Reflecting Upon the Unintended Consequences of Personal Informatics Systems: A Systematic Review of Empirical Studies

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Abstract

The HCI community has been actively developing and studying the use of Personal Informatics (PI) systems. While celebrating the headways, researchers have uncovered many unintended consequences of using PI systems, such as data-induced stress and obsessive tracking, but there has been a lack of systematic analysis of these consequences and their underlying causes. In this work, we reviewed 172 PI research articles, highlighting that tracking and interacting with personal data can adversely affect individuals' cognitive load, emotional well-being, social acts, and behaviors, while bringing practical challenges. By synthesizing the pathways through which these consequences occur, we recognized issues in the data-centric design ideology, variations across tracking needs and literacy, the evolving social dynamics, and individuals' intention-behavior gap. Reflecting on the findings, we discuss how to best leverage personal data in our lives and propose a practice-oriented research agenda to mitigate these unintended consequences.

CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**.

Keywords

Personal informatics, self-tracking, personal data, systematic review

ACM Reference Format:
Yuhan Luo, Xinning Gui, Xianghua (Sharon) Ding, Xi Zheng, Rie Helene (Lindy) Hernandez, Zhuoyang Li, and Qiurong Song. 2025. Reflecting Upon the Unintended Consequences of Personal Informatics Systems: A Systematic Review of Empirical Studies. In *Designing Interactive Systems Conference (DIS '25), July 5–9, 2025, Funchal, Portugal.* ACM, New York, NY, USA, 20 pages. https://doi.org/10.1145/3715336.3735746

1 Introduction

The past few decades have witnessed growing research on how people collect, engage with, and utilize their personal data. In part, the advancement of mobile and wearable sensing technologies has made it possible for individuals to access and interact with diverse information about themselves. More importantly, there is increasing recognition of the potential benefits that these data could bring to everyday health, well-being, and life quality [154, 155]. Since Li et al. coined the term "personal informatics" (PI) in 2010, over 500 PI-related research articles have appeared in prominent HCI and Health Informatics venues within a decade [61, 95, 170].

Looking back, we have seen PI evolve from assisting health assessment [11, 80, 98, 133] and behavior change [35, 122, 148] to facilitating collaboration [33, 128, 239] and creative expression [6, 216]. While celebrating the progress made, findings from prior studies have revealed that how people interact with PI systems does not always align with what researchers initially expect. Unintended consequences such as data misinterpretation [26, 45], emotional stress and peer pressure [48, 162], and unhealthy behaviors [54, 180] have been reported here and there. Yet, the nature of these consequences, their underlying causes, and implications for the field have not been fully articulated. Such an understanding necessitates a comprehensive review of existing empirical findings along with reflections on the setbacks in designing PI systems.

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[*] The author contributed to this work while at City University of Hong Kong.

DIS '25, July 5–9, 2025, Funchal, Portugal

ACM ISBN 979-8-4007-1485-6/2025/07
https://doi.org/10.1145/3715336.3735746

In this light, we systematically reviewed and analyzed 172 PI-related research articles involving the understanding of human experience with PI from 2010 to early 2024 in prominent HCI venues. Following the PRISMA guideline [218], we meticulously screened articles that spotted unintended consequences from tracking and interacting with personal data in their empirical findings. Differing from existing reviews of PI literature that focused on descriptive summarization of research topics, methodologies, and design implications [55, 61, 65, 95, 235], our goal is to synthesize the consequences of using PI systems that can negatively impact individuals or were unanticipated by researchers. Drawing on their study contexts, we also aim to critically examine the underlying causes of these consequences. Specifically, this review seeks to answer two research questions:

- **RQ1.** What unintended consequences are reported in existing PI literature that negatively impact individuals or were not anticipated by researchers and designers at the outset?
- **RQ2.** What are the causes of these consequences?

Our literature analysis showed that although PI systems are designed with good intentions (e.g., promoting self-knowledge, positive behavior changes, and effective care), tracking and interacting with personal data often adversely affects individuals' cognitive load, emotional well-being, social interactions, and behavioral outcomes, and introduces practical challenges. Individuals are imposed with burdens in collecting and interpreting the data; in worse cases, they experience frustration, guilt, and obsession with the data. These negative emotions can induce negative behaviors that are counterproductive to the goals of tracking. Additionally, data can bring tensions among multiple stakeholders with unrealistic expectations, interpersonal conflicts, and power asymmetry. Grounded in the empirical evidence, we traced back the origins and discussions of these consequences in the literature, and recognized that each consequence is not caused by one specific reason but stem from multiple aspects, including the data-centric design ideology, variations in individuals' tracking needs and literacy, the social dynamics around them, as well as the gaps between their intentions and behaviors. Particularly, we highlighted that data cannot fully represent real life, quantification can backfire, individuals' experiences with PI systems are largely shaped by their literacy and data comprehension ability. Moreover, humans relapse easily, not to mention that tracking and sharing personal data is subject to broader social and cultural structures.

In this review, our goal is not to diminish the value of PI but rather to encourage a more practice-oriented approach that aligns technology developments with the complexities of human behaviors and their broader socio-cultural surroundings. Our reflections led to a thorough discussion of opportunities to mitigate the challenges and negative impacts of designing and building PI systems. By advocating "data in practice," we see data as lived and data sharing as socially and culturally conditioned. Moreover, we discuss the implications of leveraging PI to empower rather than merely persuade individuals.

2 Backgrounds

2.1 A Brief Overview of Personal Informatics (PI) Research

Before the emergence of the term "personal informatics" in 2010 [138], the practice of collecting and utilizing personal data dates back several decades ago and has been studied in multiple fields outside HCI, including psychology, medicine, and behavioral science [81, 103, 137, 172, 175]. Traditionally, this practice was called "self-monitoring," which is commonly employed in clinical settings for *assessment purposes* [129, 175]. For example, clinical diagnoses and treatments could be improved by collecting and analyzing data from patients' activities and physical status [175]. In addition, consistently monitoring a behavior could lead to changes in that behavior, known as reactive effects [103]. Hence, self-monitoring also serves *therapeutic purposes* to encourage positive behavior change.

As mobile devices, sensors, and wearable trackers rapidly advanced in the late 2000s, it became easier to collect various types of personal data, such as step counts, heart rates, location, and environmental factors (e.g., temperature, and air condition). Numerous digital tools for personal data collection emerged, drawing the attention of HCI researchers to examine how such tools play parts in people's daily life [22, 35, 102, 140, 144]. Nowadays, the field of PI has been expanded with new topics and themes beyond the assessment and therapeutic applications: from satisfying curiosity [25] and facilitating social interaction [58] to archiving personal mementos [97] and living a mindful lifestyle [6]. As the community advocates for tracking more types of data to realize a "fully quantified-self", some researchers also brought up the situations where self-tracking can be misused [85] and data can be misinterpreted [48]; in worse cases, constant tracking can even trigger negative behaviors [180]. These empirical findings motivated us to take a closer look at the unintended consequences from the use of PI systems in a systematic way.

2.2 Existing Reviews of of PI

There have been several reviews in PI, including mapping or scoping reviews and systematic reviews. Most commonly, we see reviews aim to inform technology designs for health and wellbeing [55, 65, 90, 106, 125, 235]. For example, Klasnja et al. summarized mobile health interventions and their design features (e.g., automatic sensing, symptom monitoring, reminders) implemented for different health conditions [125]. Feng et al. outlined the benefits and drawbacks of the clinical use of PI by reviewing 67 studies involving patients, health professionals, and caregivers [65]. Some reviews contributed to design implications for specific technical domains, such as goal setting [55], personal data visualization [169], and ethical concerns in personal data tracking [226]. Additionally, a review from Ayobi et al. used grounded theory to analyze the methodological differences among 20 PI literature, which identified three research streams that are psychologically, phenomenologically, and humanistically informed [3]. Although these reviews have characterized the recurring themes from previous literature, they focused solely on a subarea of PI with less emphasis on how it is interwoven within diverse social and cultural contexts.

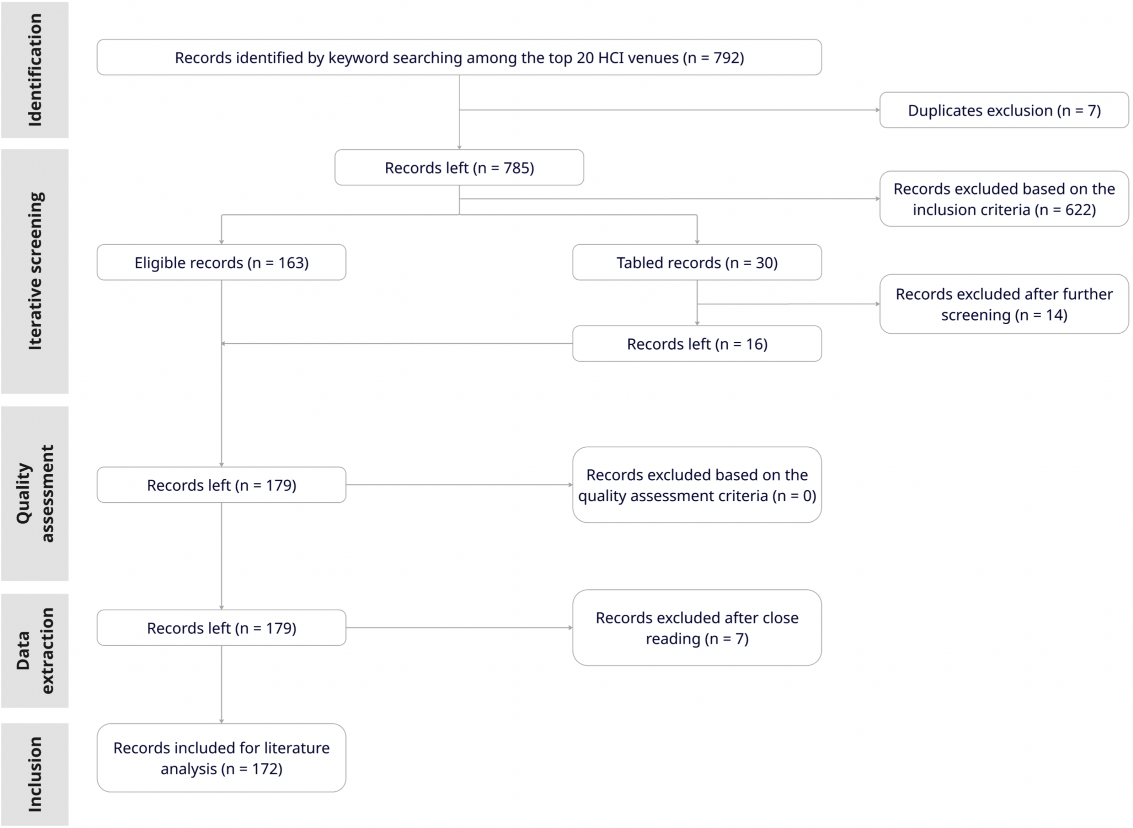

Figure 1: The paper inclusion process following the PRISMA guideline.

The most comprehensive and up-to-date reviews are Epstein et al.'s scoping review covering over 500 PI research articles [61], and Kabir et al.' meta-review on the facilitators and barriers for PI systems with over 200 literature [95]. Both reviews surfaced the motivation, methods, type of contributions, and application domains of prior literature, and also highlighted several issues in existing designs of PI systems, such as privacy concerns, ethics dilemmas, adoption challenges, and data capture burdens [61, 94]. While these reviews serve as important resources for navigating the field, they primarily integrated prior work through a descriptive lens and thus did not engage in deep critical reflections on where unintended consequences arose from and their underlying causes.

In short, our review differs from existing ones in (1) focusing on unintended consequences from tracking and interacting with personal data; (2) in-depth synthesis of the causes of these consequences; and (3) a practice-oriented research agenda to mitigate unintended consequences in PI systems and ways to account for human activities that are enmeshed within a range of social interactions and mutually constitutive with their contexts.

3 Methods: PRISMA Stage

To ensure the rigor of the literature review process, we followed the five-stage PRISMA guideline [218] to search, screen, assess, and analyze the literature. This process is illustrated in Figure 1.

3.1 Identification: Keywords Searching

As the first step, we identified a list of keywords relevant to PI from prior literature (e.g., "self-tracking," "self-monitoring," "quantified-self," "lifelogging,") [25, 138, 154, 155, 198, 228], as well as terms describing a specific domain of personal data tracking (e.g., "exercise tracking" [35, 148, 156], "food tracking" [147, 150], "sleep tracking" [22, 102]).

We target the top 20 HCI journals and conferences as of February 2024 [206], based on Google Scholar metrics [1] (e.g., *CHI*, *IMWUT*, *CSCW*, *DIS*), together with two additional conferences focusing on human use of computing technologies (i.e., *EAI Pervasive Health*, *Mobile HCI*). We visited each of the venues' official websites and recorded their publication libraries, which include the ACM Digital Library, IEEE Xplore, Scopus, Taylor & Francis Online, and Springer Link. Across the databases, we used the same set of keywords and applied the same filter (to select full research articles). All the keywords, venues, and databases are listed in Table 1.

3.2 Screening

Our literature search concluded in February 2024, resulting in 792 papers. After removing the duplicates caused by multiple editions, we collected 785 unique records.

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[1] Google Scholar uses h5-index and h5-median to compare and rank conferences and journals; each of these metrics is calculated based on the largest number and the median of the citation counts of the venue over the past five years, respectively [205].

Table 1: The search keywords and filters in our SLR (note that we did not restrict the publication date).

Search within	Keywords query	Publication venue	Article filter
Title, abstract, author keywords	"personal informatics" OR "self-monitoring" OR "self-tracking" OR "personal tracking" OR "quantified self" OR "lifelogging" OR "personal analytics" OR "health tracking" OR "exercise tracking" OR "mood tracking" OR "sleep tracking" OR "food tracking" OR "productivity tracking"	**ACM Digital Library**[*] (12 venues) *CHI* OR *CSCW* OR *IMWUT/Ubicomp*[+] OR *DIS* OR *PACM HCI*[s] OR *TOCHI* OR *UIST* OR *IUI* OR *VRST* OR *AUTOMOTIVEUI* OR *EAI Pervasive Health* OR *Mobile HCI* **IEEE Xplore** (4 venues) *Transactions on Affective Computing* OR *International Conference on Human Robot Interaction* OR *International Conference on Human-Machine Systems* OR *Virtual Reality Conference* **Scopus** (3 venues) *International Journal of Human-Computer Studies* OR *International Journal of Interactive Mobile Technologies* OR *HCI International* **Taylor & Francis Online** (2 venues) *International Journal of Human–Computer Interaction* OR *Behaviour Information Technology* **Springer Link** (1 venue) *International Journal of Universal Access in the Information Society*	Article type: Research Article

[*] The venues included in the filter under the ACM Digital Library are listed in abbreviated form for simplicity (e.g., *CHI* stands for *ACM CHI Conference on Human Factors in Computing Systems*, *VRST* stands for *The ACM Symposium on Virtual Reality Software and Technology*).

[+] Prior to 2017, the conference now known as *the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)* was called the *Ubiquitous Computing (UbiComp)*, which was included in our search and later merged with *IMWUT*.

[s] *PACM HCI* stands for *Proceedings of the ACM on Human-Computer Interaction*, a journal series launched in 2017 to publish articles accepted to top HCI conferences such as *CSCW* and *GROUP*.

3.2.1 Screening procedure and results. Each paper underwent individual review and screening by four researchers, consisting of two university faculties and two graduate students. Each researcher independently assessed the titles, keywords, abstracts, and full texts of all papers. In cases where disagreements arose, we collectively reevaluated the paper through our routine group meetings. Our initial screening excluded 622 records that were deemed irrelevant to PI (including 86 resolved disagreements) and tabled 30 papers for further discussion. We then conducted another round of screening following the same procedure and excluded 14 tabled papers. At the end of the screening stage, 179 papers were left. During this process, we had extensive discussions on what the scope of PI research covers, what unintended consequences entail, and how to determine if a paper provides sufficient information about such consequences. These discussions led us to iteratively refine our inclusion and exclusion criteria described below.

3.2.2 Inclusion and exclusion criteria. In the stage-based model, Li et al. highlight that *data collection* and *reflection* are two core aspects of PI, because effective PI systems should help people "*collect necessary personal information for insightful reflection*," which ultimately lead to positive behavior change [138]. This process, according to Lupton's description of self-tracking culture, should be carried out regularly instead of a one-time interaction with the data [154]. Later, Rooksby and Epstein et al. further extended PI as "lived informatics," acknowledging that people engage with their personal data in a variety of ways for different purposes, in which they do not necessarily aim for behavior change but may also seek to satisfy curiosity, document activities, engage in social collaborations, etc [63, 198]. Focusing on the lessons learned from human experience with PI, we developed two inclusion criteria:

***Criteria 1**: An article must study how individuals engage with (e.g., collect, curate, reflect on, act upon, make use of) data that are relevant to their behaviors, feelings, thoughts, or other aspects of daily life over time.*

***Criteria 2**: An article must contribute to empirical understandings of human subjects, reflecting the perspectives of the primary user (whose data are collected) or other stakeholders (e.g., who uses the data), such as their attitudes, preferences, intentions, and behaviors.*

More importantly, we meant to identify "unintended consequences"—findings that arose from the design of PI systems not working as expected by researchers, or instances where using PI systems led to adverse effects on individuals. These consequences might not be the primary findings of the literature, but there should be sufficient information and contexts for understanding what happened with participants regarding tracking and interacting with their personal data. Thus, we developed the third inclusion criteria:

***Criteria 3**: An article must explicitly report at least one unintended consequence of using PI systems in its findings, which reveals the limitations or drawbacks of tracking and interacting with personal data. The findings can be quantitative, such as statistical test results, or qualitative, based on participants' self-reports, but must provide sufficient information connected to the PI practice.*

With the above criteria, we excluded 547 articles that were irrelevant to PI (e.g., using eye/gesture tracking in usability studies, one-time collection of personal data without over-time engagement, public surveillance) or did not involve human subjects (e.g., analyzing existing data to identify collective patterns without confirming with end-users, assessing the accuracy of data tracking systems without revealing user perspectives, literature or app review), and 75 articles that did not provide sufficient information related to unintended consequences.

3.3 Quality Assessment

In systematic reviews, quality assessment is a critical step to ensure that the included studies used rigorous methods and produced valid results [107, 143]. Although the PRISMA guideline for quality assessment is designed mainly for evaluating clinical interventions, which may not be directly applicable to HCI research [197], we believe it is still important to assess the quality of all included studies to ensure that they used rigorous methods and produced valid results [107, 143]. We carefully examined the introduction, method, and results sections of the 179 literature, and did not exclude any records as they all had clear research questions or goals, methods, and presentation of results.

3.4 Data extraction

In this step, all the researchers in the team worked together to go through each paper and prepare the datasets for later analysis. First, we extracted the metadata, including the paper's research questions, participants' composition, study location, method, and data analysis approaches, key findings, and discussion points. Next, two researchers focused on the extracted key findings from the metadata to highlight information related to unintended consequences resulting from interacting with PI systems. During this process, we constantly referred back to the original articles and added additional notes to make sure the information was accurate and comprehensive. As a result, our extracted data included original excerpts from the papers, narratives we wrote, and notes we added to provide contexts (the full list of extracted data can be found in the supplementary materials). Upon a close reading of each paper, we excluded seven additional papers that were deemed not eligible. Therefore, a total of 172 research articles were included for analysis. To ensure accurate, nuanced, and context-aware extraction of these highly specialized qualitative data, this step was completed manually by researchers without any AI tools.

3.5 Literature Analysis

We divided our literature analysis into three parts. In the first part, we characterized the literature regarding the publication trends, target population, study location, and data analysis methods. In the second part, two researchers conducted an inductive, relexive thematic analysis to sort out the nature of unintended consequences from tracking and interacting with personal data. We used a spreadsheet to conduct the initial coding, where each of us worked through the excerpts of all the literature, highlighting segments that were potentially relevant and interesting, and assigned them with labels that are analytically meaningful (e.g., "*cognitive burden to manage and make sense of multiple data streams in fertility tracking*"). If we considered an excerpt or narrative not informative enough, we referred back to the original texts of the literature. Upon comparing and combining our initial codes, we generated a list of 380 codes. Due to the iterative nature of the analysis, we did not compute the inter-reliability of the codes [163]. Through rounds of discussions, we integrated these unintended consequences into five categories—cognitive load, emotional wellbeing, social acts, practical challenges, and behavioral outcomes. This process followed the principles of reflexive thematic analysis steps [13, 31].

In the third part, we traced back the origins of these consequences to understand how and why they occurred in the first place. Three researchers collaborated on the analysis and followed a similar approach as in the second part. Our analysis showed that rather than stemming from a single cause, each unintended consequence resulted from multiple interconnected reasons. For example, individuals with eating disorders often experience stress and frustration from calorie tracking, which is a result of overdependence on data to validate their goals and progress as well as the difficulty in sustaining a healthy eating pattern despite their awareness of its importance [54]. From this case, we derived causes involving "*unhealthy reliance on data*" and"*difficulty in converting intentions to real-world behaviors*." Taken all the causes derived, we assessed their relevance and importance, and refined each of them in a more concise and informative way. Lastly, we wove together the analytic narrative to report the prominent findings.

4 Findings

In this section, we first summarize the characteristics of the literature and then answer our research questions by describing an overview of the unintended consequences of interacting with PI and their underlying causes.

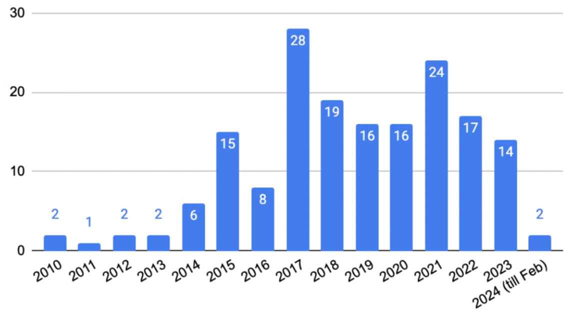
4.1 Literature Characteristics

Our literature analysis showed that PI research involving human subjects has been rising over the past decade, with a notable surge since 2015 and 2017. As Figure 2 (a) shows, the majority of literature is published in the ACM community, with CHI (n = 75, 43.60%), IMWUT/Ubicomp (n = 30, 17.44%), and CSCW/PACM (CSCW) (n = 27, 15.70%) being the most prominent, followed by DIS (n = 17, 9.88%), International Journal of Human-Computer Studies (IJHCS; n = 8, 4.65%), etc.

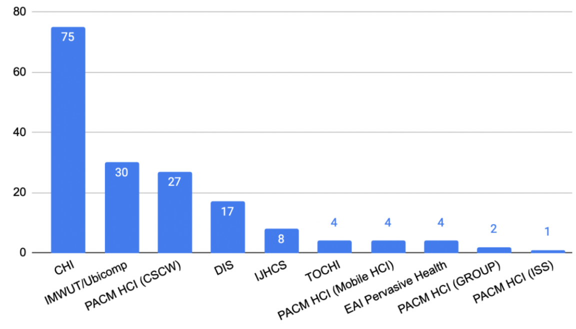
Existing PI research was predominantly conducted in Western regions (see Figure 2 (c)), with almost half of them in the US and UK. In addition, 55 papers (31.98%) did not explicitly specify their study locations, which we labeled as "unspecified." To speculate their study regions, we further reviewed these papers for context clues (e.g., whether the study was conducted in person, currency of compensation) in combination with the authors' affiliations. We found that 29 still fall within the Western regions, adding the total proportion of Western-centric studies to over 70%.

For the target users (see Figure 3), while early research often studied the general population, the growing interest in PI within the HCI community has led more research to focus on specific populations over the years. These groups include individuals with health conditions (n = 52, 30.23%), such as mental health issues (e.g., [157, 184, 212, 232]), diabetes (e.g., [70, 101, 104, 188]), fertility concerns [39, 40, 126], migraine [89, 182, 208], irritable bowel syndrome (IBS) [28, 99, 207], and Parkinson diseases [164, 166, 219]; vulnerable groups (n = 71, 41.28%) who are at a higher risk of facing discrimination, exclusion, and unequal treatment due to their socioeconomic status, age, gender, ethnicity, race, and other intersectionalities, such as racial and ethnic minorities [161], economically disadvantaged individuals [200, 202, 203], people from the immigrant community [45]; specific workforce (n = 19, 11.05%), such as office workers (e.g., [64, 122]), athletes (e.g., [128, 191]), and gig workers (e.g., [236]); and among multiple stakeholders (n = 29, 16.86%) by involving patients and healthcare professionals (e.g., [28, 30, 239]), care receivers and caregivers (e.g., [42, 91, 188]), as well as parents and children (e.g., [185, 186]).

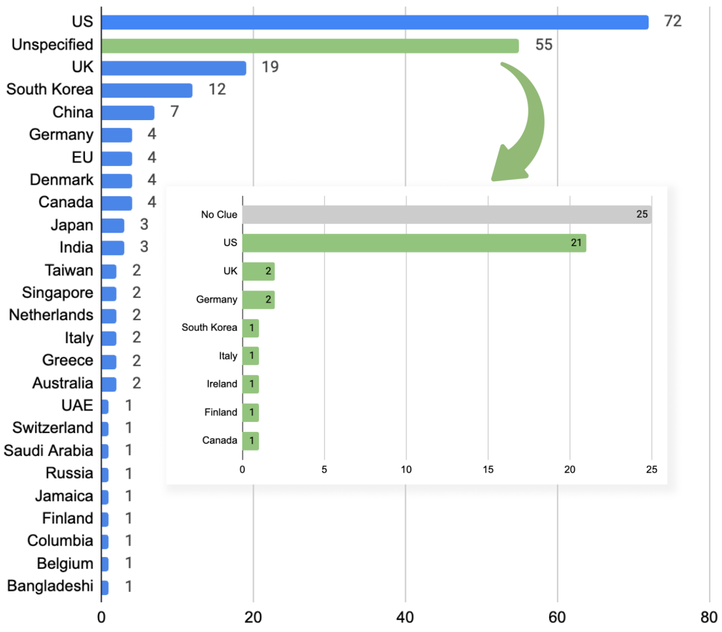
In addition, we grouped the literature based on their description of data analysis procedures: quantitative- and mixed-method papers



(a) Year



(b) Publication venue



(c) Study region (one study may cover multiple regions)

Figure 2: Publication trend of personal Informatics (PI) empirical studies covering unintended consequences.

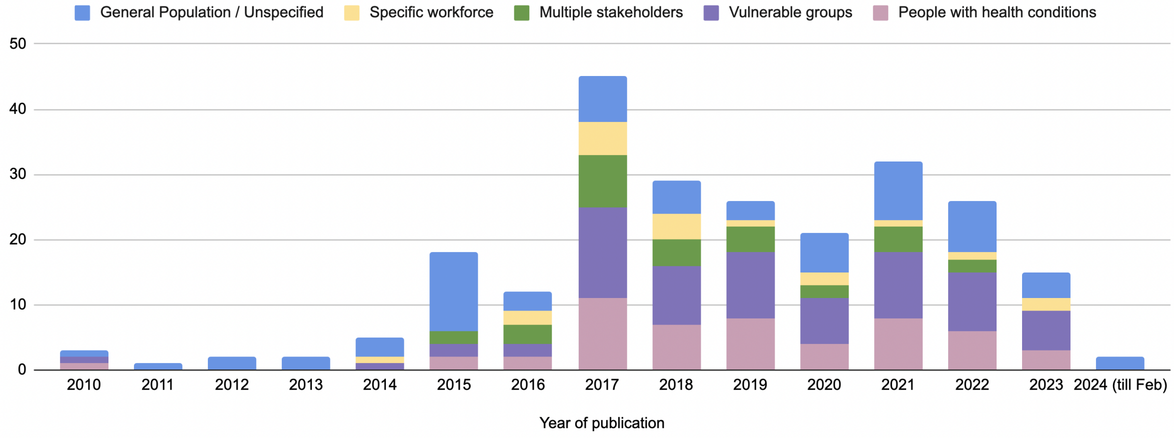


Figure 3: Participants who were involved in the studies (one paper may involve multiple groups of participants).

applied one or more statistical tests; papers that provided only descriptive statistics were not considered to have a quantitative component. Majority of the research studies employed qualitative methods (n = 121, 70.35%) such as interviews (e.g., [48, 78, 180]) and co-design workshops (e.g., 14, 115, 150) to understand how people engage with and make use of PI systems. Mixed method analysis (n = 49, 28.49%) was also commonly seen in field studies (e.g., [116, 122, 142]), where researchers analyzed both quantitative (e.g., comparing people's intention and behaviors before and after tracking) and qualitative data (e.g., subjective experience from interviews). Only two (1.16%) are pure quantitative research [2, 76].

4.2 RQ1: Unintended Consequences

Here, we describe how tracking and interacting with personal data may not work as researchers initially anticipated and can adversely affect individuals in several aspects. In Table 2, we list the five groups of unintended consequences, with the number of instances that emerged, enactment from the literature, and examples with an original data excerpt.

First, collecting and integrating data from multiple sources adds to cognitive burdens, as many types of data can not be automatically captured, especially food information often requires intensive manual logging [38, 147, 211], and subjective measures that individuals found difficult to articulate, such as mood and sleep quality [102, 135, 187, 231]. While collecting these data often requires manual efforts, their relevance to individuals' primacy concerns and interests is not guaranteed [102, 147, 178]. This burden often extends to the next stage of making sense of the captured data, often with misinterpretation of one's situation, such as drawing false conclusions about what influences one's health symptoms [49] or endless uncertainty about what leads to their conditions [26].

Second, it is commonly observed that tracking can lead to negative impacts on individuals' emotional well-being, such as stress about their data not looking good, frustration with their performance, and guilt for not meeting their goals or others' expectations (e.g., weight loss, and regular exercise) [91, 216]. These negative emotions are also observed among caregivers, often family members, such as parents who care and worry about their children's health and life [91, 104]. In some cases, individuals may become overly obsessive with tracking, where the data dominate their focus, leading them to intensely check the captured numbers and constantly seek new measures [39, 104, 215]. Such obsessed tracking can further heighten their negative emotions surrounding the data.

Third, tracking and sharing personal data can influence individuals' social acts, encompassing tensions among multiple stakeholders (e.g., patients and doctors, coaches and athletes)—unrealistic expectations, interpersonal conflicts, and power asymmetry. A typical example is in the context of doctor-patient communication, where

Table 2: Unintended consequences of tracking and interacting with personal data on individuals (a full list of details can be found in the supplementary material). Note that one article can cover multiple consequences.

Consequences	Enactment from the literature	Example
Cognitive load ($n = 72$)	Data collection and integration burden (e.g., [25, 38, 138]).	"*60% participants with prior journaling experience reported they sometimes did not journal a meal with their prior technique because it was too difficult.*" [38].
	Difficulty in making sense of the data or misinterpretation (e.g., [26, 42, 142]).	"*They tried to correlate other habits and factors (e.g., stress, smoking, sexual activity, age, and genetics) with symptoms (e.g., irregularity in menstruation) to explain or justify what they are experiencing. [...] at times it became difficult to differentiate between the symptoms of PCOS and the effects of different treatments or medications*" [26].
Emotional well-being ($n = 55$)	Negative emotions, such as stress and guilt for individuals being tracked (e.g., [158, 216]) or their caregivers (e.g., [91, 104]).	"*Students commonly experienced personal guilt and disappointment in themselves, as well as the social pressures, stigma, and embarrassment they felt regarding their data*" [105].
	Obsessive tracking, involving intensely checking the data and constantly seeking new measures, which greatly interferes one's life (e.g., [39, 104, 215]).	"*Women track multiple things and select the ones they will deposit their hopes in case the others give not encouraging results. They also start seeing any symptom as a possible measure to track*" [39].
Social acts ($n = 42$)	Tensions among multi-stakeholders, such as unrealistic expectations, interpersonal conflicts and power asymmetry (e.g., [167, 188, 208]).	"*Some providers worried about unrealistic patient expectations regarding a provider's ability to use the system and interpret the data, [...] Patients and providers also wanted to ensure their goals are considered and pursued, which could prompt disagreement and frustration if patient and provider goals are not easily aligned*" [208].
	Reinforcing societal stigma or discrimination associated with specific populations (e.g., [68, 174, 219]).	"*So far, we have explored how modes of tracking that have existed for the last century crucially inform the design of contemporary menstrual apps [...] These tools often reproduce a common stigma around menstruation through their use of coded language and jokes*" [68].
	Discomforts or embarrassment with unconventional tracking methods in social settings (e.g., [113, 124, 233]).	"*Seven participants noted that they would be inclined to use only touch in the public space for two main reasons: (1) they did not want to disturb others and (2) they were afraid that surrounding people might feel awkward seeing them verbalizing health-related queries*" [124].
Behavioral outcomes ($n = 19$)	Failing to promote or sustain positive behaviors (e.g., [19, 122, 165]).	"*The improved productivity of NF participants dropped immediately after the feedback was withdrawn. From the result, we can conclude that the distraction emphasized feedback can help people improve their productive rate, but this behavior change might not be sustained when the feedback is withdrawn*" [122].
	Negative or unhealthy behaviors counterproductive to the tracking goals (e.g., [54, 180, 234]).	"*Participants who had not yet committed to quitting said that registering resisted cigarettes made them crave a cigarette even more. Thus, the app sometimes had counter-productive effects. Ironically, one participant rewarded himself with a cigarette for resisting one*" [180].
Practical challenges ($n = 25$)	Low engagement regarding the limited usefulness or instrumental benefits perceived from the data (e.g., [15, 118, 183]).	"*Participants who were indifferent showed confusion and negativity when asked what they think of the story. To Q1, they replied with confusion. To Q3, they denied that the video represents or reflects them and didn't relate the video to their personal experience. Their answers are all brief, adding up to fewer than around 80 words (M=42.8, SD=27.1), showing a low level of engagement*" [183].
	Physical discomforts or inconvenience to daily activities (e.g., [119, 191, 192]).	"*The most common problem is physical discomfort: this is relevant to specific sports (e.g., wearing a bracelet when climbing interferes with movements and the device can be easily damaged)*" [191].

patients hope to share as much data as possible to obtain personalized treatment, but doctors often face institutional, resource, and time constraints to review and analyze the data [28, 178]. Additionally, sharing data among multiple people can reinforce the societal stigma or discrimination associated with specific populations, particularly among vulnerable groups (e.g., individuals facing women's health issues) [26, 62, 237]. For some individuals, unconventional tracking methods, such as speech input and smart glasses [147, 149, 233], can be socially uncomfortable, as they may inadvertently overshare personal information in public settings.

Fourth, although many PI systems were initially designed with the intent of promoting positive behavior changes (e.g., productivity improvement, smoking cessation), several studies did not find the changes they anticipated. Among the 56 papers aimed at achieving behavior changes, 27 (48.21%) examined individuals' behaviors through controlled experiments, but nearly half of these studies (12, 44.44%) did not observe statistically significant differences in the target behaviors (e.g., [1, 43, 44, 148, 210, 236]). For example, supporting daily exercise with a smart speaker did not lead to better adherence compared with a regular mobile app [148]; sharing physical activity with significant others did not necessarily make individuals more willing to improve [236]. In worse cases, some tracking tools even contributed to negative or unhealthy behaviors, as shown in the literature, an app aiming to help monitor smoking behaviors can trigger the urge to smoke [180], people sometimes prioritize achieving a fitness image by reducing calorie intake at the expense of their health needs [27], etc.

Lastly, several practical challenges emerged regarding low engagement with PI systems, where individuals are motivated by potential behavior change or instrumental benefits (e.g., collecting records for social interaction) expressed limited and faded usefulness of the tracked data [15, 118, 183]. Occasionally, tracking personal data can induce physical discomforts or inconvenience, mainly with tracking devices that are heavy to wear [119, 191, 192].

4.3 RQ2: The Causes of Unintended Consequences

Our analysis showed that there is no one-to-one mapping between specific causes and the aforementioned consequences; instead, these consequences stem from multiple aspects of researchers' design ideology, variations in individuals' tracking needs and literacy, and the social dynamics around them, as well as the gaps between their intentions and behaviors. Below, we elaborate on these aspects by synthesizing the takeaways from the literature.

4.3.1 The Data-Centric Design Ideology. Since the "quantified self" movement opened up the opportunities to "*know yourself through numbers*," personal data have been granted authority and power that symbolize whether people have achieved their goals, what are superior versus inferior values, and what constitutes one's identity and self-image [25, 27, 130, 215]. Within this strand that strives to gather objective and trustworthy information from personal data, an implicit assumption is that more data are likely to generate more knowledge about ourselves. Indeed, studies have found that integrating multiple data can help individuals uncover unknown relationships (e.g., food consumption and stomachache symptoms [99]), identify outliers (e.g., sleep patterns in different locations [24]), and even perform predictions (e.g., blood glucose predicted by nutrients intake [46]). However, in the meantime, the limitations of the "data-centric" ideology have emerged as empirical findings accumulated, which often led to burdens on individuals' cognitive load and emotional well-being, and can further heighten stigma associated with specific populations and negative behaviors reported in 4.2. The underlying pathways are mainly three-fold.

First, ***data are derived measures but not direct representations of everyday life***. The complicity of human behaviors and the uncertainty of the surrounding environments make it difficult to simplify everything into numbers [25, 62, 112, 116, 117, 142, 234]. As examples, step counts capture how far a person walks, but cannot truly represent their physical activity levels [74, 121]; a photo of a dish captures the food components present, but does not reflect what a person actually consumes [38, 147]; heart rate variability captures one's physiological stress, but may not be the best metrics to characterize their mental stress [48]; the usage of digital devices captures how much time a person spends on different apps, but may not represent how productive they are [122]. Thus, even though the data itself is accurate, the "data-driven insights" can be unreliable and even lead individuals to draw false conclusions about themselves. In several studies [46, 48, 99], including the evaluation of Health Mashup mentioned earlier [8], researchers have observed instances where participants noted that personal data contradictory to real-life situations.

Second, ***collecting more data involves more efforts, but does not always bring more knowledge***. In part, there are still many types of data that cannot be automatically captured, especially qualitative and subjective data, such as mood and sleep quality [102, 135, 187, 231]. Collecting these data often requires manual efforts or wearing additional on-body devices, but the relevance of the data remains unclear [102, 147, 178]. Particularly, collecting multistream data involves both cognitive and behavioral efforts, but not all collected data are relevant to the target activity or health condition [102, 120, 178, 192, 239]. As Oh et al. observed in their clinic interviews, most of the data patients kept tracking were not the data that clinicians needed for health assessment; thus, patients struggled to manage and prioritize their tracking practices amidst different tools and numbers [178]. Furthermore, in making sense of multi-stream data, those who lack data literacy or domain expertise can feel overwhelmed to interpret the hidden messages [5, 40, 48, 116, 239]. For complicated health conditions such as multiple sclerosis [5] and women's health issues [26, 40], tracking and gathering multiple types of data may not help them find answers to their questions, but ended up creating more confusion and frustrations. In addition, several studies pointed out that it is not guaranteed that valuable insights can be derived from personal data. As a result, people rarely engage with tracking or revisiting their data. This was exemplified in the scenarios of constructing personal mementos with photos of home objects [97], seeking patterns from personal records [24, 57, 201], and learning from long-term household activities captured by wearable cameras [145]. As Lindley et al. brought up, these personal archives have the potential to trigger meaningful reflections, but oftentimes the mundane nature of what is being captured may not lead to personally meaningful insights or not worth recording [24, 105, 127, 145, 216].

Third, ***quantification can backfire***. By examining how participants reacted to their quantified selves with a series of numbers representing their life, prior studies found that stress introduced by quantification is often overlooked in the early stage of PI system design [2, 34, 53, 54, 93, 105, 150, 156]. This phenomenon is particularly prevalent in managing health conditions with stigma (e.g., women's health, weight management, mental health), where individuals tended to have a stronger emotional experience with their personal data [26, 39, 54, 54, 173, 195, 237]. This is mainly because the ways that their personal data are presented could erode their self-esteem. For instance, those with eating disorders can become overly obsessed with their weight and calorie intakes and end up taking"unhealthy data-driven" actions such as over-exercise and intentional vomiting [54]. Similar findings have been reported in situations involving intensive peer competitions such as collegiate athletics' sports training [33] and online game [130], where superior numbers often carry persuasive influence that symbolize one's capability and inferior numbers can undermine their motivations. In these situations, individuals turned their focus to improving the data instead of improving themselves, as they had little knowledge about how their data were analyzed and impacted their performance. Moreover, as personal data tracking has expanded to a means for self-expression and social interaction [18, 29, 75, 196, 231], the ways that data are presented can impose burden to those who are obsessed with impression management for social validation [40, 78, 100, 130]. In some situations, individuals see data as their self-identities, and may intentionally curate and present their data to appear more "socially acceptable," which does not necessarily align with their personal life trajectories [27, 215]. For instance, Chung et al. found that food bloggers who share their diet on social media tended to post food intake to meet the social norm expectation and deviate from their original health goals [27]. Thomas et al. found that people selectively presented their social media posts by removing disliked information for more pleasant personal archives [215]. In their discussions, researchers noted that this phenomenon could potentially foster social comparison and peer pressures, further perpetuating stress and unrealistic standards to individuals [130, 210, 215].

4.3.2 Variations in Individuals' Tracking Needs and Literacy. When seeking answers to why people do not engage or even abandon using PI systems, researchers found that one reason was ***the mismatch between the system design and individuals' needs of tracking***. This mismatch often arises with novel tracking technologies such as wearable devices, which were commercialized primarily to promote competitive fitness with numerous performance metrics and goal-setting features, but the general population may not prioritize such intense tracking [32, 76, 82, 134, 190]. Even the tracking devices could satisfy users' curiosity about their activities at the beginning, they may lose appeal as the novelty wears off or the data fails to provide meaningful and long-term insights, because the fixed system design often fails to adapt to the ever-changing user needs [32, 134, 195]. In other cases, the needs of special populations such as older adults and those with disabilities, are often not part of the consideration of the system design [15, 171, 195]. For example, while activity trackers usually aim to encourage users to increase their physical activity by focusing on step counts, calories burned, or active minutes, this design overlooks the fact that many older adults prioritize other goals, such as symptom management (e.g., reducing chronic pain, managing arthritis) and functional training (e.g., maintaining balance, improving mobility, or performing daily tasks independently) [15]. In this light, Choe and Luo et al. argued that PI systems should be flexible and customizable [25, 150], which allows individuals and other stakeholders to decide what to track and how to track rather than imposing rigid system constraints that may not align with users' evolving needs and contexts.

In addition, individuals' ***literacy in health and their data comprehension ability***, largely shapes their ability to make efficient and meaningful use of the data. Adequate health literacy is essential for monitoring multi-faceted phenomena such as sleep and stress that are not directly measurable but instead inferred from specific data points [22, 48, 102, 131, 185, 194], or managing health conditions (e.g., PCOS, fertility) that are difficult to diagnose [26, 40, 48]. For instance, while sleep tracking has become prevalent with metrics including deep and light sleep hours or wake-up times, sleep medical experts have highlighted that 'a healthy night of sleep' varies for different individuals, depending on factors such as their ability to stay attentive during waking hours or the ease of falling asleep [194]. However, individuals often lack the necessary knowledge and guidance to efficiently understand their sleep quality. In cases where people manage complicated and uncertain health conditions, their very first challenge often arises from recognizing the signs and symptoms that need to be tracked [26]. Besides, researchers have highlighted that self-tracking is "knowledge-intensive," requiring not only the background knowledge about what is tracked [33, 40, 48, 190], but also the ability to read and comprehend the data and their presentations [52, 109, 161]. When it comes to exploring the data, some PI systems offer abstract or metaphorical visualizations to engage individuals (e.g., using traffic lights to indicate well-being status), but those who are less familiar with such representations often find themselves lost amidst the data, struggling to grasp the takeaways [52, 109, 161]. This disconnection can hinder their ability to derive meaningful insights, limiting the effectiveness of these systems in supporting self-reflection and decision-making. With the growing commercialization of AI-powered personal informatics (PI) systems, users are often required to understand complex metrics and interpret AI-driven insights, making it critical to develop literacy in health knowledge and data comprehension abilities [66].

4.3.3 The Social Dynamics of Data Sharing. As PI systems have evolved from being primarily utilized by individuals to being adopted by multiple stakeholders, we have seen research studying the practice of sharing personal data to facilitate information exchange and collaboration between patients and clinicians [28, 86, 87, 118, 239], caregivers and care-receivers [16, 91, 119, 187, 232], parents and children [19, 92, 104, 200, 201, 221, 223], athletes and coaches [33, 128], etc. In these studies, PI serves as an information hub that enables one party to better understand the other so that they can communicate and collaborate more effectively. However, ***data sharing is subject to the hierarchic relationships involved***, particularly in the presence of power imbalances arising from individuals' expertise (e.g., patients and clinicians), resources (e.g., children and parents), or organizational levels (e.g., employer and employees). The power imbalances can impact the level of control individuals have over the collection and sharing of their personal data, even though they may feel uncomfortable about the sharing process [28, 118, 128, 146, 150, 178, 185, 196, 208, 222]. This is one of the primary reasons for tension among multiple stakeholders in self-tracking. For example, due to the fear of judgment and discrimination, patients may hesitate to share unhealthy behaviors (e.g., alcohol intake) with clinicians [28, 208, 227], children might be reluctant to share the details of their daily routines (e.g., bedtime) with parents [84, 104, 179, 185], and employees may be unwilling to share their productivity data with their employers [149, 196].

Furthermore, ***data sharing requires a mutual engagement that can be difficult to sustain***. While some individuals are passionate about sharing their personal data, the other party may lack the resources to engage in the sharing process. This was commonly observed in patient-clinician communications, where patients are eager for clinicians to have a deeper understanding of their health conditions through data sharing, yet clinicians might not have the time and infrastructural support to verify and manage the data [69, 118, 227, 239]. In a few cases, researchers investigated tracking in intimate relationships [40, 41, 195], noting the disproportional labor distribution between partners in fertility tracking, where the responsibility of actively seeking measures and solutions primarily falls on women. This imbalance can further exacerbate negative emotions experienced by the individual bearing the greater burden, potentially straining their relationships.

4.3.4 The Intention-Behavior Gap.

Early research, even before the introduction of the term "Personal Informatics," had explored the potential of self-monitoring to enable positive changes [35–37, 144]. This perspective considers personal data as a reference for setting goals and encouraging progress, which echoes the stage-based model by placing "action" as the last stage of PI [138]. Since Consolvo et al. pioneered a metaphoric approach to encourage physical activities by mapping individuals' step counts into flowers and butterflies in a stylized wallpaper on mobile phones in 2008 [36], researchers have begun exploring various design features to be incorporated into PI for desired changes, including strategically framing personal data visualization (e.g., [17, 88, 93, 122, 180]), supporting goal setting and planning (e.g., [1, 43, 44, 136, 177, 217, 230]), gamification and rewarding mechanism [77, 114, 191], and building communities to boost motivations through peer support (e.g., [18, 29, 64, 75, 114, 162, 165, 196, 210]).

While recognizing the effectiveness of PI in facilitating behavior change, researchers have discussed that framing personal data primarily as a means to "persuade" individuals often overlooked the gaps between human intention and their behaviors. Despite being aware of the need for change or having access to the necessary information, people often struggle to act effectively due to the ***cognitive, informational, environmental, and time constraints***, or *bounded rationality*, suggesting humans are not fully rational in the way they make choices within limited resources [209]. Particularly, human behaviors are deeply shaped by their living environments [19, 44, 148, 236] and social context [96, 156, 203]. In Chen et al.' work aimed at reducing adolescence' smartphone addiction, they found that tracking and presenting participants' phone usage to increase their awareness was not enough to promote meaningful changes because of their inadequate self-regulation ability, lack of alternative choices, and living environment constraints [19], which was also highlighted by other researchers in various behavior change contexts [73, 181, 233]. When individuals are pressured to meet specific goals but fail to do so, they are likely to develop negative emotions and tensions with others in their lives (e.g., patients felt shamed to be judged by clinicians [28]).

It is also noteworthy that ***people relapse easily***. Even though behavior change is observed during the study period, it does not mean that the change can be sustained in the long run. Although we found only two papers continued to track individuals' behaviors after withdrawing the PI intervention, both showed that once the PI intervention was withdrawn, individuals may revert to their previous behavior patterns or even perform worse than before [122, 196]. Specifically, Kim et al. found that while strategically framed visualization of productivity data by highlighting the distracted digital activities can boost people's motivations to stay productive, a significant productivity loss was observed after withdrawing the visualization [122]. In Rivera-Pelayo et al.' experiment of shared mood and productivity tracking at workplace, individuals' work performance significantly increased, but after stopping tracking, their productivity notably dropped [196]. A possible explanation, as the researchers found from interviewing the participants, could be that the stress of being monitored helped increase individuals' productivity during the intervention period, but the effect could not last in the long run [122, 196]. Additionally, researchers noted that relapse could even occur in the process of tracking, especially for tracking negative behaviors [147, 180]. For example, tracking one's smoking intention can trigger rather than reduce their desire to smoke [180].

5 Discussion

In the preceding sections, we have identified and articulated three main causes of unintended consequences from tracking and interacting with personal data: the data-centric design ideology, the individualized tracking needs, literacy, and social context, and the gap between their intentions and behaviors. Here, we discuss the opportunities toward a more sustainable and critical way of using data that respects its power and constraints, drawing on the "turn to practice" movement in HCI research [132] to re-ground studies from *data-centric* to *data in practice*.

5.1 From Data-Centric to Data in Practice

Several sociologists described the data-centric ideology as "dataism" or "datafication" [176, 220], "*a belief in the objective quantification and potential tracking of all kinds of human behavior and sociality through online media technologies*" and "*involves trust in the (institutional) agents that collect, interpret, and share (meta)data*"[220]. The ideology fundamentally resides in the *positivist* theories. Derived from traditional sciences such as physics that seek to form idealistic and simplified models to describe complex phenomena in the world, positivist theories seek to distill the complexities of social phenomena to similar idealistic and simplified models, which are often quantitative and mathematical [83, 199]. By doing that, however, the details of particular contexts, occasions, and practices are abstracted away. Such a positivist approach is manifested in a majority of existing PI literature—utilizing the data to know thyself, to enable desired changes, or to aid collaboration or socialization—where the captured data are taken as a direct reflection of objective and independent properties of activities, while the particular details of context, occasions and practices are lost [8, 138, 140, 160]. With these quantified data, it is hoped that various correlations between different properties could be derived and made available to inform individuals about themselves and further guide them to make decisions and take actions.

However, our everyday activities and lives are essentially and foremostly situated; no properties are objective, independent, or absolute to be captured as such [50]. But rather, their meanings and relevance are emergent and subject to a process of interpretation and reinterpretations, and are dynamically and continually changing all the time [50]. This has already been illustrated in many empirical studies: drawing data-driven insights that fit real-life situations can be challenging and even unrealistic, as much of the data deemed relevant to the target activity may turn out to be irrelevant and even misleading, or the relationships between the target behavior and its surrounding contexts cannot be simply delineated through static formulas [8, 46, 48, 99, 101, 112, 156]. Even though prior work has attempted to collect and quantify as much data as possible and "let the insights emerge" [8, 22, 24, 99, 139, 139], our analysis showed that more data does not always bring more knowledge and may introduce more noise and burdens.

This reflection resonates with Dourish's critique of how "context" was approached in HCI research twenty years ago [51]: while "context" was increasingly recognized as important in designing interactive systems, it was often viewed as a representational problem. This perspective often takes "context" as something informational, stable, delineable, separable (from the activity and socio-cultural surroundings), and can be automatically encoded. Drawing on a *phenomenological* perspective, Dourish argued that the "context" related to one's behaviors is not fixed or even stable, but dynamically evolves over time, subject to changes caused by various forces, so is "*a relational and occasional property with a dynamic scope that arises from activity*" [51]. Taking this phenomenologically informed approach, we now turn to discuss how PI system design towards the "practice" paradigm that encompasses human activities, computing, historical interaction processes, as well as cultural and social environments as interwoven within the practice [132].

5.1.1 *Data as Lived.*

First, we see personal data as lived and evolving information surrounding the target activities or conditions rather than their stable metrics. As such, the ways that individuals explore and reflect on their data should similarly be an active process, rather than merely gaining static "insights" (e.g., how coffee intake is related to one's sleep quality, whether the time of the day affects how many steps a person walks) mentioned many prior studies (e.g., [22, 138, 139]). This call aligns with the idea of "self-reflection": a subjective and ongoing process where individuals seriously and actively analyze and evaluate their own thoughts, feelings, attitudes, and behaviors for self-growth [12, 67, 72]. Beyond quantifying and categorizing types of data-driven insights that are derived at one time (e.g., step counts and weather are positively correlated), attention should shift toward exploring deeper questions. These questions include what constitutes meaningful reflection across self-tracking stages, and how to facilitate the transition from shallow reflection (e.g., "*I feel happier when I exercise more*") to more in-depth ones (e.g., "*my recent physical activities have decreased, partly due to a busy work schedule but also because I've felt less motivated when exercising alone. This contrasts with my previous enjoyment of solo workouts. The underlying reason might be ...*"). To support such in-depth reflection, a starting point can be collecting more qualitative, expressive, and implicit personal data beyond quantitative, explicit and restrained values. Rather than telling users what their daily activities and experiences are, the data should serve as cues that open up richer interpretations for individuals to incorporate into their fluid and dynamic social practices, e.g. by maintaining the data's original forms, including unstructured texts, photos, audio, videos, and social media posts, preserves the nuances and details that can enrich individuals' data exploration experiences [56, 147, 215].

Without the restriction imposed by quantification, individuals are encouraged to engage in a more contemplative interaction with their personal archives rather than taking the data as a measurable standard. As Wang et al. discovered in their recent study with older adults, individuals sometimes "*preferred immersion over tracking*" for certain activities such as mental well-being, cognitive health, and social connectedness [224]. This preference for immersion does not imply abandonment of tracking; rather, it highlights the importance of identifying which aspects individuals find personally meaningful to track, which can minimize unnecessary interpretation burdens and provide individuals with a dynamic understanding of how their data intersects with their daily practices. As AI technologies advance in processing large unstructured information [159, 213, 225, 238], researchers can make PI systems adapt the data acquisition and analysis procedures, and design interfaces to actively communicate with users and seek their feedback for potential "new contexts." As one direction, a few studies have explored the use of conversational interfaces to gather information about individuals' activities, thoughts, and their living environments via natural language input [127, 141, 148].

5.1.2 *Data Sharing as Socially and Culturally Conditioned.*

As described in Section 4.3.3, PI systems are increasingly accommodating multiple users and stakeholders, indicating that personal data and insights generated are not confined to individuals but are integrated into broader social and cultural contexts. In such cases, the interactions between multiple stakeholders and data become deeply embedded within a broader, more intricate social structure. This structure is shaped by interpersonal relationships between individuals as well as by the underlying infrastructures and cultural norms. Adopting the data-centric perspective, prior work often placed emphasis on the data as the media for individuals to know each other and as the bridge to connect them. Inevitably, the complexities of the underlying social and cultural structures and infrastructures are not well considered, and can bring out tensions and conflicts regarding data access and relationship dynamics that researchers did not anticipate initially [9, 28, 118, 128, 146, 178, 185, 222]. To mitigate these tensions, we emphasize that the data being shared needs to take socially and culturally conditions into account, which involves the interpersonal relationships between the individuals who engage with the data as well as in the time and space where data sharing happens [79].

At the interpersonal level, the design of the data-sharing mechanisms should consider the relationships between those who share and receive data. For instance, the extent of data access might differ between close family members and more casual acquaintances. Similar to Epstein et al.'s mapping review [61], our review shows that prior work in PI frequently overlooks privacy concerns and risks. While some studies have touched upon the privacy risks of PI, there is limited empirical research dedicated to investigating specifics of these risks or strategies to address them, with a few notable exceptions including [60, 71, 184]. These studies shed light on potential opportunities for respecting and reinforcing the boundaries inherent in various types of relationships when it comes to sharing personal data, such as enabling customized privacy settings regarding who can access the data and to what extent for those with complicated mental health concerns [184], giving individuals the autonomy to fined-grain the data to be shared on social media [60], and employing an avatar-based pseudonym in communal data sharing [71]. Additionally, researchers noted that abstract composition of personal data, such as customized heart rate visualization with 3D printing materials, could be meaningful to individuals who created the data representation but does not necessarily reveal concrete information to others [6, 111].

As people increasingly utilize PI systems as part of navigating social infrastructures and building navigation competence [9, 33, 79, 130, 189], it becomes crucial to consider the implications of data sharing within the broader institutional level. For patients to share their health data with health providers, the burden associated with data sharing does not exist only in collecting, integrating, and managing the data [28, 239], but also in adapting the data to work with fragmented healthcare services for making plans and negotiating with stakeholders [79]. Consequently, patients may be overwhelmed by the complexity of various services and fail to effectively communicate their struggles and manage their health [79, 178]. On the health professionals' side, even though they recognize the benefits of data sharing, they may lack the time, resources, and capacity to organize, process, and analyze the data. As a result, the sharing process ends up burdening both parties instead of enhancing collaboration. These challenges underscore the need for a collective effort from the government, policymakers, hospital authorities, and healthcare industry to build a supportive infrastructure that can facilitate efficient information exchange in clinical settings, so as to ensure that data-sharing practices contribute positively to healthcare outcomes rather than strain the system and over-exploitation of resources from individual stakeholders. When it comes to PI system and device design, this means that we should adopt a practice-oriented design approach that engages with existing practices, institutional arrangements, and infrastructures [229]. Relatedly, in situations of data sharing on social media, the ways that the sharing platform is designed and moderated can also affect the social norms within the community and potentially create unhealthy data obsession and competition [39, 100, 130]. Therefore, in online communities where data are valued for exchanging ideas and providing peer support, joint efforts between the technical teams of community developers and the administrators, such as moderators, are required to foster a friendly communication culture and constantly monitor and adapt policies to ensure a safe space for data sharing.

5.2 From Data for Persuasion to Data for Empowerment

While acknowledging the values that PI can provide, such as positive behavior changes (e.g., increase in physical activities [37], improvements in productivity level [122]) and sense of achievement [148], our findings suggested that existing work largely derived values in PI from a persuasive perspective. That is, "persuading" individuals to improve their data as a way to improve themselves [1, 44, 148, 210]. This approach, as discussed above, has its limitations because data cannot fully represent reality. Moreover, several studies have shown that such persuasion-focused design (e.g., highlighting the goals that are not achieved) can cause unintended emotional stress, including rumination, guilt, and self-blame [40, 53, 122, 168]. Partially, the stress was induced by the authority that data were granted to symbolize one's successes and failures. Additionally, some designs of the PI interface may pass "invisible judgments" into the data presentation, such as by visually framing the data with negative connotations, which can further exacerbate the feeling of inadequacy and stress (e.g., use red color to highlight high-calorie intake may lead to eating disorder behaviors [54]).

To mitigate these unintended stresses and derive values in PI beyond persuasion, we see personal data as a means to empower individuals [204] rather than a way to evaluate or persuade them. Empowerment, despite its various definitions, is commonly recognized as "*a process by which people, organizations, and communities gain mastery over issues of concern to them*" in psychology [193]. In the HCI community, empowerment is extended to multiple aspects, particularly in creating "*empowering experience*" that promotes users' autonomy or self-esteem, and "*skills and education*" that helps users acquire skills or knowledge to benefit them [204], from which we see opportunities to empower individuals with PI.

5.2.1 *Data for Cultivating Positivity and Creativity.*

Empowering data-tracking experiences should enhance individuals' self-esteem and self-autonomy by cultivating positivity and resilience rather than enhancing peer comparison or social expectations. This is especially important in managing sensitive and stigmatized health conditions, such as fertility issues [39] and eating disorders [54, 150]. For instance, researchers have found that positive memories play important roles in alleviating emotional distress. This can be implemented by highlighting positive moments (e.g., a visual gallery of joyful photos) [91], visualizing data on playful and creative objects (e.g., 3D printing materials) [108–111, 111, 214]. In particular, Terzimehić et al. found that using internet memes for daily journaling could help people perceive negative events as more positive in retrospect, owing to the emotional and often humorous connotations of memes [214]. In another example, Maitland et al. highlighted the importance of PI systems recognizing partial goal completion as a strategy to boost individuals' confidence [156]. This idea aligned with Choe et al.'s investigation on visual framing of personal data, which demonstrated that highlighting achieved progress rather than the remaining challenges significantly enhanced individuals' self-efficacy towards achieving their goals [23].

Besides, allowing people to customize what data to track about themselves and how to represent the data, can offer them a high level of self-autonomy [6, 171, 191, 216]. As Ayobi et al. found, the seemingly burdensome bullet journaling practice with pen and paper allowed individuals to engage in mindful reflective thinking, because they were empowered to create narratives from their own lives without the constraints typically imposed by digital tools [6]. While a few research efforts have begun to build digitally customizable PI systems that allow individuals to decide what to track [4, 46, 123], their primary focus remains rooted in a dataistic perspective by prioritizing data quantification, categorization, and correlation over the qualitative and expressive dimensions that are crucial for empowerment. Echoing the "data in practice" call mentioned above, while collecting and processing data that are qualitative and unstructured (Section 5.1.1), future research can explore design strategies for individuals to actively integrate and transform their data into personalized and artistic presentations—like those creations in the popular book *Dear Data* [153], where individuals are empowered to create visualizations of their daily activities and small sentiment, such as number of hugs and times of complaints. Additionally, drawing from the theory of embodied cognition, there has been growing interest in using bodily actions to delineate personal feelings, such as hand-gesture-based emotion tracking [152]. These approaches opened new possibilities for integrating embodied and expressive techniques into self-tracking practices, directing individuals into an more creative and open-ended mindset towards their data rather than solely focusing on improving the data.

5.2.2 *Data for Enhancing Literacy.* Effectively reading, interpreting, and making sense of data demands a combination of literacy skills that span across data comprehension, visualization techniques, and domain-specific knowledge [48, 151, 178]. As researchers found, health literacy significantly affected one's ability to share and explain their health data at clinics [151]. However, the majority of existing PI systems are designed with limited consideration of the target users' literacy. As our findings showed, patients often have little knowledge about whether the data they tracked is relevant to their health conditions [178]; athletes are guided by their data to conduct training without a clear understanding of how the data contributes to their health and performance [33]. This empirical evidence prompted us to consider not only how to take individuals' literacy levels into account when designing PI systems, but also how to actively enhance their relevant literacy through the adoption of these systems.

Essentially, the interface that presents personal data should be able to adapt its language and visual cues appropriate to various literacy levels. While graphic charts are mostly commonly employed for individuals to identify trends and patterns [21, 24, 59], such design may not be inclusive for individuals with limited visualization literacy or data expertise. Thus, additional presentations can be incorporated, including but not limited to natural language descriptions of key trends [8], and voice interaction that allows individuals to proactively inquire about their data [124, 148]. Furthermore, existing tools designed to improve data literacy, visualization literacy, or health literacy often rely on generic data sources, which may not resonate with everyone [7, 10, 47]. PI systems, on the other hand, offer a unique advantage by utilizing data that is intimately connected to the individuals' personal activities and life situations, which holds promise to motivate and engage users as well as foster proactive learning and exploration experiences. To better leverage this advantage, PI researchers can incorporate learning components into their designs. For example, enhancing visualization literacy could involve displaying the same dataset through various visual formats (e.g., multiple chart types to illustrate data trends [24]); improving health literacy might involve using real-world analogies and visual cues to explain the data (e.g., illustrating how certain amounts of calorie counts can be mapped to the food that people are familiar with [20]).

6 Limitations

We acknowledge that our literature corpus might have omitted other relevant work published in venues beyond the scope of our search, some early work without the specific keywords (e.g., "personal informatics," "self-tracking"), and the latest work published after February 2024, but we have incorporated those known works in the discussion to the best of our knowledge. After identifying the 172 research articles, we did not employ forward and backward sampling based on citations of the included papers because the size of our literature corpus is much larger than a typical review.

However, we believe that the key findings of our review would not be affected by the possible omission of certain papers, because we focused on qualitative insights rather than quantitative statistics, and the findings we report here are themes across various studies instead of individual paper-focused. Additionally, it is important to note that conducting such a review is a meticulous and time-consuming process, involving multiple iterations of screening, analysis, and discussions among the team members. Our review follows a rigorous and systematic procedure, covering a large set of research articles from top-tier HCI venues, and took over two years to complete.

7 Conclusion

Through a critical examination of 172 empirical research articles, we identified five widely observed unintended consequences of using PI systems: burdens on cognitive load, negative impacts on emotions, tensions with social acts, counterproductive behaviors, and practical challenges. By tracing back the origins of these consequences, we synthesized their root causes involving the data-centric design ideology, individualized tracking needs and literacy, the social dynamics around them, and their intention-behavior gap. Our findings provided a perspective that acknowledges and articulates the limitations of granting data with authority and power to reflect real-life situations, make decisions, and take action. Rather than diminishing the values that PI can promote better well-being and life quality, we echo the "turn to practice" movement in HCI, calling for future research to re-ground studies from data-centric to data in practice and aiming to empower rather than persuade individuals. Taken together, our review not only enriched and broadened the existing landscape of PI research through a critical lens but also contributed to discussions on future research directions to better situate the interaction between individuals and the PI systems.

Acknowledgments

We thank Xumu Jiang for helping with the initial screening of the literature; this work is supported by City University of Hong

Kong (#9610597 and #9229183). The paper has undergone several revisions since our first submission in 2023, thus it has been quite a journey to make it here. We are grateful for all the insightful reviews we received along the way, which helped us iteratively strengthen the arguments, refine the analysis, and eventually get the work published.

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