personal data does not match their expectations (Karlsson, 2019), such as failing to achieve a weight loss goal despite multiple trials. This mismatch and the misinterpretation of data may negatively influence self-trackers' perceptions of self (Lupton, 2017). This misinterpretation, in turn, results in their disengagement with data and with self-tracking (Ancker et al., 2015; Murnane et al., 2018). Hence, it is imperative to understand how self-trackers make sense of their data and what challenges they encounter during this sensemaking process. This understanding will assist the design of a new generation of STT that support informed decision-making about health and wellbeing, promote long-term engagement with data, and prevent premature abandonment of self-tracking.

To date, very few HCI studies examine self-trackers' sensemaking practices as their core focus (e.g., Katz et al., 2018b; Raj et al., 2017, 2019; Young & Miller, 2019). In addition, these studies investigate sensemaking in singular activities (such as sleep) or behaviors (such as a physical activity), making it challenging to transfer their findings to other contexts. Other studies that touch upon sensemaking practices mainly discuss these practices as a peripheral topic, e.g., presenting only one implication about sensemaking among others (e.g., Hollis et al., 2018; Niess et al., 2020). Still, the literature lacks a coherent, integrated and dedicated source on designing STT that support trackers in making sense of their data. In this paper, we address this gap by a systematic literature review that tackles the following research questions:

1. How do self-trackers make sense of their self-tracking data?
2. What are the challenges they encounter during this sensemaking process?
3. What are the implications for designing STT to overcome these challenges and support self-trackers' sensemaking practices?

We scrutinized and synthesized 91 articles published before 2021 in personal informatics and self-tracking literature. With this, we created an information source that could guide designers and researchers who study and design for data sensemaking in self-tracking practices in three ways. First, for the first time in the literature, we identified four sensemaking modes through which self-trackers make sense of their data (i.e., *self-calibration*, *data augmentation*, *data handling,* and *realization*). Second, we present four high-level design implications for designing STT that support self-trackers' data sensemaking practices (i.e., *customized tracking experience, guided sensemaking, collaborative sensemaking,* and *learning sensemaking through self-experimentation*). Finally, we provide a research agenda with eight directions for advancing HCI studies on data sensemaking practices.

Our paper begins with a background that explains what is meant by data and sensemaking in self-tracking. Then, we describe our review methodology and explain the search keywords, search venues, inclusion, and exclusion criteria, along with our analysis procedure. The results section presents the analysis of our corpus, the sensemaking modes and the activities we discovered, and the design implications we propose. Finally, after reflecting on the results, we provide a research agenda and future directions for studying and supporting the data sensemaking practices of self-trackers.

2. Data sensemaking in self-tracking

Data is at the bottom of the data information, knowledge, wisdom (DIKW) pyramid (Rowley, 2007). It is raw and abstract (Ackoff, 1989; Bellinger et al., 2004). In most cases, data refers to symbols that require representations to make them understandable and usable (Zeleny, 1987). The usefulness of data increases when it is processed and turned into *information* (i.e., answers to what, who, and when questions), *knowledge* (i.e., answers to how-to questions), and *understanding* (i.e., answers to why questions) (Ackoff, 1989; Bellinger et al., 2004; Zeleny, 1987). Transition of data to wisdom (i.e., the top layer of the pyramid) requires human input. For Rowley (2007), cognitive input turns data into wisdom while this input increases data's meaning and applicability. For others (Ackoff, 1989; Bellinger et al., 2004), even though computers can turn data into information, knowledge, and understanding, wisdom requires human values and soul, which machines will never possess.

In self-tracking, people use data to reflect on (i.e., what question) and take action (i.e., how-to question) about their physical, emotional, mental and physiological conditions. The form of data can be both countable and objective, such as the number of daily taken steps (e.g., Coskun, 2019; S. T. Doherty et al., 2014), fertility window (e.g., Figueiredo et al., 2017), menstruation cycle (e.g., S. Fox et al., 2019), and uncountable and subjective such as the experience of moods (e.g., Rivera-Pelayo et al., 2017), felt symptoms (e.g., Mishra et al., 2019), and experience of pain (e.g., Johansen & Kanstrup, 2016). One commonality in these examples is that trackers contribute to digital statistics when they create data and/or share it with others.

Data sensemaking starts with uncertainty and is followed by information seeking to resolve this uncertainty (Kuhlthau, 1993). Russell (2003) states that people face complex information and try to make sense of it by creating representations of these complexities in this process. Similarly, sensemaking in self-tracking is cognitively demanding (Katz et al., 2018b; Prioleau et al., 2020; Rapp & Tirabeni, 2018) and resolves the uncertainty (e.g., being able to understand unfamiliar and complex data types such as genomics (Shaer et al., 2016)), while it potentially requires intense knowledge to resolve these uncertainties (Figueiredo et al., 2017; Jenkins et al., 2020; Lomborg et al., 2020; Oygür et al., 2020; Pingo & Narayan, 2019; Rapp, 2018; Rapp & Tirabeni, 2018; Shaer et al., 2016; Young & Miller, 2019). Klein et al. (2007) define sensemaking as the "deliberate effort to understand events" triggered by surprises or unexpected changes and therefore helps people see problems. Hence, sensemaking is not about seeking the truth but creating exploratory and expressive stories from data (Weick et al., 2005). Thus, it becomes the "journey" people follow to find meaningful information (Blandford & Attfield, 2010).

Understanding this journey is critical for designers to better support self-trackers' sensemaking practices and help them turn personal data into insights about their lives. However, this is not a trivial task. Self-tracking practices are situated (Abtahi et al., 2020; Howell et al., 2018; Jenkins et al., 2020; Lupton et al., 2018; Park & Chen, 2015; Pingo & Narayan, 2019; Pink et al., 2018; Raj et al., 2017; Sumartojo et al., 2016; Woźniak et al., 2020), and lived (Kaziunas et al., 2018; Lupton et al., 2018). Hence, the interaction of many interconnected, data-related, and lifestyle factors influence self-trackers' sensemaking. For example, a wearable activity tracker possibly fails to provide meaningful suggestions when it suggests running routes without considering the crime rate in the self-trackers' neighborhood (Saksono et al., 2018); a bowl that tracks children's eating habits can negatively change parents' dinner habits when they are fully occupied with taking care of child's eating (Jo et al., 2020); or shared physical activity data of factory-workers can create social pressure and stress on them (Heikkilä et al., 2018).

Furthermore, data sensemaking in self-tracking is not merely about understanding numbers and data visualizations. Lupton (2017) argues that digital data has already become the material of sensemaking experiences and turned the process of reflection on digital personal data into a sensory experience. For example, women who track their menstruation cycles and log their subjective experiences in an app run the risk of mediating the body as the "object" of self-tracking (Homewood et al., 2020). In line with these arguments, Ayobi et al. (2018) question the necessity of digital tools in self-tracking practices. While digital tools could work well as extensions of the physical world, they are not necessarily better than their physical ancestors (Ayobi et al., 2018).

In summary, designing for data sensemaking requires designers to consider many interrelated, contextual, and inherently complex factors simultaneously. These can cover people's motivations to track, their experience in tracking, the involvement of others in tracking, social norms, privacy, and so on. As a result, the ambition of facilitating data sensemaking can develop into significant challenges for designers (Heikkilä et al., 2018). Thus, it is significant for HCI research to explicate self-trackers' data sensemaking practices and provide guidance for designers in supporting these practices through design. However, although a few studies examine self-trackers' sensemaking practices (e.g., Raj et al., 2019), the literature still lacks a coherent, integrated and dedicated source on designing STT that support these practices.

3. Methodology

We carried out a systematic literature review (similar to Xiao & Watson, 2019) to better understand self-trackers' data sensemaking practices across different tracking contexts, such as physical activity tracking, sleep tracking, disease management, etc. We identified and analyzed relevant publications by following a similar approach used in HCI literature reviews (e.g., Koelle et al., 2020; Moher et al., 2009) and PRISMA scoping (Moher et al., 2009).

3.1. Keywords and search engines

We identified four relevant databases based on the related studies and previous reviews in HCI (e.g., Klock et al., 2020; Salminen et al., 2020) and self-tracking related literature reviews (e.g., D. A. Epstein et al., 2020; Jin et al., 2020; E. T. Kersten-van Dijk et al., 2017). These databases were *ACM Digital Library, IEEE Explore, Web of Science, and Scopus*. While the first two databases helped us find papers within HCI and related domains, the last two databases helped us find papers that investigate personal informatics as their core focus but are published outside the HCI venues.

We used two sets of keywords to identify relevant papers from these databases. The first set consists of keywords related to "sensemaking" which are sensemaking, sense-making, make (made) sense, meaning, meaningful, and meaningfulness. The second set consists of keywords related to self-tracking, which are self-tracking, personal informatics, and quantified self. We searched for papers including at least one of the keywords in the first set (e.g., sensemaking) and one of the keywords from the second set (e.g., personal informatics) in any searchable field. We performed our search in January 2021, indexing publications from 2020 or earlier.

3.2. Selection criteria

Our search resulted in 722 articles. We filtered 91 articles by applying several inclusion criteria and following the systematic procedure described in (Klock et al., 2020). Figure 1 summarizes our article selection process

In the identification stage, we first excluded short communications, editorials, extended abstracts, papers that report unfinished or work-in-progress studies, and papers that are not available for download ($n = 69$). Following, we removed the duplicates ($n = 197$). In the screening stage, we excluded papers that do not explore data in the context of self-tracking and personal informatics and those that are not grounded or not aimed at informing the personal informatics literature ($n = 220$). In the eligibility check stage, we examined in which scope the search keywords are used in the remaining articles. We excluded papers that (i) use the

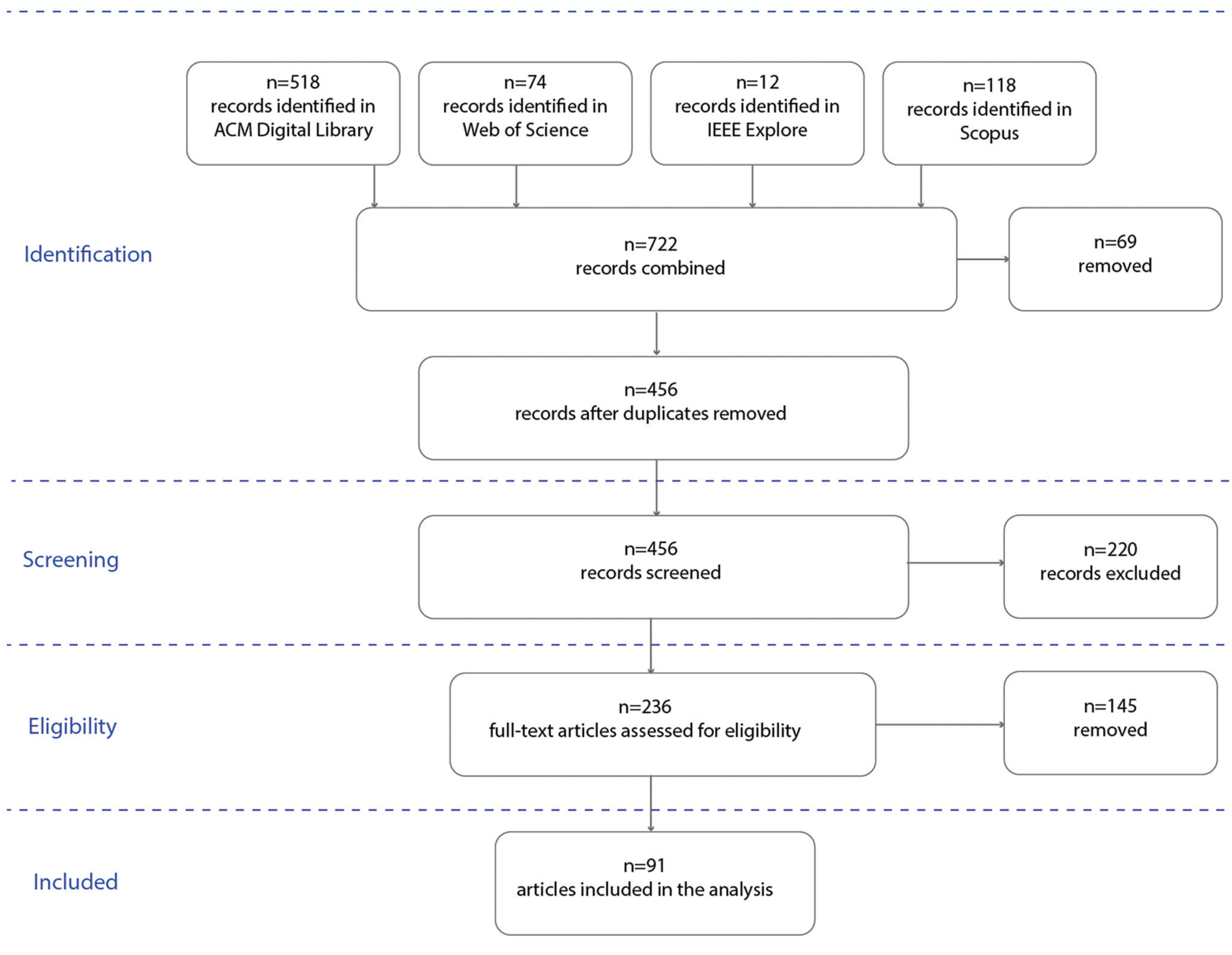

Figure 1. PRISMA flow chart of the article selection process.

search keywords solely for describing the soundness of the results (e.g. "the study results are meaningful" or "these results make sense"); and (ii) refer briefly to the meaningfulness of tracking data without connecting it to data sensemaking.

3.3. Analysis

We performed thematic data analysis in an iterative fashion (Braun & Clarke, 2006). We combined inductive and deductive coding approaches to answer our research questions. Each author read and coded ten articles per turn to this aim. We first looked for paragraphs (i.e., out units of analysis) that contain content related to data sensemaking and then annotated them with our notes. Following, we transferred the selected paragraphs into an Excel sheet and coded each paragraph according to three predetermined categories that match our research questions: (i) data sensemaking activities, (ii) factors that facilitate and the challenges trackers face during these activities, and (iii) implications for supporting these activities (See Table 1 for an example code and our notations).

After each turn, we regularly came together and discussed our codes to have a shared understanding of the emerging themes. Once we finished the initial coding, we categorized the codes according to their thematic relevance through affinity diagramming. Accordingly, we had 236 lines of codes for sensemaking activities in the first round. In the second round, we grouped them into 23 activity types. In the third round, we integrated all emerged activities into seven categories and grouped them under four sensemaking modes (Table 2). We coded implications in a similar way.

4. Results

In this section, we start by giving an overview of our corpus. Then, we present the four sensemaking modes and the challenges self-trackers face during these modes. Finally, we present the implications for supporting data sensemaking practices in self-tracking.

4.1. Overview of the corpus

HCI studies on self-tracking and personal informatics have started to appear in the late 2000s (e.g., the seminal work of Consolvo et al. (2009) and Li et al. (2010). Looking at our corpus, while the first studies discussing self-trackers' sensemaking practices only appeared later in 2014, there has been

Table 1. An example code from our initial coding.

A paragraph from the paper (Kaziunas et al., 2018)	Our notes on sensemaking activities	Our notes on challenges	Our notes on implications
As a result of such complexities, many people turn to the CGM-in-the-Cloud Facebook group for help to interpret personal data. An active and passionate group of Nightscout volunteers, for instance, offers technical support through the Facebook group 24/7. […] Many individuals also use CGM-in-the-Cloud to share insights on diabetes management and collectively arrive at best practices. Scrolling through the group's Facebook feed shows how people help interpret one another's data. For example, a confused parent posting a screenshot depicting the graph of their child's blood glucose levels after dinner will elicit comments such as, "My kid's graph looked like that when they were having a growth spurt" or "Did you happen to eat pizza?" (a notoriously tricky food for balancing blood sugars). It is in these moments of advice sharing and collective sense making of data that it becomes visible just how much DIY diabetes systems were enacted through mutual dependencies and collective support structures.	Collaborative sensemaking: Users often look for external help from communities to make sense of their or their loved one's data. This usually happens when sensemaking task is complex for them.	Complexity of sensemaking: When the users lack knowledge about their body, potential causes of variations in data, and how to use this information in one's life, sensemaking becomes highly complex.	Create online tracking communities: Allow users to connect with fellow trackers or people who are knowledgeable in making sense of similar personal data through online communities.

Table 2. An example code from our follow-up analysis.

Example codes from the 1st round	Example code from the 2nd round	Example code from the 3rd round
Learning about the tracking terminology Learning about the relations between variables Learning about oneself Learning about others	Increasing awareness on how to make sense of data	Self-calibration Knowledge acquisition

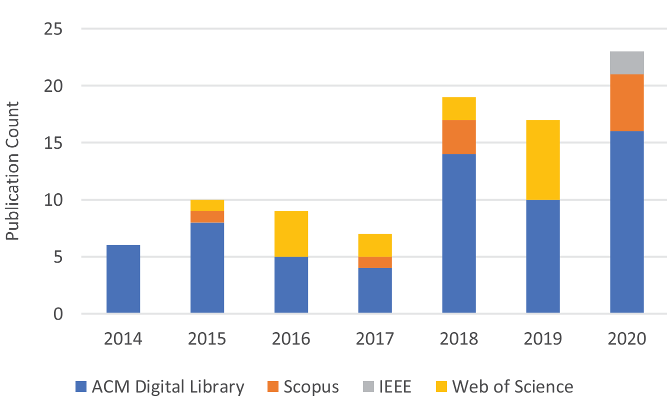

Figure 2. Number of Papers published over the years.

an increasing interest within the last three years. 65% of our corpus consist of articles published since 2018 (Figure 2).

The articles in our corpus focused on diverse tracking goals and behaviors. The most prominent ones were tracking for better disease or condition management ($n = 19$), physical activity tracking ($n = 17$), and mental wellbeing and affective health ($n = 10$). We observed that researchers extensively collect qualitative data to capture subjective and experiential aspects of sensemaking regardless of the data collection method used. The methods used to collect this data were interviews ($n = 49$), content analysis of online data ($n = 12$), observations ($n = 9$), co-creation workshops ($n = 9$), focus groups ($n = 4$) and diaries ($n = 2$).[1] While all the studies collect short-term data or include single-data collection moments, 15 studies collect longitudinal user insights. Almost all the studies recruited Western populations (USA, Europe, and Australia) participants. We only found two papers that recruited participants from eastern populations (South Korea).

4.2. Modes of data sensemaking

Our thematic analysis revealed seven activities self-trackers perform to make sense of their data. These activities occur in relation to four distinct sensemaking modes a self-tracker goes through during data sensemaking: *self-calibration, data augmentation*, *data handling*, and *realization* (Table 3).

The first mode is *self-calibration*. This mode happens once either self-trackers when they have a new tracking goal, i.e., when they are motivated to monitor the aspects of their life such as behaviors, symptoms, feelings and so on for the first time, or when they readjust their goal. In this

Table 3. Modes and activities of data sensemaking in self-tracking.

Mode	Activity	Questions to self	Source
Self-calibration	Identifying relevant tracking aspects	Which data should I track? How am I going to use this data?	(Adams, 2019; Doherty et al., 2020; Figueiredo et al., 2018; Figueiredo & Chen, 2020; McKillop et al., 2018; Mishra et al., 2019; Niess & Woźniak, 2018; Park & Chen, 2015; Raj et al., 2019; Shaer et al., 2016; Woźniak et al., 2020; Young & Miller, 2019)
	Knowledge acquisition	How can I increase my competency in making sense of tracking aspects?	(Alqahtani et al., 2020; Doherty et al., 2020; Hollis et al., 2018; Katz et al., 2018a; Kaziunas et al., 2018; Kou et al., 2018; Liang et al., 2016; Liu et al., 2015; Marcu & Spiller, 2020; Otiono et al., 2019; Pingo & Narayan, 2019; Prioleau et al., 2020; Rapp, 2018; Saariketo, 2019; Sanches et al., 2019; Sharon & Zandbergen, 2017)
Data augmentation	Data annotation	Is the data sufficient for me to get meaningful insights? How can I enrich it with my experiences and feelings?	(Alqahtani et al., 2020; Ayobi et al., 2020; Elsden et al., 2016; Elsden et al., 2016; Figueiredo & Chen, 2020; S. E. Fox et al., 2020; Heikkilä et al., 2018; Jo et al., 2020; Lupton et al., 2018; Niess et al., 2020; Pink et al., 2018; Pols et al., 2019; Potapov & Marshall, 2020; Rapp & Tirabeni, 2018; Rapp et al., 2019; Rooksby et al., 2014; Smith & Vonthethoff, 2017; Spotswood et al., 2020; Sumartojo et al., 2016; Thudt et al., 2018)
Data handling	Data curation	How can I make the data ready for my interpretation?	(Abtahi et al., 2020; Ayobi et al., 2020; Choe et al., 2014; Crawford et al., 2015; Elsden et al., 2016; Figueiredo et al., 2017; Friske et al., 2020; Gulotta et al., 2015; Khot et al., 2014; Lee et al., 2015; Liang et al., 2016; Mishra et al., 2019; Petelka et al., 2020; Pink et al., 2018; Prioleau et al., 2020; Raj et al., 2017; Rapp, 2018; Rapp & Tirabeni, 2018; Rooksby et al., 2014; Shaer et al., 2016; Sharon & Zandbergen, 2017; Snyder et al., 2019; Thudt et al., 2018; Young & Miller, 2019)
	Identifying relevant information for data exploration	Which tracking aspects and relations should I look for? How does my data vary? Is there a pattern?	(Abtahi et al., 2020; Alqahtani et al., 2020; Bae et al., 2014; Choe et al., 2014; Chung et al., 2019; Elsden et al., 2016; Figueiredo & Chen, 2020; Jenkins et al., 2020; Katz et al., 2018b; Liang et al., 2016; Liu et al., 2015; Mishra et al., 2019; Otiono et al., 2019; Oygür et al., 2020; Rapp & Tirabeni, 2018; Ravichandran et al., 2017; Rooksby et al., 2016; Shaer et al., 2016; Tang & Kay, 2017; Thudt et al., 2018)
Realization	Reasoning and reflecting	What does my data tell me? Why so?	(Alqahtani et al., 2020; Ancker et al., 2015; Bae et al., 2014; Chung et al., 2016; Chung et al., 2019; Elsden et al., 2016; Feustel et al., 2018; Figueiredo et al., 2018; Figueiredo et al., 2017; S. E. Fox et al., 2020; Graham et al., 2016; Katz et al., 2018a; Kaziunas et al., 2018; Kendall et al., 2015; Kou et al., 2018; Liu et al., 2015; Lupton et al., 2018; Otiono et al., 2019; Oygür et al., 2020; Park & Chen, 2015; Pina et al., 2017; Puussaar et al., 2017; Raj et al., 2017; Tang & Kay, 2017; Thudt et al., 2018; Vandenberghe & Geerts, 2015; Young & Miller, 2019)
	Confrontation	Does this data reflect my behavior and experience? Is this normal? Do I agree with what the data tell? What am I going to do with this new understanding?	(Adams, 2019; Choe et al., 2014; Elsden et al., 2016; Figueiredo et al., 2018; Figueiredo et al., 2017; Fox et al., 2020; Hand & Gorea, 2018; Heikkilä et al., 2018; Howell et al., 2018; Karlsson, 2019; Kendall et al., 2015; Kim et al., 2019; Liang et al., 2016; Lomborg et al., 2020; Lomborg et al., 2018; Lupton, 2015; Lupton et al., 2018; McKillop et al., 2018; Murnane et al., 2018; Niess & Woźniak, 2018; Pols et al., 2019; Raj et al., 2019; Rapp & Tirabeni, 2018; Saariketo, 2019; Sanches et al., 2019; Smith & Vonthethoff, 2017; Thudt et al., 2018)

mode, they prepare themselves for future sensemaking activities by setting new goals or revising existing ones, identifying tracking aspects to monitor their goal achievement, and seeking knowledge of the tracking domain (e.g., learning about medical terminology). While doing so, they ask themselves questions like, "How can I make the data ready for my interpretation? Which tracking aspects and relations should I look for? How does my data vary? Is there a pattern?"

We should note that, in relation to this mode, self-trackers might have performance and learning oriented goals (Locke & Latham, 2006; Seijts et al., 2004; Seijts & Latham, 2005). Performance goals are related to performing and arriving at a certain outcome achievement (Seijts et al. (2004) (e.g., taking 10,000 daily steps). Learning goals help acquire new knowledge and skills, discover new things, and implement strategies or procedures related to the tasks (e.g., discovering the reasons for fluctuations in blood sugar level). However, this does not imply that self-trackers cannot have two orientations simultaneously (e.g., while increasing daily step count can be regarded as a performance-oriented goal, discovering how increased physical activity affects blood sugar level can be regarded as a learning-oriented goal).

The second mode is *data augmentation*. Once self-trackers set their –performance and/or learning – goals, they start collecting data by using various STT like smartwatches, activity trackers, smartphones, and so on. We found that, during data collection, trackers do not always confine themselves to the digital data derived from these tools. Instead, they complement this data with experiential and sensorial data they generate (e.g., how self-trackers feel and what they observe during physical activity). In a way, they augment digital data to make it richer and more representative of their lived experiences. Thus, we call this mode *data augmentation*. While augmenting their data, self-trackers ask themselves questions like, "Is the data sufficient for me to get meaningful insights? How can I enrich it with my experiences and feelings?"

The third mode is *data handling*. When self-trackers feel that they accumulate sufficient data about their behavior, symptoms, or feelings they prepare it for further analysis. This preparation includes i) curating data via combining different behavioral, bodily and contextual data, removing outliers or negatives from data, identifying gaps in data and prioritizing data types, and ii) identifying relevant information by exploring the relations between different tracking aspects and looking for patterns in data. In *data handling* mode, self-trackers ask themselves questions like, "How can I make the data ready for my interpretation? Which tracking aspects and relations should I look for? How does my data vary? Is there a pattern?"

The last mode is *realization*. In this mode, self-trackers understand the significance of their data and decide what to do with the new understanding through engaging in two activities. First, they seek plausible explanations of the data patterns by reflecting on their past data, remembering the context where the data was collected, and collectively reflecting on it with others (e.g., other trackers, healthcare providers, friends). Then, they triangulate data derived from various sources to ensure that the explanation they come up with can be trusted. Second, once they reveal the information in the data, they determine whether they use this information to validate their perceptions of their behaviors, symptoms, or feelings, negotiate with it to find a balance between what it tells and their perceptions, or disengage from it. While doing so, they ask themselves questions like, "What does my data tell me? Why so? Does this data reflect my behavior and experiences? Is this normal? Do I agree with what the data tell? What am I going to do with this new understanding?"

We note that these modes do not represent a set of steps that self-trackers should follow linearly to make sense of their data. For instance, some self-trackers may not engage in the *self-calibration* mode if they feel competent and prepared for tracking. Alternatively, they may not want to participate in data collection actively (e.g., annotating the data to record personal experiences and feelings). Instead, they may *handle* their data without *augmenting* it. Thus, it is not obligatory for self-trackers to engage in all the modes to be able to make sense of their data. Furthermore, there might be overlaps in some modes. For example, self-trackers can be in *self-calibration* and *realization* mode simultaneously when they attempt to know more about a tracking aspect (i.e., knowledge acquisition in self-calibration mode) to better understand an anomality in data (i.e., reasoning and reflecting in realization mode).

Furthermore, the way a self-tracker experiences sensemaking may differ from person to person and domain to domain. For example, in the case of identifying relevant tracking elements, self-trackers could have different goal types and may track different aspects. While a self-tracker, who is monitoring daily step count can have a behavioral goal (e.g., taking 10,000 steps a day to be more physically active), another one, who is tracking mood changes or symptoms, can have a learning goal (e.g., learning more about one's mental health condition). While the tracking aspect is a countable metric in the former example, the one in the latter is uncountable and more subjective.

Therefore, the sensemaking modes we identified in this paper should be understood as discrete, but not sequential, categories, which consist of activities experienced differently by different self-trackers to extract meaningful insights from their data. Next, we elaborate on each sensemaking mode.

4.2.1. Self-calibration

Self-calibration mode involves two activities that provide self-trackers with a baseline for future sensemaking activities. These are (i) identifying relevant tracking aspects and (ii) knowledge acquisition for sensemaking.

4.2.1.1. Identifying relevant tracking aspects. Tracking requires self-trackers set a new (or revise an existing) behavioral goal (Niess & Woźniak, 2018) and identify the relevant tracking aspects to observe their progress towards this goal (Raj et al., 2019). It is essential for self-trackers to know the meaning of these aspects (Shaer et al., 2016) and be supported by making the connections between these aspects and their goals (Doherty et al., 2020; Sanches et al., 2019). Since sensemaking in self-tracking is highly individual (Figueiredo et al., 2018; Shaer et al., 2016) and situated (Park & Chen, 2015), goal setting and tracking aspect identification go hand in hand, which makes this activity personally meaningful for self-trackers, helping them gather meaningful insights about their life (Niess & Woźniak, 2018). Hence, in this mode, they set qualitative goals (e.g., being able to conceive when tracking fertility) in addition to quantitative ones (e.g., taking 400 micrograms of folic acid per day) and decide the form of the data (qualitative and/or quantitative) to be used in sensemaking.

Tracking aspect identification becomes a critical activity for self-trackers, who have learning goal orientations rather than performance ones, and self-track for managing a health condition, in cases where they monitor symptoms (McKillop et al., 2018; Mishra et al., 2019), pain (Young & Miller, 2019) or a chronic disease (Lomborg et al., 2020). Here, the data type could vary from a health condition (e.g., migraine symptoms (Park & Chen, 2015)) and treatment efficacy (Young & Miller, 2019) to contextual factors that affect this condition (e.g., the temperature or humidity). The variation in data types and the fact that pain and symptom data may not mean the same for everyone (Young & Miller, 2019) make the data sensemaking challenging. Furthermore, the difference between what self-trackers infer from data and what it really depicts creates uncertainty, doubts, and anxieties about their disease management (Lomborg et al., 2020). To overcome these challenges, most self-trackers increasingly become aware of their data needs, the meaning of tracking aspects (Figueiredo & Chen, 2020), and the importance of contextual factors that might influence their behavioral goals (Woźniak et al., 2020). This awareness, which is gained by tracking and reflecting on their data continuously, helps them adjust their goals and relevant tracking aspects (Raj et al., 2019).

4.2.1.2. Knowledge acquisition for sensemaking. Sensemaking in self-tracking is a knowledge-intensive activity. It requires self-trackers to know their body, their conditions, and the meaning of the tracking aspect. If they do not know much about these aspects, they might have a hard time deriving meaningful insights from data, e.g., what happens in one's body during sleep (Liu et al., 2015), or what do calories refer to (Alqahtani et al., 2020). This hardship is amplified when the STT use unfamiliar or too technical language to present data, such as correlation, anomaly, or medical terminology (Marcu & Spiller, 2020; Prioleau et al., 2020), and when self-trackers do not know the relation between different factors, such as the genome sequence and disease risk (Otiono et al., 2019) and stress level and sleep quality (Liang et al., 2016). In parallel, when they are already aware of their condition and how it influences their health (e.g., low blood glucose was probably caused by exercise (Katz et al., 2018a; Kaziunas et al., 2018), deriving meaningful insights from personal data and transferring this meaning into behavior becomes manageable.

Lack of knowledge in one's condition and how tracking aspects work also creates a fear of misinterpreting the data (Doherty et al., 2020; Hollis et al., 2018). This lack of knowledge also results in frustration for self-trackers, who adhere more importance to data over lived experiences (Doherty et al., 2020; Pingo & Narayan, 2019). To overcome this challenge, self-trackers sometimes turn to online communities and seek others' help and support. By interacting with other self-trackers, looking at and reflecting on others' data, and comparing their data with others, they learn how to interpret their data (Liu et al., 2015; Otiono et al., 2019; Rapp, 2018). They become competent in generating meaningful insights for and about themselves as they continue using STT and interpreting their data (Kou et al., 2018), such as understanding how many calories a food contains only by looking at it (Sharon & Zandbergen, 2017).

4.2.2. Data augmentation

In data augmentation mode, self-trackers complement digital and automatically data derived from STT by adding their subjective observations and perceptions. We found that augmentation often happens in the form of *data annotation* activity.

4.2.2.1. Data annotation. The way behavioral data is collected, created, and grown in self-tracking is entangled and interwoven with self-trackers' everyday activities (Pink et al., 2018; Rooksby et al., 2014; Sumartojo et al., 2016). The richness of daily life cannot be holistically reflected in data primarily defined by STT (e.g., heart rate, distance, elevation, movement, etc.). In the same vein, some self-trackers do not like the idea of reducing their life into simple numbers (Alqahtani et al., 2020; Elsden et al., 2016; Figueiredo & Chen, 2020; Niess et al., 2020; Smith & Vonthethoff, 2017). Therefore, they actively contribute to behavioral data collection by annotating automatically generated data. They edit this data and add personal notes or visuals to enrich its meaning. For instance, self-trackers can express how they feel during an activity by annotating a data point with a phrase like "towards the end of the last lap, I felt exhausted."

Data annotation has several benefits for sensemaking. It gives digital data a personality that matches with self-trackers' identity because it allows them to process their data and reflect on it in an out-of-ordinary, richer, and individualistic way (Elsden et al., 2016; Lomborg & Frandsen, 2016). Another benefit is creating a sense of ownership. For some self-trackers, unfamiliarity with the terminology of the data presentations creates a barrier to sensemaking. Hence, they label and comment on data by using their own words, making the data their "own" (Ayobi et al., 2020). Data annotation creates a sense of agency when the self-trackers are given a chance to represent themselves through their own interpretations (Fox et al., 2020). This way, they generate content for richer self-reflections (Heikkilä et al., 2018) about their health condition or for their goals by labeling, tagging, adding images, or commenting on their data (Ayobi et al., 2020; Elsden et al., 2016; Jo et al., 2020; Potapov & Marshall, 2020; Rapp et al., 2019; Rapp & Tirabeni, 2018; Thudt et al., 2018). Furthermore, data annotation opens a new space for extracting alternative meanings from data (Spotswood et al., 2020), as the same data can have different meanings for different self-trackers (Pols et al., 2019). Lastly, it can encourage trackers to reflect on their data not only after but also during the data collection, which in turn, allows them to modify the way they perform an activity (Lupton et al., 2018).

4.2.3. Data handling

Data handling is the mode in which self-trackers play with their data the most to prepare it for analysis and reveal information residing in data. This preparation is done by *data curation* and *identifying relevant information for data exploration*.

4.2.3.1. Data curation. The data collected by STT is not always ready for sensemaking, requiring self-trackers to process it for their own analysis. Since the same data might have different meanings to different individuals (Raj et al., 2017) and is open to different interpretations (Friske et al., 2020), processing data is vital when the tracked behavior or condition is very personal (e.g., Vulvodynia reported in

Young & Miller, 2019). One way to prepare personal data for sensemaking is data curation. In this activity, self-trackers review, select, or prioritize different data types, depending on their information needs (Abtahi et al., 2020; Choe et al., 2014; Rooksby et al., 2014; Shaer et al., 2016). They combine data derived from different sources (e.g., weather data with cycling data) to make possible interpretations of their multidimensional and complex data (Choe et al., 2014; Figueiredo et al., 2017; Prioleau et al., 2020). They engage with data to create subjective narratives (Ayobi et al., 2020; Sharon & Zandbergen, 2017) and find meaningful interpretations about self (Choe et al., 2014; Gulotta et al., 2015).

During data curation, self-trackers also hide or remove data parts when there is ambiguity in meaning (Khot et al., 2014) and when there are data irrelevant to their goal (Snyder et al., 2019). Whilst some prefer to remove the outliers to create more significant meaning (Lomborg et al., 2020), others opt for preserving them to create personal stories and make better reflections about themselves (Lee et al., 2015). Furthermore, some self-trackers hide data when it is not associated with their identity (Elsden et al., 2016; Rapp & Tirabeni, 2018) or their ideal self (Rapp, 2018) or when there is a mismatch between what they feel and what the data presents (Gulotta et al., 2015). In addition, some prefer hiding data due to privacy reasons. Data hiding occurs, for instance, while representing exercise identity on social platforms (Elsden et al., 2016; Rapp & Tirabeni, 2018) or when sharing highly sensitive data such as mental illness (Petelka et al., 2020) with peers or health professionals.

Another activity trackers perform during data curation is repairing their data. Although STT collects very detailed information about self-trackers' daily life, it can present broken data (e.g., missing data for a particular time because a self-tracker forget their STT at home before going on a vacation), or the dataset may lack the details that matter to them (Elsden et al., 2016). Since missing or broken data can hinder their sensemaking processes, some self-trackers attempt to repair their data by trying to remember the data collection instance, the reason for gaps in data and filling these gaps by manually adding data points (Pink et al., 2018).

While data curation contributes to extracting personal meanings from data (Gulotta et al., 2015; Raj et al., 2017; Thudt et al., 2018), it amplifies the risk of oversimplification or misinterpretation of data (Snyder et al., 2019). Hence, successful data curation depends on the data editing abilities of the STT being used (Choe et al., 2014). When the tools do not allow easy data curation, it may result in intensive manual data collection and editing, which poses a burden on self-trackers (Figueiredo et al., 2017; Mishra et al., 2019). One way to facilitate data curation is, thus, to reduce the amount of non-automated data tracking with easy to use data curation tools (Choe et al., 2014; Liang et al., 2016) or to provide the trackers with minimum-viable data (Mishra et al., 2019) that would be necessary and meaningful for the aspects they track (e.g., symptoms over time).

4.2.3.2. Identifying relevant information for data exploration. Another data handling activity that self-trackers perform is exploring the data to find variations and patterns like peaks and valleys. While some studies suggest that looking at historical and long-term data facilitates identifying relevant information and patterns in data (Abtahi et al., 2020; Alqahtani et al., 2020; Bae et al., 2014; Choe et al., 2014; Elsden et al., 2016; Trace & Zhang, 2019), others indicate that even a single day data or a data point can help self-trackers gather meaningful insights (e.g., sudden, and unpredictable migraine attacks when the weather is hot (Park & Chen, 2015). The lack of variation in behavioral data (e.g., taking the same number of steps every day) can block trackers from identifying relevant information for sensemaking (Liang et al., 2016). Data variation encourages them to explore the reasons for patterns and anomalies in data, opening the way for more profound reflections (Alqahtani et al., 2020; Jenkins et al., 2020; Thudt et al., 2018). However, in the absence of data variation, trackers are not engaged in more profound reflection, or they do not attempt to uncover new meanings in data as they are already aware of what it means. To address this challenge, researchers suggest simplifying (Oygür et al., 2020) and personalizing (Shaer et al., 2016; Thudt et al., 2018) data visualizations and connecting the data to personal experiences, actions, and outcomes (Otiono et al., 2019).

Though gaps in data hinder sensemaking (Liu et al., 2015), they can also help uncover relevant information, particularly when these gaps are due to the irregularities of self-trackers' everyday life and not due to technical problems. Trying to identify why a gap exists in the data prevents misinterpretations and helps self-trackers make sense of their missing data (Tang & Kay, 2017), (e.g., this is because I forgot my Fitbit at home). Alternatively, the absence of data can give insights into trackers' life (Rooksby et al., 2016), (e.g., blank periods in data can mean that the tracker gave a break).

Identifying relevant information can also occur in the form of hypothesis testing or self-experimentation (Choe et al., 2014). Self-trackers identify hypotheses meaningful to their life (e.g., I sleep less when I eat late, or my blood sugar level tends to be high than usual when I eat lunch at the cafeteria) and test those hypotheses by looking at the correlations between their data and the daily experiences (Abtahi et al., 2020; Katz et al., 2018b; Mishra et al., 2019). Nonetheless, identifying meaningful correlations between different tracking aspects and daily experiences might be challenging. Data complexity (Otiono et al., 2019; Shaer et al., 2016) (e.g., trying to make sense of genome data) and lack of ability to understand the relationship between different variables (Alqahtani et al., 2020; Oygür et al., 2020) (e.g., trying to make sense of how sleep behavior is influenced by mood) can block self-trackers from identifying relevant information. Despite these challenges, self-experimenting prevents them from solely focusing on objective data (i.e., numbers, graphs, charts, etc.), encourages them to attend to lived experiences (Chung et al., 2019; Rapp & Tirabeni, 2018; Ravichandran et al., 2017; Rooksby et al., 2016), and helps them validate their own perception of their behavior (Liang et al., 2016). This way, they discover personal meanings and values in data (Figueiredo & Chen, 2020).

4.2.4. Realization

In the *realization* mode, self-trackers are engaged in two activities. They first contemplate what the data presents about their progress towards their goal through *reflecting* on *and reasoning* about the causes of variations and gaps in data. After they extract information from the data through reasoning and reflecting, they confront this information. During the confrontation, they choose between affirming it, negotiating with it, or disengaging from it depending on the (mis)match between what they expect and what the data points out.

4.2.4.1. Reasoning and reflecting. As we stated previously, finding a pattern or a variation in the data triggers self-trackers' reflection and encourages them to search for reasons and justifications for the patterns and variations. Thus, reasoning and reflecting activities are entangled with handling activities, and they can occur concurrently or sequentially. For example, self-trackers utilize the contextual information where the data is collected when reflecting on their data. (Kou et al., 2018; Park & Chen, 2015). To illustrate, when managing migraine, self-trackers make associations between their usually unpredictable migraine attacks and contextual factors such as hot weather (Park & Chen, 2015). In doing so, they try to remember the data collection moment (e.g., the weather on a particular day) to add contextual information to existing data and better justify the existence of a pattern or a variation (Lupton et al., 2018; Tang & Kay, 2017; Thudt et al., 2018). This reminiscence, in turn, triggers self-reflection (Alqahtani et al., 2020) and helps them create new meanings from historical data (Elsden et al., 2016; Lomborg & Frandsen, 2016; Sanches et al., 2019). However, remembering data collection moments requires time and effort, which most self-trackers find difficult (Liu et al., 2015). Besides, constant reflection on data is not always desirable for them, as it may lead to tracking-burnout (Raj et al., 2017). Thus, some self-trackers prefer a less effortful solution, for example, deciding to use an insulin pen immediately after noticing that blood sugar level is high instead of exploring why this is the case.

Due to the complexity of data, using self-knowledge for reflection does not easily reveal plausible explanations of patterns and variations (Chung et al., 2019; Graham et al., 2016; Kaziunas et al., 2018; Oygür et al., 2020; Pina et al., 2017) and does not always lead to actionable information (Katz et al., 2018a; Liu et al., 2015). Furthermore, trackers may fear misinterpreting their data due to a lack of prior experience (e.g., pregnancy) and knowledge of the tracking domain (e.g., what is considered normal during pregnancy) (Chung et al., 2016; Doherty et al., 2020). In such situations, self-trackers tend to turn to others' data for identifying the causes of patterns in their data. This activity is not only done for defining what is normal (e.g., changes happening to the body during pregnancy (Doherty et al., 2020) and assessing one's performance compared to others, but also it is about making a better reflection on one's data (i.e., whether someone has a similar behavioral pattern (Bae et al., 2014; Feustel et al., 2018; Graham et al., 2016).

Self-trackers choose to reflect on their -and others' data-together with others who track the same or similar behaviors. This way of reflecting occurs by participating in online communities to understand the symptoms and the underlying causes collectively and to get emotional support (Figueiredo et al., 2018; Fox et al., 2020; Young & Miller, 2019). When they collectively reflect on each other's data to find plausible explanations for recurring patterns, sensemaking becomes a collaborative and social activity (Chung et al., 2019; Figueiredo et al., 2017; al., 2018; Otiono et al., 2019). For instance, in disease management (Kendall et al., 2015; Raj et al., 2017), self-trackers reflect on their data in the presence of a healthcare professional with an expectation of finding answers to their questions about their condition. During this process, they may prefer to have a more passive role by leaving the sensemaking and decision-making task to the healthcare professionals, as they believe the professionals are better positioned to make sense of data. Alternatively, they might have a more active role where they and professionals bring different inputs to the reflection activity. While the self-trackers contribute to this activity with experiential knowledge (e.g., understanding data collection context and bodily sensations), professionals provide technical or medical knowledge (Raj et al., 2017; Vandenberghe & Geerts, 2015). In such a setting, professionals guide the trackers in the self-reflection process by analyzing the patterns and anomalies in data and asking them questions to help them remember the data collection instance.

Collaborative reflection on data has three benefits for self-trackers. First, it reduces the effort required to interpret complex data (e.g., an athlete's performance metrics (Rapp & Tirabeni, 2018) or sharing the load with healthcare providers when reflecting on patient-related data (Doherty et al., 2020). Second, it leads to discovering multiple narratives rather than one true narrative, as the same data can contain different meanings for different people (Doherty et al., 2020; Jo et al., 2020; Kou et al., 2018; Lupton, 2015; Saariketo, 2019). When others reflect on self-trackers' data, they have a chance to change the meaning conveyed by it (Friske et al., 2020; Mishra et al., 2019). Third, during collaborative reflection, self-trackers learn how to make sense of their data, increasing their competence in interpreting health-related data (Young & Miller, 2019). That is to say, collaborative reflection creates a link between reasoning and reflecting (*realization mode*) and knowledge acquisition (*self-calibration mode*).

Despite its benefits, collaborative reflection might also raise some issues. First, since it requires others to access personal data, trackers may feel reluctant to share their data because of privacy concerns (Doherty et al., 2020; Jo et al., 2020; Potapov & Marshall, 2020). Thus, it is essential to give them a sense of control over their data (Doherty et al., 2020; Rapp & Tirabeni, 2018). They should be able to filter, conceal and flexibly explore their data (Bussone et al., 2019; Rapp & Tirabeni, 2018) while they decide on whether the data is worth sharing with others (Pingo & Narayan, 2019) and when is the right time to do so (Katz et al., 2018a). Second, talking to an expert about one's health through reflecting on personal data might be stressful. Thus, self-trackers may prefer sharing their data with friends and other trackers to reduce the stress of tracking a health condition (Potapov & Marshall, 2020). Third, there might be mismatches between self-trackers' and healthcare providers' expectations of the sensemaking activity since they use different data representations, have a different understanding of problems, and prioritize different types of problems that need attention (Chung et al., 2016; Friske et al., 2020; Raj et al., 2017).

4.2.4.2. Confrontation. Once self-trackers extract information from their data (e.g., reasons of a data variation), they decide what to do with this information. Depending on the tracking context and self-trackers' perceptions, they either confirm this information, try to negotiate it, or disengage from it (Adams, 2019; Kim et al., 2019; Lupton, 2015). While seeking answers, self-trackers also become aware of their behavior and develop a perception of their performance. When there is a match between this perception and what the data tells, they tend to confirm the information extracted from the data and start thinking about "what this new understanding yields and what needs to be done next."

On the other hand, when what the data tells and what the trackers expect from it do not match, self-trackers may experience a sensitive and difficult-to-manage situation. While the mismatch between data and self-trackers' expectations can be an opportunity for them to be actively involved in making sense of what the data entails (Thudt et al., 2018), it sometimes results in frustration (Figueiredo et al., 2017). For instance, although remembering the data collection instance can add context to data, there can be mismatches between what is remembered and what data tells due to the flaws of human memory (Gulotta et al., 2015). The mismatch also occurs (i) when there is a conflict between trackers' own judgment of themselves and what the data tells even though the data is accurate (Howell et al., 2018; Lupton et al., 2018); (ii) when the STT present counterintuitive insights (Raj et al., 2019), and (iii) when these tools make unrealistic predictions about their future performance (Figueiredo et al., 2017; Saariketo, 2019; Thudt et al., 2018).

When self-trackers' expectations do not match with the presented data, tension between them and the STT emerges (Lomborg et al., 2018; Lupton et al., 2018; Smith & Vonthethoff, 2017). In such situations, they triangulate data by combining multiple data sources (e.g., nutrition data, stress data, emotion data) to ensure their interpretation is correct (Choe et al., 2014; Heikkilä et al., 2018; Sanches et al., 2019). They look for potential justifications for what is presented and seek an answer to the question of "is this normal?" (Pols et al., 2019). They start questioning the reliability and truthiness of data (Elsden et al., 2016; Niess & Woźniak, 2018), which also influences their continuous interest in using STT (Figueiredo et al., 2017). In other words, they negotiate with the data to create a complete and coherent story and their own sense of "truth" (Elsden et al., 2016).

In some cases, these mismatches can lead self-trackers to disengage from the data Disengagement can occur if the tracked behavior is associated with negative experiences (such as enigmatic disease tracking as reported by McKillop et al. (2018) or activity tracking of heart disease patients (Lomborg et al., 2020)). In those cases, data tracking activity reminds the self-tracker of their condition, making them feel sick, and discouraged further use of STT. Furthermore, some self-trackers can attain too much importance and attach feelings to data (Lomborg et al., 2020). Some can even desperately hope that the data will make them get better (Klock et al., 2020). For those, self-tracking can be emotionally challenging, overwhelming (Murnane et al., 2018), and confusing (Kendall et al., 2015; Murnane et al., 2018), particularly when they endeavor to achieve a long-term and uncertain goal (Karlsson, 2019; McKillop et al., 2018). For instance, in the case of fertility tracking, failing to achieve the goal results in emotional stress (Figueiredo et al., 2018), leading to disengagement from data.

There are other instances when self-trackers disengage from data. For example, when STT reveal inadequacies about their behavior (Hand & Gorea, 2018); when STT does not show the intuitive correlations in behavioral data (Liang et al., 2016); or when they represent the lived experience and make judgments about this experience (Murnane et al., 2018), without providing a direct measurement of the outcome or symptom tracking reported in (McKillop et al., 2018). In such situations, self-trackers feel confused, frustrated, and worried (Kim et al., 2019). Because they do not understand what makes the STT predictions reliable (Lomborg et al., 2018), and they doubt the accuracy of these predictions (Liang et al., 2016). Then, instead of negotiating with the data, they simply escape from valuable behavioral data (Rapp & Tirabeni, 2018) and tracking activity (Lomborg et al., 2020).

4.3. Design implications

So far, we have presented four modes of data sensemaking and seven activities self-trackers perform in these modes and elaborated on the challenges they encounter. Understanding these modes, activities, and challenges can help designers contemplate data sensemaking practices in self-tracking. To provide additional guidance for designers and help them better design STT supporting sensemaking activities, we examined the design implications suggested by the studies in our corpus. We identified the following design implications:

1. provide a customized tracking experience for a better-tailored sensemaking experience
2. guide trackers throughout the sensemaking modes for a more accurate sensemaking experience

Table 4. Implications for customized tracking experience.

Implications	Benefit	References
Let the tracker decide the parameters to track and define new ones	Discover meaningful connections between goals, personal values, and data	(Doherty et al., 2020; Rapp et al., 2019; Woźniak et al., 2020)
Allow annotating data	Discover multiple narratives and reveal multiple meanings from the data Ensuring trust in data	(Ayobi et al., 2020; Elsden et al., 2016; al., 2016; Heikkilä et al., 2018; Jo et al., 2020; Marcu & Spiller, 2020; Raj et al., 2019; Snyder et al., 2015; Spotswood et al., 2020; Young & Miller, 2019)
Enable manual data collection	Add context to tracked data	(Chung et al., 2016; Elsden et al., 2016)
Provide nuanced visualizations and avoid normalization	Prevent negative consequences of misinterpretations	(Bussone et al., 2019; Katz et al., 2018a; Mishra et al., 2019; Prioleau et al., 2020; Rapp, 2018)
Support mindful reflection	Relate objective data to lived experiences	(Ayobi et al., 2020; Hand & Gorea, 2018; Kou et al., 2018; Niess & Woźniak, 2018; Pols et al., 2019; Rapp & Tirassa, 2017; Sharon & Zandbergen, 2017)

3. support community building around data sensemaking
4. support continuous self-experimentation and learning

4.3.1. Customized tracking experience

Customization in tracking experience gives self-trackers control over their data by allowing them to select what the dataset contains and how the data is collected, represented, and interpreted (Potapov & Marshall, 2020) and decide the tracking parameters that are meaningful for their life (Ayobi et al., 2020; Mishra et al., 2019; Rapp & Tirassa, 2017; Saariketo, 2019; Snyder et al., 2015; Tang & Kay, 2017; Vyas et al., 2020). The ability to decide what to track helps them build connections between their goals, personal values, and data (K. Doherty et al., 2020; Rapp et al., 2019; Woźniak et al., 2020). For instance, in self-tracking for disease management, STT can help trackers build an individualized management plan for tracking the disease symptoms and their underlying causes (Young & Miller, 2019). Furthermore, in regard to customization, self-trackers would like to have control over the way the data is collected. They may want to incorporate contextual factors into their data sensemaking practice because factors like life events, injuries, or health issues can affect their goal achievement progress (Lupton et al., 2018; Vandenberghe & Geerts, 2015; Woźniak et al., 2020) and tracked data may lose its meaning when it is detached from the context (Rooksby et al., 2014). Designers can ensure a customized sensemaking experience for self-trackers by using various strategies (Table 4).

One outstanding strategy is allowing the self-trackers to collect data manually (Chung et al., 2016; Sumartojo et al., 2016) and annotate automatically-collected data with tags, labels, or sketches (Rapp et al., 2019). Annotation helps them complement the numerical data with their observations and subjective statements and make the data personally meaningful (Ayobi et al., 2020; Elsden et al., 2016; al., 2016; Feustel et al., 2018; Heikkilä et al., 2018; Jo et al., 2020; Marcu & Spiller, 2020; Snyder et al., 2015; Spotswood et al., 2020; Young & Miller, 2019). Furthermore, it helps record subjective experiences (e.g., mood during physical activity), enables the discovery of narratives and multiple meanings in the data (Friske et al., 2020; Rapp & Tirassa, 2017), and provides them with a chance to "correct" the tracked data to ensure trust in data (Elsden et al., 2016; Raj et al., 2019).

Despite the benefits, data annotation and manual data collection require self-trackers' effort and time and should be done without burdening the tracker (Bussone et al., 2019; Choe et al., 2014; McKillop et al., 2018). One way to achieve this is to automatically combine behavioral data with available contextual data that the self-tracker finds meaningful. For example, in physical activity tracking, STT can complement heart rate data with the time of the day, temperature, and duration of physical exertion (whether the tracker is jogging or running to catch a bus). This way, self-trackers would be provided with more tailored support in data interpretation, and STT can save them from putting excessive cognitive efforts into data sensemaking (Alqahtani et al., 2020; Gulotta et al., 2015; Heikkilä et al., 2018; Kou et al., 2018; Mishra et al., 2019; Potapov & Marshall, 2020; Sanches et al., 2019)

Customization of tracking experience is mostly required when self-trackers try to identify relevant information in data (*data* handling) and when they are reflecting on this information (realization). To support these activities, STT should use more nuanced visual representations tailored to the characteristics of different tracker populations (D. Epstein et al., 2020; Lomborg & Frandsen, 2016; Prioleau et al., 2020; Snyder et al., 2019), and refrain from solely visualizing commonalities or making normative visuals, such as the terms like "average, above average, normal" (Epstein et al., 2014; Liu et al., 2015; Pols et al., 2019). This implication is especially relevant for self-trackers from vulnerable user groups, as normalization might lead to misinterpretations (Ayobi et al., 2020; Snyder et al., 2019), and negative consequences (e.g., seeking for unrealistic "best self" (Figueiredo & Chen, 2020)).

Alternatively, STT should allow self-trackers to decide on how tracking aspects are presented (e.g., numerical, textual, pictorial, normative) (Ayobi et al., 2020; Epstein et al., 2014; Oygür et al., 2020; Rapp & Tirassa, 2017; Saariketo, 2019; Snyder et al., 2015; Tang & Kay, 2017), filter the ones relevant for their goals, explore meaningful relationships between them easily (Bussone et al., 2019; Katz et al., 2018a; Mishra et al., 2019; Prioleau et al., 2020; Rapp, 2018) and create their own data representations as they sometimes do not understand representations used by healthcare providers (Figueiredo & Chen, 2020; Raj et al., 2017; Thudt et al., 2018). Finally, STT should support mindful reflection while

Table 5. Implications for guided sensemaking.

Implication	Benefit	References
Reflective prompts and questions	Identify an appropriate or effective course of action Support active decision-making	(Choe et al., 2014; Chung et al., 2019; Rapp & Tirabeni, 2018; Young & Miller, 2019)
Providing predictions about goal achievement	Anticipate how current behavior might affect trackers' future state	(Abtahi et al., 2020; Alqahtani et al., 2020; Gouveia et al., 2015; Rapp & Tirabeni, 2018; Rapp & Tirassa, 2017)
Explaining the meaning of numbers and tracking terminology	Resolve uncertainties and ambiguity in data	(Katz et al., 2018b; Liang et al., 2016; Lomborg et al., 2020; Shaer et al., 2016)
Showing the logic behind how a tracking aspect is calculated	Bridge the gap between STT's sensing capabilities and their expectations	(Kaziunas et al., 2018; Niess & Woźniak, 2018; Ravichandran et al., 2017)
Identify correlations between different data types, patterns, and anomalies, as well as explain the causes of these	Decrease users' cognitive effort required for sensemaking	(Alqahtani et al., 2020; Gouveia et al., 2015; Liang et al., 2016; Raj et al., 2017; Rapp & Tirabeni, 2018; Ravichandran et al., 2017; Young & Miller, 2019)

self-trackers investigate digital data to extract meaning from it. It should leave room to interpret the data in the self-trackers' own way so that they can relate objective data to their lived experiences such as events, feelings, other behaviors, etc. (Ayobi et al., 2020; Hand & Gorea, 2018; Kou et al., 2018; Niess & Woźniak, 2018; Pols et al., 2019; Rapp & Tirassa, 2017; Sharon & Zandbergen, 2017).

4.3.2. Guided sensemaking

Self-trackers have varying characteristics, goals, knowledge, and skills (e.g., McKillop et al., 2018; Rapp & Tirabeni, 2018; Woźniak et al., 2020). While some monitor their behavior to improve their performance and have extensive knowledge about the tracking domain (e.g., elite athletes), others track their behavior out of curiosity without the knowledge of how tracking parameters influence each other. Furthermore, some self-trackers may not have sufficient data literacy for understanding what the data tells (e.g., correlations, averages, variations, outliers, etc.). Thus, STT should not treat trackers as if they have the same level of ability and knowledge to make sense of digital data (Oygür et al., 2020). In order to enhance trackers' ability to comprehend data, data representations should be simplified (Pina et al., 2017; Prioleau et al., 2020), and visual representations should be preferred over numeric presentations (Oygür et al., 2020). In doing so, heavily ambiguous feedback should be avoided (Doherty et al., 2020; Kim et al., 2019), and self-trackers should be encouraged to make reflections in small time intervals (e.g., daily or weekly (Liu et al., 2015)). Besides simplification and visual representation of data, self-trackers expect STT to provide guidance on how to extract meaningful insights from data. There are various ways of providing such guidance (Table 5).

The first is using reflective prompts and questions when trackers configure tracking goals and when they review data on their own (Choe et al., 2014; Chung et al., 2019; Rapp & Tirabeni, 2018). For example, when self-trackers check their monthly physical activity data, STT can show a question like, "Have you noticed that you are exceeding your physical activity goal for a month? What might be the reason?" This type of guided reflection will help them identify an appropriate or effective course of action (Young & Miller, 2019) and support active decision-making aligned with their personal goals (Kendall et al., 2015).

The second way of providing guidance is by providing predictions about trackers' goal achievement trajectory so that they can anticipate how their behavior might affect their future state (Abtahi et al., 2020; Alqahtani et al., 2020; Gouveia et al., 2015; Rapp & Tirabeni, 2018; Rapp & Tirassa, 2017). For instance, an STT can notify the self-tracker by saying, "if you maintain your current performance, you will achieve your physical activity goal for this month."

The third way is explaining the meaning of numbers and tracking terminology, particularly in the case of reflecting on patient data (Katz et al., 2018b; Liang et al., 2016; Lomborg et al., 2020; Shaer et al., 2016). For instance, in diabetes management, the STT can explain the differences between average, low, and high blood sugar levels by comparing them with the participants' behavior (fasting, before meal, 1–2 hours after eating, and bedtime). These explanations could increase trackers' awareness of their condition, thus could help them resolve any uncertainties and ambiguity in the data (Doherty et al., 2020; Kou et al., 2018).

The fourth way is showing the logic of calculating tracking aspects transparently (Kaziunas et al., 2018; Ravichandran et al., 2017) and how progress towards a given goal is measured (Niess & Woźniak, 2018). For example, in the case of diabetes management, when trackers select a data point where their blood sugar level is low, a notification can explain how the blood sugar level is calculated and inform the tracker about factors that influence it, like physical activity or stress. This would help self-trackers bridge the gap between STT's sensing capabilities and their own expectations (Ravichandran et al., 2017). This could enable them better assess the accuracy of data and prevent them from misinterpretations (Hollis et al., 2018).

The fifth way is helping trackers identify correlations between different data types, patterns, and anomalies in data through increased autonomy of STT (Alqahtani et al., 2020; Gouveia et al., 2015; Liang et al., 2016; Rapp & Tirabeni, 2018; Young & Miller, 2019). For example, machine learning algorithms can be used to illustrate how data is influenced by self-trackers' everyday behaviors or contextual factors (Raj et al., 2017). This way, STT could also provide them with early explanations for the causes of the patterns and variations (Fox et al., 2020; Marcu & Spiller, 2020; Ravichandran et al., 2017). Such guidance on how to find

Table 6. Implications for collaborative sensemaking.

Implication	Benefit	References
Allow trackers to connect with others Allow them to share, view, annotate and comment on data Reward each other	Learn from each other Participate in shared reflection	(Alqahtani et al., 2020; Bhat & Kumar, 2020; Kaziunas et al., 2018; Rapp, 2018; Rapp & Tirabeni, 2018; Rapp & Tirassa, 2017; Spotswood et al., 2020; Young & Miller, 2019)
Enable trackers to reflect on their data together with care providers	Better decision making (in disease management)	(Alqahtani et al., 2020; Rapp & Tirabeni, 2018)
Utilize abstract representations, give trackers control over their data (sharing, recoding) and have default sharing rules	Preserve tracker privacy	(Doherty et al., 2020; Jo et al., 2020; Potapov & Marshall, 2020; Rapp & Tirabeni, 2018)

Table 7. Implications for learning sensemaking through self-experimentation.

Implication	Benefit	References
Enable trackers to formulate and test a hypothesis about themselves	Increase knowledge about the self, condition, and data	(Katz et al., 2018b; Rapp & Tirabeni, 2018; Ravichandran et al., 2017)
Shift the attention from number to experience and narratives	Reflect on personal experiences, choices, and goals Facilitate decision making (in setting a new course of action)	(Chung et al., 2019; Doherty et al., 2020; Katz et al., 2018b; Rapp & Tirabeni, 2018)

and explain the causes of patterns and variations is likely to decrease the cognitive effort required for sensemaking (Prioleau et al., 2020).

4.3.3. Collaborative sensemaking

Despite being an individual and subjective activity, sensemaking in self-tracking has a social component (Lupton, 2014). For instance, self-trackers participate in online communities to seek support from others to make sense of their data. Thus, STT should support both self-trackers' individual and collaborative sensemaking practices (Table 6).

One way to support collaborative sensemaking practices is to create online groups or communities where common tracking goals are shared (Rapp, 2018) (e.g., managing diabetes, tracking pregnancy). In such communities, self-trackers can learn from each other and participate in shared reflection, and thus develop a shared knowledge about the self-tracking activity (Alqahtani et al., 2020; Rapp & Tirabeni, 2018). Such communities can also be established among health care providers, caregivers, and patients for diseases management purposes. Self-trackers' (in that case, patients') engagement in collaborative reflection with their healthcare providers may lead to a better decision about disease management and increase STT acceptance in the medical community (Alqahtani et al., 2020; Rapp & Tirabeni, 2018).

Such online communities bring along individual reflection on personal data into a social context, and therefore, the interactions among stakeholders of online communities should be designed sensitively. First, the online community should provide the conditions that facilitate collaborative reflection. These may include allowing trackers to (i) connect with people who are knowledgeable in making sense of similar personal data (Kaziunas et al., 2018; Rapp & Tirassa, 2017) (ii) share data with others, as well as view, annotate and comment on somebody else's data ((Bhat & Kumar, 2020; Rapp & Tirassa, 2017; Young & Miller, 2019), and (iii) reward each other for their achievements (Spotswood et al., 2020). Second, since shared data is personal and private, self-trackers' privacy should be preserved. This could be done by (i) utilizing abstract representations and allowing trackers to recode these representations on their own to increase anonymity (Potapov & Marshall, 2020), and (ii) setting default rules about what kinds of data are to be shared (Rapp & Tirabeni, 2018) or giving users control over what to share (Doherty et al., 2020; Jo et al., 2020).

4.3.4. Learning sensemaking through self-experimentation

Self-trackers increase their competence in making sense of their data in time as they continue tracking and reflecting. Thus, STT should be designed to support their learning needs. These needs include learning about self, learning about the condition, learning about data, and learning about relations between different tracking aspects (Rapp & Tirabeni, 2018) (Table 7). This emphasis on learning shifts the purpose of self-tracking activity from "tracking" to "knowing" (S. E. Fox et al., 2020). Learning can be supported through allowing self-trackers to learn from their tracking experiences gained through exploring and experimenting with different data types, goals, and behaviors (Kou et al., 2018; Raj et al., 2019). In that respect, STT should enable self-trackers to formulate and test hypotheses about themselves (Katz et al., 2018b; Rapp & Tirabeni, 2018; Ravichandran et al., 2017). However, hypothesis testing in self-tracking does not need to be systematic, rigorous, and scientifically accurate. In contrast, in self-experimentation, STT should steer self-trackers' attention from numbers to experiences (Rapp & Tirabeni, 2018) and narratives (Doherty et al., 2020). This would help them reflect on their experiences, choices, and goals (Chung et al., 2019) and facilitate decision-making, such as changing behavior after reflecting on data (Katz et al., 2018b).

5. Discussion

This review aimed to address three questions: (1) how do self-trackers make sense of their self-tracking data; (2) what are the challenges they encounter during this sensemaking process, and (3) what would be the implications for designing STT to overcome these challenges and support trackers' sensemaking practices? To answer these questions, we carried out a systematic literature review in which we thematically analyzed the findings of 91 peer-reviewed articles. Our analysis yielded four modes of data sensemaking and four design implications, which could guide the design of a new generation of STT tools in supporting data sensemaking. In this section, we first discuss the significance of these contributions towards designing for better data sensemaking in STT. We then finish our paper by providing a research agenda for future HCI research on data sensemaking.

5.1. Towards designing for better data sensemaking practices in STT

Our first contribution to the HCI field is articulating the four distinct modes that self-trackers go through in data sensemaking (see section 4.2). Accordingly, in *self-calibration* mode, self-trackers calibrate themselves with their tracking goal and determine the essential tracking aspects for measuring goal achievement. In *data augmentation* mode, they collect data and augment it by annotating or combining it with expressive input. Once self-trackers feel that they have sufficient data for sensemaking, they follow a series of activities to *handle* their data. They play and engage with their tracked data to prepare it for their own analysis and understanding. These modes can also be regarded as information gathering and knowledge generation about the self (Ackoff, 1989; Kuhlthau, 1993). In *realization* mode, they extract the information from their data by reasoning, reflecting on, negotiating with, and confronting it. This mode is similar to the understanding (i.e., answers to why questions) of the wisdom hierarchy (Rowley, 2007). We found that, during this mode, self-trackers might disengage from their data and tracking activity if their data conflicts with their own understanding of self.

There are several ways that these modes can assist in designing tools for better data sensemaking. First, we think that they offer a holistic perspective that could help design researchers analyze user insights to identify the challenges of self-trackers in data sensemaking. For instance, researchers can use our findings and determine the mode (e.g., self-calibration) and activity (e.g., knowledge acquisition for sensemaking) a particular user group struggles the most in making sense of their data (e.g., people who would like to track their nutrition for managing diabetes).

Second, the modes could be a valuable starting point when it comes to designing for a completely new tracking need (e.g., communicating heart problems to children). While the capabilities of sensor technology enable quantifying medical data (e.g., heart rate), developing user-centered data interactions for the emerging needs might be difficult for designers (e.g., what is the best practice to communicate fluctuation in heart rate with children). In that case, the designers can use the modes of sensemaking to follow an activity-oriented design process rather than focusing solely on the tool itself. They can utilize the activities of data sensemaking to create potential usage scenarios (e.g., working closely on how children make relations between their physical activity and heart data in relation to realization mode and reasoning and reflecting activity) and reflect on the ways to creatively communicate data at every mode and activity of data sensemaking.

Third, the modes could be used as a resource for re-imagining data sensemaking. Consider the diabetes patients (a) who are recently diagnosed and (b) who were diagnosed 20 years ago as two self-tracker examples. It is not difficult to imagine how an STT could serve as a tracking tool in general. However, the data sensemaking needs of these example users (a–b) will differ. While the former will probably need to navigate, *self-calibrate,* and learn more about the aspects to track as they may lack adequate knowledge of their condition, the latter would be more interested in the *reasoning about and reflecting on* data *(realization mode)*. Hence, while the output data (e.g., blood glucose level) will be similar, the way the STT will facilitate data sensemaking will be different for these self-trackers. Designers should consider each groups' data sensemaking needs along with the modes and re-imagine the STT usage accordingly.

Our second contribution is four design implications we distilled from our corpus by examining the design implications discussed in each individual paper. These behavioral-level implications could provide initial guidance to designers when they are designing self-tracking tools to support sensemaking practices. In other words, these implications represent general considerations that need to be attended during the problem framing and idea generation stages, rather than instantiations or prescriptions describing a specific design solution (Sas et al., 2014). Overall, our implications suggest that designers should aim for delivering a customized tracking experience, guide self-trackers through sensemaking modes, provide essential conditions for collaborative reflection, and support learning through self-experimentation. On the other hand, the specific design suggestions we identified under these implications could provide more concrete and prescriptive guidance for designers. The implications could become a way of converging and diverging the knowledge presented in the modes of data sensemaking. For instance, designers may translate the design implications (e.g., enable manual data collection) into design goals by using the benefits of the implications (e.g., add context to tracked data) as the starting point. Alternatively, the benefits of implications can directly be used as design goals of STT, and the implications could be used as the source of ideation. Here, designers should be aware of the fact that all the modes of data sensemaking are interconnected, not sequential, and hence the creativity of the designer plays a role in diverging and converging the knowledge into design practice.

5.2. Research agenda for future HCI research on data sensemaking

We see that our findings evidence nine research directions in how we perceive, design, and study STT from a data sensemaking standpoint. These directions allocate new responsibilities for designers and researchers of future self-tracking tools. We believe that awareness of these directions would pave the way for new STT that support significant data sensemaking practices.

5.2.1. Exploring pragmatic and hedonic roles of STT in data sensemaking

In our review, we found that self-tracking is an emotionally loaded activity. Data can create anxiety and mental pressure when it provides constant negative feedback (e.g., informing the tracker about the continuous high-stress level). Thus, even though the current STT seem to focus more on the pragmatic needs of self-trackers (e.g., collecting data), our findings show that they should go beyond addressing the self-trackers' pragmatic needs and consider their hedonic needs as well (e.g., hoping to get better with data). For instance, designing a compassionate STT that accommodates self-trackers to flourish (Åström et al., 2021) is suggested as a way to avoid this emotional discomfort (Hollis et al., 2018). We argue that design practice should better cope with these challenges by accepting that data sensemaking is more than seeing numbers or beautiful visual graphics on app interfaces. Instead, it is more about helping trackers create a better understanding of themselves by breaking down negative experiences into positive ones and focusing on the subjective aspects of tracking. Therefore, future research should explore how design can balance STT's pragmatic (i.e., fulfilling the primary function of tracking) and hedonic roles (i.e., supporting users' learning and coping behavior) in data sensemaking.

5.2.2. Acknowledging collaborative sensemaking practices

In our corpus, there were many studies that explored how different groups, such as parent-children, athlete-coach, and patient-healthcare providers, reflect on personal data. These studies indicated a transition from individual self-tracking practices to more collective tracking practices. This transition brings along a replacement of the ego-centric view of personal informatics (i.e., overemphasis on "self") with collective data sharing, monitoring, and reflection practices (Karyda et al., 2020), which in turn, brings new challenges for designers and researchers. For example, sharing data and reflecting on others' personal data can raise data privacy and data security issues. Thus, the research on STT that support collective sensemaking practices should investigate ways to build trust and data privacy to serve the goals of multiple user groups.

5.2.3. Towards meta-informatics

Our analysis revealed that while early users of STT tracked majorly single types of data (e.g., the number of steps), current users can track diverse types of data (e.g., blood sugar, heart rate variability). When there is an increase in the diversity of the data that self-trackers can and wish to track, a particular need emerges for special tools that can synthesize data derived from different data sources. These tools do not necessarily collect data but fetch it from multiple STT and analyze and present it to self-trackers in a meaningful manner. In our review, we found that self-trackers commonly do this type of data curation manually. Based on this evidence, we envision that future tools could facilitate self-trackers' data curation activities through increased automation, more or less serving as *meta-informatics tools*. We think that the field is open to discovering the meta-informatics needs of self-trackers, examining ways of combining data, integrating multiple platforms into meta-informatics, and finding a balance between tools' and self-trackers' autonomy.

5.2.4. Balancing the quantified self with the qualified self

The notion that "not possible to improve if not quantified" has been the foundation of STT for a while. However, this view has been criticized by Toner (2018) as it reduces attention to the body's function but makes it more data-dominant and goal-oriented. One's goals and needs in tracking can change from being quantified to more qualitative and subjective aspects of self-tracking (Niess & Woźniak, 2018). These aspects could also yield higher-level reflection about self (Cho et al., 2022). While most STT offers actionable data, we see that they should allow self-trackers to make their own interpretations (Rapp et al., 2019). For instance, showing numbers should only help them find their way, rather than dictating the responses and action points (Jenkins et al., 2020). Therefore, we believe that future studies should investigate the ways to support more qualified-self practices through data sensemaking by supporting knowledge generation about self through words, expressions, and even voice memos. However, this suggestion does not mean that quantitative data is not important for data sensemaking. Instead, future research should explore how STT could find a balance between quantitative and qualitative aspects of self-tracking to support more meaningful, subjective, and yet trustworthy sensemaking experiences.

5.2.5. Exploring different tracker roles in sensemaking

Looking at the activities self-trackers go through in sensemaking modes, we observed three roles that they can undertake. First, they can behave like *data scientists* who do not perceive more data as a burden but appreciate it to generate self-knowledge. Second, a self-tracker can be an *experiential learner* whose primary goal is to learn from data by trial and error, self-experimentation, or by interacting with others. Third, a self-tracker can be a *negotiator* who deals with the data when it does not match the ideal self. It should be noted that a self-tracker can have these roles simultaneously or in different modes of sensemaking. Yet, since the roles moderate their interaction with and expectation from data, we believe exploring them will contribute to designing STT that is tailored to the roles of self-trackers.

5.2.6. Novel ways of data sensemaking

Currently, numbers and graphs are the common ways of presenting self-trackers' data. However, we should not assume that all self-trackers are "data scientists" who can see, understand and react to their data. This assumption can result in premature interpretations of behavior, as not everyone can see (e.g., people with visual impairment), understand (e.g., children who have limited data knowledge), and react to (e.g., people who have limited data literacy) those numbers and graphs. Hence, we propose that data can be presented in different ways than only numbers, visuals, and graphs to help self-trackers better interpret and understand their health data. For example, there are a few studies that investigate the roles of data objects in reflective self-tracking (e.g., Karyda et al., 2020) and the use of 3 D printed artifacts in understanding physical activity data (Khot et al., 2014; al., 2020). While these examples provide promising evidence, we think that the field is open to discovering other creative ways of data presentation that will enable and foster more inclusive data sensemaking.

5.2.7. Improving the inclusivity of data sensemaking studies

Notably, almost all the studies included in our corpus were carried out with Western populations (mainly the USA, Europe, and Australia). This might negatively skew the perception that STT is used only by Western societies. A few recent studies have recognized the importance of investigating self-tracking beyond WEIRD (Western, Educated, Industrialized, Rich, Democratic) user groups (e.g., Niess et al., 2021; Wilkowska et al., 2021). Still, to improve the inclusivity of future STT, we need more studies to specifically understand how data sensemaking practices differ across cultures and populations. Hence, we think that future research is open to cross-cultural and across cultural studies beyond Western societies.

5.2.8. Conducting more longitudinal studies

Despite the fact that sensemaking is a continuous process where self-trackers' goals, expectations, and competence in sensemaking change through time, we found that *a* limited number of studies in our corpus collected longitudinal data from self-trackers ($n = 15$ out of 91). Therefore, future research should examine sensemaking through more longitudinal studies to help the field better address the evolving sensemaking needs of self-trackers and support long-term sensemaking practices.

5.2.9. Towards a theory of data sensemaking in self-tracking

HCI literature is already rich in models and frameworks that explain how self-trackers set goals (Niess & Woźniak, 2018), how they interact, engage with, and abandon STT (e.g., Epstein et al., 2016; Li et al., 2010). However, none of these models shed light on the self-trackers' data sensemaking practices. Current attempts to investigate the sensemaking of clinical health data (Raj et al., 2017) and explore the experience of meaning in HCI (Mekler & Hornbaek, 2019) are promising. Still, the HCI literature lacks a theory that guides understanding data sensemaking practices in a more analytical way. This paper took an early step to fill this gap by presenting the four modes of data sensemaking in STT. We invite other researchers to build upon our work to develop a theory of data sensemaking in STT. We believe that this way, we can richly and more effectively inform the design of personal informatics and self-tracking tools.

6. Conclusions

In this paper, we reported the results of a systematic review of 91 articles published in the past 20 years and touched upon self-trackers' sensemaking process, either as a central or as a related topic. Based on our findings, we identified and described self-trackers' experiences, struggles, and challenges in four distinct modes of data sensemaking. We also identified four design implications to facilitate the design of new generation STT, which are aimed at supporting self-trackers' data sensemaking practices. Finally, we curated a research agenda that pose new responsibilities for advancing data sensemaking studies in personal informatics literature. We believe that the findings we present in this paper help designers and researchers understand self-trackers' sensemaking practices more analytically and coherently.

Note

1. Note that some articles utilized more than one method.

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