A Meta-Synthesis of the Barriers and Facilitators for Personal Informatics Systems

KAZI SINTHIA KABIR, Kahlert School of Computing, University of Utah, USA
JASON WIESE, Kahlert School of Computing, University of Utah, USA

Personal informatics (PI) systems are designed for diverse users in the real world. Even when these systems are usable, people encounter barriers while engaging with them in ways designers cannot anticipate, which impacts the system's effectiveness. Although PI literature extensively reports such barriers, the volume of this information can be overwhelming. Researchers and practitioners often find themselves repeatedly addressing the same challenges since sifting through this enormous volume of knowledge looking for relevant insights is often infeasible. We contribute to alleviating this issue by conducting a meta-synthesis of the PI literature and categorizing people's barriers and facilitators to engagement with PI systems into eight themes. Based on the synthesized knowledge, we discuss specific generalizable barriers and paths for further investigations. This synthesis can serve as an index to identify barriers pertinent to each application domain and possibly to identify barriers from one domain that might apply to a different domain. Finally, to ensure the sustainability of the syntheses, we propose a *Design Statements (DS)* block for research articles.

CCS Concepts: • **General and reference → Surveys and overviews**.

Additional Key Words and Phrases: Personal informatics, self-tracking, meta-synthesis, barriers and facilitators

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1 INTRODUCTION

Many personal informatics (PI) systems provide personalized feedback to support users in their everyday lives. For instance, fitness trackers collect users' physical activity data and send feedback to encourage more physical activity. However, the implementations of these systems need to consider the diverse barriers and facilitators that users may encounter while engaging with them (e.g., workload, interpersonal contexts) that influence the system's effectiveness. For instance, while reminders are widely considered helpful for supporting adherence, one practitioner in Colusso et al.'s study commented about designing such systems [31]:

> *"... system notifications are great, but guess what? Doctors have a hundred other notifications in their day, so we have to think about that problem differently ..."*

The PI literature extensively studies how people *collect* data and *reflect/act* on the data using these systems. However, the research findings are scattered across an enormous volume of literature that is growing at an increasing pace [50]. Even for researchers who focus on PI in their research, it is impractical to expect that they will have this wealth of knowledge readily accessible in their minds. The challenge is even greater for researchers across disciplines and practitioners in industry. Researchers and designers often design systems that encounter

Authors' addresses: Kazi Sinthia Kabir, kskabir@cs.utah.edu, Kahlert School of Computing, University of Utah, Salt Lake City, Utah, USA, 84112; Jason Wiese, jason.wiese@utah.edu, Kahlert School of Computing, University of Utah, Salt Lake City, Utah, USA, 84112.

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the same barriers already documented in the literature and, thus, invest resources only to discover the same challenges that have been previously documented [92, 200]. These situations result in inefficient allocation of time and resources and can impede progress in research. Furthermore, industry practitioners, constrained by limited time for reading papers, seek assistance from alternative resources (e.g., blog posts, slack) [31].

A meta-synthesis of the literature can make this knowledge more accessible, and can help researchers see where they contribute their new ideas to existing knowledge and develop new research questions. Therefore, the core contribution of this work is synthesizing the PI literature to date with a particular focus on the different barriers and facilitators for *collecting data* and *reflecting/acting* on the data using these systems.

This work synthesizes 214 PI articles from the *'personal informatics paper browser'* [1]. We carefully reviewed these articles for an in-depth understanding of the different barriers and facilitators they describe for 1) *collecting* personal data and 2) *reflecting/acting* on the personal data using PI tools in real-life. We then synthesized these insights into eight primary categories, each containing a deeper analysis of the different barriers and facilitators for *collection* and *reflection/action* based on the literature. This paper also discusses insights that can be drawn based on this synthesis. We delve deeper into the gaps and nuances in the existing knowledge that open paths for future exploration. To make it easier and more scalable to synthesize future research, we propose a *Design Statements (DS)* block that could be included in future research articles. In summary, this work makes the following contributions:

- Identifies eight broad categories of barriers and facilitators for *collection* and *reflection/action* using PI tools synthesized from more than ten years of PI research.
- Discusses generalizable insights, gaps, and nuances in the existing literature for further investigation.
- Proposes including a contribution statement in research articles to make the design recommendations easily accessible for readers within academia and beyond.

2 BACKGROUND AND MOTIVATION

PI systems are defined as *"systems that help people collect personally relevant information for self-reflection and self-knowledge"* [120]. A wealth of literature has studied people's usage of these systems. However, the rapidly evolving literature poses a challenge for researchers to stay up-to-date with the enormous volume of knowledge and subsequently, PI research often encounters the same barriers already documented in the literature.

2.1 Barriers and Facilitators for PI Systems

PI systems have gained much attention in the past decade in research and industry, especially for supporting health and well-being [199]. Researchers have explored PI systems for supporting a broad set of application domains, like reducing substance use [185], supporting a healthy lifestyle [61, 112], managing finances [54], and improving productivity [138]. In academic research, these systems have been shown to be effective and acceptable to users [74]. However, in the real world, even when these systems are deemed usable, people may encounter diverse barriers to usage that designers did not anticipate [174, 175, 186].

Prior literature has worked to delineate different stages of self-tracking. Li et al. defined the stages of self-tracking as *preparation, collection, integration, reflection, and action* [120] in their stage-based model of PI systems. They further discussed different barriers and facilitators for each stage based on user surveys. However, more recent literature argued against the assumption that the goal of PI systems is *action* and that instead, people may have diverse goals for tracking, like determining causality, self-knowledge, or self-experimentation [54, 144]. As a result, Epstein et al. proposed a model that divided the *preparation* stage into *deciding and selecting* and combined *integration, reflection, and action* into *tracking and acting*. They also introduced two other stages: *lapsing and resuming*. A later review of the PI literature again by Epstein and colleagues indicates that PI research extensively studies the *collection*, *reflection*, and *action* stages, and in that work, they chose to adopt Li et al.'s stages in their

analysis [50]. Therefore, we focus our meta-synthesis on these stages. However, since not all self-tracking desires explicit action, in our synthesis, we study the barriers and facilitators for *reflection* and *action* together and note them as '*reflection/action*.'

2.2 The Proliferating Body of PI Literature

PI literature is growing rapidly, with over 70 articles published per year since 2015 [50]. This poses a critical challenge for researchers and designers to stay informed about the content of this literature. For instance, even though multiple papers published in 2014-2015 reported that people tend to avoid tracking undesirable data in diet tracking (e.g., [19, 33]), PI papers published in 2019 did not anticipate this phenomenon for diet tracking as well as other domains like substance use or mental health management (e.g., [119, 208]). Bruun et al. explicitly reported in their paper that some of their findings were reported in the past literature and were unintended findings for them [15]. This is unsurprising since it is incredibly challenging for any researcher to keep track of the constantly expanding research knowledge. However, Kabir et al. emphasized that anticipating some of the barriers and facilitators earlier in the design process could reduce the time and resources needed for iterative user-centered design [92].

Note that these articles were mostly published in SIGCHI and UbiComp venues. However, even for PI experts who stay up to date with these venues, it has been challenging to keep track of all the known barriers for PI systems reported in the literature. While this is certainly a challenge for interdisciplinary researchers, it is far more difficult for design practitioners with limited time and resources to study academic articles [32].

To make PI literature more accessible, Epstein et al. coded a set of PI articles published through 2019 with their tracking domain, stages of tracking based on Li et al.'s model [120], contribution types, motivation for tracking, study method, etc. [50], and created the living repository called *'personal informatics paper browser'*. This browser allows authors to submit their papers for inclusion in the repository [1]. It is an excellent resource for PI researchers; however, one challenge remains: reading all of those papers and having it readily accessible in mind. Prior works have systematically reviewed the PI literature to understand the broader impact of these works [73, 187] and identify challenges and opportunities [7, 202]. Based on the literature and their prior work, Gulotta et al. identified eight barriers to users' engagement with achievement-based PI systems [71]. However, they do not explicitly report their process for identifying these barriers. In their systematic review, Epstein et al. [50] also coded the papers with one of nine 'everyday challenges' for PI tools that they have identified (if applicable). However, a deeper analysis of these challenges was not within the scope of their review.

A literature synthesis focusing on the barriers and facilitators for using PI systems could make the knowledge more easily accessible, support their translation across disciplines and industry design practices, and open up new paths for research explorations. However, to our knowledge, no prior work has synthesized the entire PI literature to understand the different barriers and facilitators that people encounter while adopting PI systems. In summary, we identify a need for a meta-synthesis of the PI literature that can help researchers make the knowledge around barriers and facilitators for engagement with PI systems more accessible to cross-disciplinary research and design.

3 METHODS

We reviewed 214 PI articles to identify barriers and facilitators for users' engagement with PI systems in the *collection* and *reflection/action* stages. Since meta-synthesis is not as common in UbiComp and HCI as in other domains, our methods are partially informed by similar work in healthcare and medicine [83, 115, 200] along with our adaptations following best practices within UbiComp and HCI. This section describes our methods in detail such that this process can provide methodological guidance for other researchers.

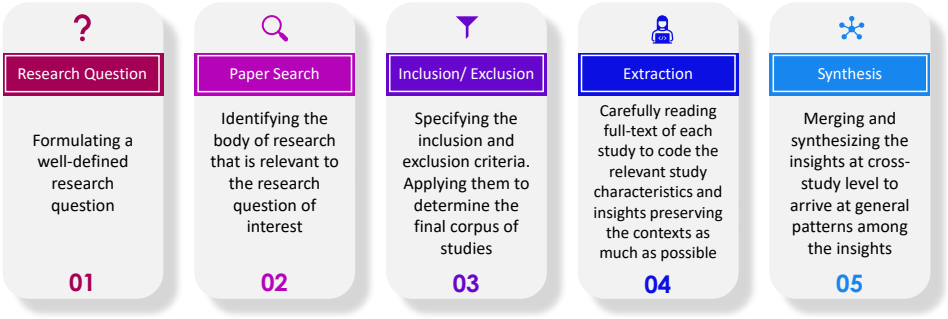

Fig. 1. The step-by-step process that we followed in this work for conducting meta-synthesis of literature

Framing the research question: Unlike typical systematic literature reviews, researchers should start a meta-synthesis by defining well-specified and theoretically informed research questions [83]. Therefore, the first step for meta-synthesis is framing the research question (see Figure 1) that is "*broad enough to be of interest but small enough to be manageable*" [115]. In the PI literature, studies heavily focus on the *collection, reflection* and *action* stages [50] of Li et al.'s stage-based model of PI systems [120]. This motivates our research questions in two ways- 1) there is a wealth of PI literature focusing on these three stages making this domain broad enough to explore, and 2) barriers and facilitators for users' engagements in these three stages have the potential to impact the effectiveness of the system (discussed in Section 2.1). Therefore, we specify our research questions as follows:

- What barriers and facilitators are known in the literature that impact the *collection* of accurate data in PI systems?
- What barriers and facilitators are known in the literature that impact the usage of PI data through *reflection/action*?

Paper search: Ideally, the paper search for meta-synthesis should be as exhaustive as possible [83, 200]. Epstein et al.'s *'PI paper browser'* [1] contains an extensive corpus of PI literature indexed by ACM Digital Library, IEEE Xplore, and PubMed. 523 of these articles were published in 2019 or earlier [50]. The browser allows other researchers to submit their publications for inclusion in the repository voluntarily. The researchers who maintain the *'PI paper browser'* then include them in the repository with the relevant codes [1]. In this way, 49 articles published in 2020 or later were further added to the browser. We build on this extensive corpus of literature provided by Epstein et al. Therefore, we retrieved the corpus from *'PI paper browser'* on June 3, 2022, and found 572 papers. These papers were then uploaded to a shared reference management system named *Paperpile*[1].

Inclusion and exclusion of papers: *'PI paper browser'* coded the papers with their contribution types (e.g., *empirical, artifact, methodological, etc.*) following the categorization of Wobbrock & Kientz [205]. We first used these codes to exclude the *survey* papers and then read the abstract and results to exclude other papers with *opinion, theoretical, methodological, and artifact* contributions that do not present any *empirical* findings based on studying users. None of the papers were coded with *dataset* contribution. However, if any paper with the contribution types mentioned above also reported *empirical* findings based on user studies, we included them in our initial corpus.

Next, we carefully read the findings reported in the paper to exclude other papers that do not report users' engagement with the system in the *collection* and *reflection/action* stages (e.g., reports on system accuracy). After

[1]https://paperpile.com/app

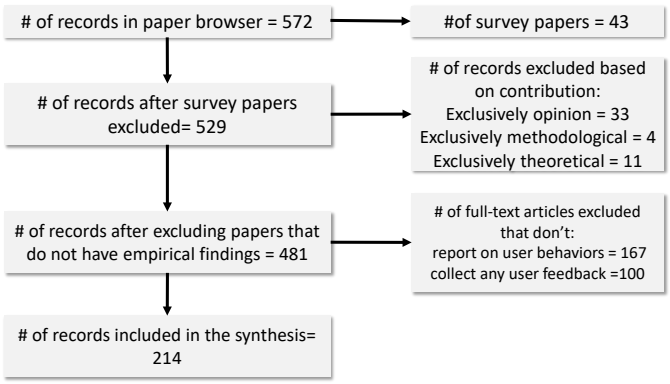

Fig. 2. The flow diagram for systematically extracting the papers for synthesis from the *'PI paper browser'*

these exclusions, we had a corpus of 214 papers that reported participants' engagement with the PI systems in the *collection* and/or *reflection/action* stages (see Figure 2).

Extracting and coding the data: We extracted the relevant information from the 214 papers in the next phase. Guided by our research questions mentioned earlier, we identify the following information as relevant to our synthesis:

- Application domain
- Participants' demographics
- Method of tracking
- Barriers & facilitators for *collection*
- Barriers & facilitators for *reflection/action* (if any)
- If the feedback was adaptive
- If the system considers users' receptivity
- How the system deals with incomplete data (if reported)

We carefully read the sections describing the methods, results, and other relevant discussions of the 214 papers to extract and code these details. While extracting the information from each article, we summarized very loosely to draw the inferred themes and concepts from the narrative. For instance, the statement from one article [5] that participants engaged in "*correcting entries to improve the accuracy of their documentation*" was summarized as the concept that participants were 'altering' the data. However, as literature suggests [200], we tried to preserve the original text's meaning as much as possible.

Next, we created affinity notes [127] from the extracted data on barriers and facilitators users encounter in *collection* and *reflection/action* stages separately through an open coding process in *ATLAS.ti*[2]. In this process, we created 174 affinity notes on barriers and facilitators in the *collection* stage and 117 affinity notes on barriers and facilitators in the *reflection/action* stages. Each affinity note was potentially linked to more than one paper. As an example of the process, we show how two findings from two articles were both assigned the affinity note *'deleted/altered data'* and one of them was also assigned the affinity note *'tracked in retrospect'*:

> *'Participants engaged in retrospective styles of tracking when checking and correcting entries to improve the accuracy of their documentation, given that the severity and perception of symptoms may change'* [5] → [deleted/altered data], [tracked in retrospect]
> *'they could delete data they did not desire to share.'* [109] → [deleted/altered data]

[2]https://web.atlasti.com

Synthesis of the data: We copied each affinity note into *Miro*[3]. Two researchers with strong PI expertise synthesized the data to ensure the soundness of analysis through triangulation [158]. We used the affinity notes to create affinity diagrams and iteratively grouped the notes to understand the patterns in these interactions. We tracked the number of papers that report on each affinity note to observe the frequency of these behaviors in the literature. As literature suggests, the recurrence of themes can add strength to the validity of the analysis [56]. We created separate affinity diagrams for barriers and facilitators for *collection* and barriers and facilitators for *reflection/action*. We adopted a bottom-up approach and let the categories naturally emerge from the data. When we found a new pattern in the affinity notes, we defined a new category.

However, after the first grouping of the affinity notes, we observed repeated themes between the categories of barriers and facilitators for *collection* and *reflection/action*. Therefore, the two researchers performed a re-analysis of the affinity notes specifically focusing on the types of barriers and facilitators instead of the PI stages (i.e., *collection*, *reflection/action*). Finally, we found eight categories of barriers and facilitators for users' engagements in the *collection* and *reflection/action* stages. Within each category, we then grouped the barriers and facilitators for *collection* and *reflection/action* together for deeper insights based on the stages. To view this synthesized knowledge together, we also generated a heatmap with the application domains, their relevant barriers and facilitators, and the frequency of those engagements in Figure 4.

3.1 Limitations

We acknowledge that qualitative data can be analyzed from different perspectives, and the researchers' backgrounds may influence the qualitative analysis. However, we ensured that within that perspective, the analysis of the affinity notes was consistent. Furthermore, we only synthesized the articles indexed by the *PI paper browser* in this work. Though the PI paper browser captured a range of work from computing, sensing, and health informatics, this selection process might have excluded other articles reporting similar issues. However, we believe this work encompasses extensive research findings reported in the PI literature published in SIGCHI and UbiComp venues and offers a synthesis for deeper insights into them.

4 RESULTS

Synthesizing the findings reported in the 214 PI papers, we observed eight categories of barriers and facilitators users encounter in the *collection* and *reflection/action* stages while using PI tools. These categories reveal different individual perspectives, personal, interpersonal, and situational contexts, system-induced harm, fluctuations in motivation, design and implementation issues, and situations threatening data integrity as barriers to *collection* and *reflection/action* in PI tools. Each of the following subsections presents these categories and further delineates the barriers and facilitators specific to *collection* and *reflection/action* and discusses them in detail.

4.1 Threats to Data Integrity

People collect data using PI tools to improve their behavior or condition or for self-knowledge. Irrespective of the goal, there are situations where they collect data in a way that threatens the integrity of the data. For instance, people manipulate the data to portray a 'good' image of themselves or change the the data's granularity to balance the tracking burden. When the data's accuracy becomes questionable, people tend to perceive the data and the resulting feedback as untrustworthy. Consequently, these issues threatening data integrity are barriers to using PI tools. Factors threatening data integrity were the most frequently reported category in the literature.

4.1.1 Impacts on Collection. A wealth of literature reported that people manipulate self-tracked data to maintain a positive self-image, often by cheating, skipping undesirable data, or altering entries. Other issues that threaten

[3]https://miro.com

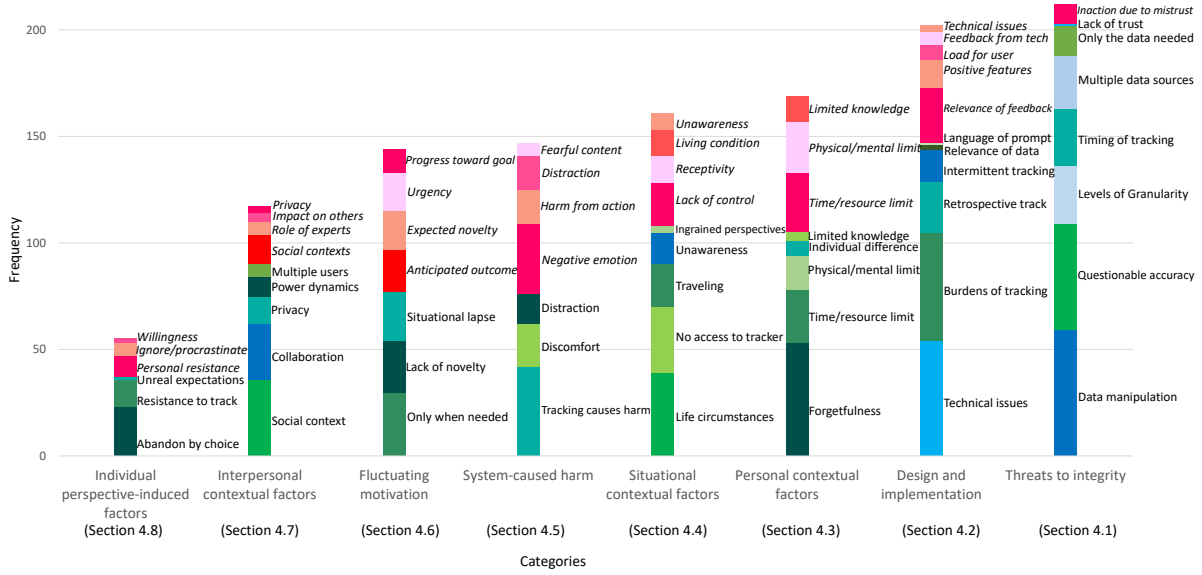

Fig. 3. The number of papers that report on each of the eight categories of barriers and facilitators for *collection* and *reflection/action* using PI tools. Different colors represent the sub-categories within each category, and their height represents their frequency. Straight text right to the bars also differentiates barriers and facilitators for *collection*, and italic text represent barriers and facilitators for *reflection/action*. Note that some papers reported on multiple sub-categories within each category. To observe the prevalence of the engagement types, we counted the frequency of each sub-category. The bars in this chart show the aggregated frequency for each category. The numbers in parentheses for each primary category represent the subsection numbers in this paper where they are discussed.

collection integrity are non-compliance with measurement protocols, misunderstanding questionnaires, subjective data influenced by memory and context, and adjusted granularity of data. Literature also noted that duplicate or redundant data can arise from multiple sources or simultaneous measurements. This section discusses these scenarios that impact the data in the *collection* stage.

Data manipulation. Articles widely reported that people care about having a 'positive image' of themselves through the data (e.g., [19, 206]). Consequently, people cheat with the self-tracked data or tweak them to have a more acceptable self-image (e.g., [88, 105]). Moreover, 16 articles reported that people skipped tracking undesirable data (e.g., high-calorie food [34], poor mental health [145]). Seven articles explicitly reported shame or guilt contributing to such behavior (e.g., [11, 152]). Some people adjusted their tracking to force a particular outcome or diagnosis [57, 203]. In these situations, the system will have untruthful data or no data at all. Again, people often deleted or altered the data they tracked (21 articles). The reasons for deletion and alteration of data include privacy concerns [109, 145], improving the accuracy of data [5], and the desire to keep data tidy [177]. Some people reported a desire to track things not supported by their tool. Such users tried their workaround by replacing the meaning of a variable with what they wanted to track. This strategy was observed in chronic condition management [97]. However, data manipulation most commonly occurred in diet (12 articles) and physical activity tracking (14 articles, see Figure 4).

Questionable accuracy. Fifty articles reported scenarios of *collection* that threaten the data accuracy (e.g., [6, 135]). In some applications, failure to comply with the measurement protocol resulted in inaccurate data (e.g., sleep [22],

			Physical activity	Chronic condition	Sleep	Diet	Mental health	Productivity	Childcare	Substance use	Women's health	Overall health	Weight	Senior care	Medication	Patient care	Sports activity	Finances	Location	Indoor air	Fluid intake	Phone usage	Screen time	Heart rate	Personal communication	Workplace environment	Music listened to	Commuting practices
Threats to data integrity (Section 4.1)		Questionable accuracy	7	10	9	7	11	2	2	0	1	2	0	0	1	1	1	0	0	0	0	1	0	1	0	1	0	0
		Abandoning due to lack of trust	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Data manipulation	14	6	7	12	6	4	2	2	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
	C	Tracking only the data needed	1	8	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Levels of granularity	4	10	1	4	3	0	2	0	2	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
		Multiple sources of data	3	5	1	1	1	5	0	0	2	2	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
		Timing of tracking	3	5	3	5	3	3	1	0	3	0	0	1	1	0	0	0	0	0	0	0	1	0	1	1	0	0
	R/A	Inaction due to mistrust	2	3	2	1	1	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Design and implementation (Section 4.2)		Language of the Prompt	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Retrospective tracking	1	6	3	6	4	1	2	0	1	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
		Intermittent tracking	6	3	1	2	0	0	0	0	0	2	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0
	C	Technical Issues	20	4	6	9	5	1	3	1	2	2	2	2	2	1	0	0	0	0	1	1	1	1	0	0	0	0
		Burdens of tracking	17	7	3	10	7	2	4	1	2	1	3	0	1	1	1	1	1	0	0	0	0	1	0	0	0	0
		Relevance of data to track	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Positive features	5	0	1	1	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Technical issues	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
	R/A	Impractical load for users	2	1	3	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0
		Feedback from technology	4	0	2	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Relevance of feedback	8	2	4	2	0	2	1	2	2	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0
Personal contextual factors (Section 4.3)		Limited knowledge/skill	2	0	1	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Physical & cognitive limits	1	7	0	0	4	0	1	0	0	1	1	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0
	C	Forgetfulness	21	3	11	7	4	2	2	1	2	2	1	1	3	1	0	1	1	0	0	1	0	0	0	0	0	0
		Limited time & resources	3	8	1	4	2	0	1	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
		Individual differences	1	2	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Limited knowledge/skill	2	2	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
	R/A	Limited time & resources	12	5	5	1	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
		Physical & cognitive limits	12	5	3	2	2	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
Situational contextual factors (Section 4.4)		Traveling	10	1	4	3	0	0	1	1	0	0	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0
		Diverse life circumstances	11	6	5	4	6	1	2	1	0	0	1	1	1	3	0	1	1	0	0	1	0	1	0	0	0	0
	C	Unawareness	0	3	0	2	3	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
		No access to tracker	16	2	5	5	1	0	3	0	0	0	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0
		Ingrained perspectives	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Lack of control over situation	6	2	5	0	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
	R/A	Living condition	3	1	5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
		Unawareness	5	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
		Receptivity to feedback	6	3	1	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
System-caused harm (Section 4.5)		Tracking causes harm	10	9	6	7	6	1	1	2	4	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	C	Distraction	4	4	2	1	4	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Discomfort	10	2	7	2	2	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Negative emotional reaction	6	7	3	4	4	2	1	2	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
	R/A	Fearful content	1	2	0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Harm from reflection/action	1	2	3	0	2	1	0	4	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
		Distraction	8	1	1	1	3	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
Fluctuating motivation (Section 4.6)		Situational lapsing	6	6	0	3	0	1	0	2	3	1	1	1	0	0	0	1	1	0	0	0	0	1	0	0	0	0
	C	Tracking only when needed	2	10	1	3	2	0	3	0	1	1	0	2	0	2	0	0	0	1	0	0	0	0	0	0	0	0
		Lack of novelty	8	5	4	4	1	0	1	0	0	0	0	2	0	0	0	1	1	0	0	0	0	0	0	0	0	0
		Progress toward goal	6	2	1	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	R/A	Urgency of situation	3	3	3	1	3	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
		Expectations of novelty	7	1	1	0	1	1	0	3	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
		Anticipation of outcome	7	2	2	2	4	1	0	2	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Interpersonal contextual factors (Section 4.7)		Aspects of collaboration	3	7	2	3	5	0	3	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0
		Power dynamics	0	4	2	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	C	Multiple users of PI tool	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
		Social contexts	8	6	7	7	3	0	1	1	1	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	1	0
		Privacy concerns	2	1	2	0	2	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0
		Social context	5	3	1	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	R/A	Impact on friends and family	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Role of experts	1	3	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
		Privacy concerns	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Individual perspective-induced factors (Section 4.8)		Abandonment by choice	11	1	5	1	5	3	1	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
	C	Resistance to tracking	2	4	0	1	1	2	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
		Unrealistic expectations	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Resistance to technology	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R/A	Ignorance or procrastination	3	0	0	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Willingness to change	1	1	1	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 4. A heatmap representing the frequency of each sub-category of barriers and facilitators for users' engagements with *collection* and *reflection/action* in self-tracking for different application domains. Each cell lists the number of papers we examined in that domain that discusses that barrier. The sub-categories within each primary category are grouped together for *collection (C)* and *reflection/action (R/A)* and differentiated with different color shades (light green or white). A '0' in a cell indicates that no article reported that barrier for that application domain.

blood pressure [104, 196]). In ecological momentary assessment (EMA)-based self-tracking, users misunderstood the questionnaire and responded with incorrect data [142, 193]. Eighteen articles reported that it was difficult to maintain consistency in subjective data tracking, and data was influenced by their memory, context at the moment, and prior experiences (e.g., [103, 120, 134]). Scenarios threatening the data accuracy were more frequently reported in mental health (11 articles) and chronic condition management (10 articles, see Figure 4).

Tracking only the data needed. Fourteen articles reported that people track specific things that they care about or are important to them (e.g., [64, 140]). This strategy was frequent in chronic condition management (8 articles, see Figure 4). One explanation for chronic symptom tracking (e.g., migraine) is that people may not experience all the symptoms listed in the tracker, and, therefore, they skip the symptoms irrelevant to them [182]. Other people may adopt this strategy to reduce the burden of tracking over a long time (e.g., [5]) or to balance other complexities of life (e.g., [184]).

Levels of granularity. People may have different choices about the granularity of the data they track. While a few articles reported that their participants wanted to track detailed data (e.g., [64, 93]), others reported that participants reduced the granularity of the data to reduce the burden of tracking (e.g., [102, 196]). In some cases, the granularity of the tracked data varied depending on the participant's perception of the condition (e.g., tracking more details when having more disease symptoms [26, 184]). This issue is more frequently observed in chronic condition management (10 articles, see Figure 4). Since participants already have the burden of chronic health issues, they may balance the burden of tracking by adjusting the granularity.

Multiple sources of data. Sometimes, same data comes through multiple sources leading to duplicate, redundant, or conflicting data [47, 194]. Sixteen articles reported situations where people logged the same data using multiple devices. This issue was more commonly reported in productivity tracking (5 articles, e.g., [44, 110]) and chronic condition management (5 articles, e.g., [166, 182]). Sometimes, people take multiple measurements simultaneously, leading to redundant data [173, 196]. Again, when people track collaboratively, data from multiple stakeholders may lead to multiple copies of the data [160]. Articles also reported situations where activities happening over multiple days might lead to duplicate data (e.g., research activities in productivity tracking) [113]. In a few cases, participants took measurements with other people's devices when they did not have access to their own devices resulting in multiple data sources [17].

Timing of tracking. The timing of data collection can also pose threat to the collected data's integrity (reported in 27 articles). Four articles reported the difficulty of tracking activities that happen over time (e.g., buffet dinner [33]). In such situations, users might miss tracking certain items or be forced to track them later. However, articles also report that retrospective data is subject to recall bias [26, 34], especially if the data is subjective data [124, 169]. Again, in some applications (e.g., IBS symptoms), tracking was expected within a certain period. However, the symptoms to be tracked appeared outside of that period, and the user did not track them [97, 183]. Interestingly, one article reported that parents of infants had to track at the end of the day, and since that was already past midnight, the record showed that they logged in the next day [76]. The system might misinterpret these scenarios if they are not appropriately addressed. Again, in some applications, the accurate measurement of the data depends on the time they were measured (e.g., ovulation [36, 80]). If the user fails to comply with the timing instructions, the data might be incorrect even if they were logged in real-time. The *timing of tracking* issue was more often reported in diet tracking (5 articles) and chronic condition management (5 articles, see Figure 4).

Abandonment due to lack of trust. One article reported that people may abandon tracking if they do not trust the PI tool. People stopped tracking when the system generated unacceptable output (e.g., a false alarm in the middle of the night [201]).

4.1.2 Impacts on Reflection/Action. Next, we discuss our observation on the influence of trust on users' *reflection/action* based on the synthesis.

Inaction due to mistrust. One key component that drives the users' *reflection/action* based on feedback is their trust in the feedback. Nine articles reported that users did not respond to the feedback because they did not trust them (e.g., [97, 148, 171]). For instance, users sometimes downplayed the insights provided in the feedback when they did not trust the accuracy of the data [87].

4.2 Impact of Design and Implementation

It is well-known in HCI and UbiComp that the design and implementation of tools influence their adoption by the users. In this synthesis, we identified specific design and implementation factors of PI tools that influence users' engagement in *collection* and *reflection/action* stages. Some contributing factors are the relevance of the data to track, the amount of burden for the users, the language of the notifications, and technical issues. We also noted specific design features that were helpful for the users. This section highlights the aspects of design and implementation that influence engagement.

4.2.1 Impacts on Collection. Users' responses to data collection prompts can be influenced by how they perceive the prompts and the amount of effort required for such collection. The burden of tracking is a key contributing factor, including carrying extra devices, complex data collection processes, and manual tracking. Users appreciated the tool when designs accommodated retrospective and intermittent tracking for users who cannot track in time due to cognitive or physical limitations, forgetfulness, or social contexts. This section presents these observations based on the literature synthesis.

Language of self-report prompt. People's response to a self-report prompt may also depend on how they perceive the prompt [141]. For instance, if they perceive that the prompt is asking for data assuming a worsening health condition, they might avoid responding to that prompt fearing an undesired diagnosis. This issue was reported in one article on chronic condition management for older adults.

Retrospective tracking. Twenty-five articles reported that people tracked data in retrospect for various reasons, including data lost for technical issues [139], unable to track due to cognitive or physical limits [5], forgot to track [64, 194], and unable to track in social contexts [23]. Some articles also reported that users tracked in real-time; however, they logged additional details in retrospect [150, 172], or corrected entries in retrospect to improve accuracy [5]. Retrospective tracking was more common in diet (6 articles) and chronic condition management applications (6 articles, see Figure 4).

Intermittent tracking. Fifteen articles reported that people using self-tracking systems pause and resume tracking intermittently to adjust for diverse scenarios of life, including holidays, weather, injuries [54], changes in life circumstances [54, 98], owning multiple devices [149], and reducing the burden of tracking [52, 173, 191]. This tracking strategy would result in no data for specific periods that may impact the system's effectiveness. Intermittent tracking was more frequently reported in physical activity tracking (6 articles, see Figure 4).

Burdens of tracking. Another frequent issue reported in the literature is the burden associated with tracking (reported in 51 articles). Some specific burdens mentioned in the literature include carrying an extra device for tracking [28, 99], complex process of data collection [33, 120], required granularity of the data [42, 121], and a manual process for tracking [10, 145]. Burdens of tracking were most frequently reported as a barrier for physical activity tracking (17 articles, see Figure 4).

Relevance of data. The relevance of the data for tracking also impacts users' motivation to track them. Two articles explicitly reported that participants did not track when the data felt irrelevant to them [17, 45].

Technical issues. Fifty-four articles reported technical issues that may result in partial, missing, or even overload of data. People could not track certain activities or dietary items since they were not listed in the database [33, 75]. In a few cases, the tracker's battery died in the middle of tracking an activity [66, 126]. Seven articles reported that the tracking device did not fit well or got misplaced, leading to inaccurate data (e.g., [126, 193]). Participants paused tracking when the tracker generated too much heat or drained the battery of their phone [22, 75]. Participants also removed their tracking device to prevent damage (e.g., from water while swimming) to the device [62, 191]. On the other hand, people sometimes used multiple devices or took multiple measurements, creating a data overload for the PI system [173, 194]. In a few cases, automated trackers misinterpreted the context and assigned a wrong default [53, 111]. For instance, one menstrual tracker could not account for longer than average menstruation periods. The tracker misinterpreted that the user forgot to record the end of the menstruation period and automatically recorded it on behalf of the user even though, in reality, the menstruation period was not over [53]. While technical issues were reported in nearly all application domains, they were more often reported in physical activity applications (20 articles, see Figure 4).

4.2.2 Impacts on Reflection/Action. Similar to *collection*, the design and implementation of PI tools influence how users *reflect/act* on the feedback from these tools. The synthesis showed that some users find *reflection/action* prompts burdensome and impractical, leading to reluctance to engage. The perception of feedback differs between human-generated and technology-generated sources, with some users disregarding feedback from computers. Positive design features that enable actionable and easily understandable feedback are more effective. Next, we discuss these design and implementation issues from the viewpoint of their impact on *reflection/action*.

Impractical load for users. Seven articles reported scenarios where the *reflection/action* imposed an impractical burden on the users and, subsequently, users were reluctant to engage with them. For instance, when the activity tracker keeps increasing the goal indefinitely (e.g., 10k, 12k, 14k steps), users perceive such increments as impractical and ignore the reminders to take more steps [14]. Additionally, when feedback was too concrete and did not offer alternative options, people found them harder to attain [40, 133]. Participants in other articles also reported that feedback from PI systems sometimes overwhelmed them with too much information [42, 65, 139].

Relevance of feedback. People reflect/act more on feedback when they perceive the feedback as personally relevant [107, 183]. While it is well-reported in the literature (12 articles), fifteen articles also reported challenges for personalized feedback. Seven articles reported that when personalized feedback is generated based on incorrect data, the feedback becomes irrelevant to the person and, therefore, is ignored [148, 201]. Perceived relevance of feedback is an influencing factor for *reflection/action* in most application domains (see Figure 4). Participants mentioned that the feedback did not feel acceptable to them since they over-simplified complex life issues [14].

Feedback from technology. Six articles reported that people may perceive feedback from a human and technology differently. Some participants ignored feedback when they believed it was generated by a computer rather than by a real person [39, 93, 114]. For instance, one participant in Ha et al.'s study said that they do not care what Google AI thinks about their workouts [72]. In Lazar et al.'s study, participants stated that computerized feedbacks are just advice, not prescription, and, therefore, they did not respond to them [117]. Articles also reported that participants perceived that a device was acting as an authority and did not like that [117, 139].

Positive features. Thirteen articles also reported positive design features supporting *reflection/action*. Participants respond more to directly actionable feedback [49, 109]. Gouveia et al. further reported that participants found easily glanceable feedback more helpful [69].

Technical issues. Three articles reported technical issues that limited people's responses to feedback. Due to technical problems, people may receive feedback late [62], at the wrong time [8, 130], or not receive it at all [8].

4.3 Personal Contextual Factors

The next category of barriers is the personal contextual factors related to users' skills, physical and cognitive abilities, and available time and resources. This section sheds light on these personal contextual factors.

4.3.1 Factors for Collection. We observed six personal contextual barriers that limit people's usage of PI tools in the *collection* stage. The following discussion presents these barriers for *collection* in PI tools.

Limited knowledge or skill. The skills required for measurements or logging may limit users' engagement with self-tracking even when the users intend to track [108, 207]. Limitations in users' existing knowledge and concepts might also limit their engagement [93]. This issue was reported explicitly in four articles.

Physical or cognitive limitations. People's physical or cognitive limitations could challenge accurate tracking of their condition. Even when a person intends to track, they might be unable to do so due to pain [29, 132, 182], cognitive disabilities [9, 157], or physical disabilities [5, 20]. Unsurprisingly, this issue was more frequently reported in chronic condition management (7 articles) and mental health (4 articles) applications.

Forgetfulness. Another frequently reported issue is the forgetfulness of users (53 articles). People may forget to use the tracking tool [122, 195], to recharge the tool [84, 191], to carry the device or the charger while traveling [38, 54], or to start or stop tracking, resulting in partial data [101, 118]. While forgetfulness is a barrier to tracking in most application domains, it was more commonly reported in physical activity (21 articles) and sleep tracking (11 articles).

Limited time and resources. Twenty-four articles reported that participants abandoned or lapsed in *collection* due to limited time and/or resources. For instance, participants frequently reported that their overwhelming schedules limited tracking (e.g., [91, 120]). Articles also noted that tracking sometimes adds to existing burdens of the participants [102, 173]. Subsequently, participants sometimes avoided tracking when they knew that they would be unable to follow the feedback based on the data [117]. Limited time and resources were more often reported as a barrier in chronic condition management applications (8 articles, see Figure 4).

Individual differences. HCI and UbiComp literature acknowledges that one solution does not fit all the users. In agreement with that statement, seven articles reported individual differences in how frequently people track [120] and what data they want to track [16, 177]. Moreover, the same activity might have different meanings for different people (e.g., reading news could be perceived as work or as a break activity [44]).

4.3.2 Factors for Reflection/Action. In the synthesis, we found three personal contextual factors that limit *reflection/action* based on self-tracked data. While these factors are similar to the personal contextual factors for *collection* at a high level, we discuss them separately to highlight the specific challenges for *reflection/action* (e.g., changing habits, different commitments).

Limited knowledge or skill. Thirteen articles reported different barriers around skills required to reflect/act on feedback. The most commonly reported skill barrier was the lack of enough knowledge to reflect/act on feedback, especially when the feedback is not directly actionable [123, 184]. People may also have limited ability to read and understand due to age [151] or cognitive condition [162]. Some articles also reported participants' difficulty comprehending medical jargon used in the feedback [142, 209]. Four articles reported that people's preconceptions about desired health and behaviors often hinder acting on technology-generated feedback (e.g., [39, 93]).

Limited time and resources. Twenty-eight articles reported that people ignored feedback when they had limited time or resources to reflect/act. The workload on a given day significantly influences whether a person will reflect/act on feedback or not [124, 137]. While some participants reported not having enough time to reflect/act on feedback [89, 125], others did not have time to even look at the feedback [21, 84]. One article also mentioned the

lack of enough resources to reflect/act on feedback in the self-care activities of people with spinal cord injuries [16]. Seventeen of these articles reported conflicting priorities as a barrier to *reflection/action* (e.g., [4, 16, 134, 160]). For instance, a user ignored feedback on a bad body posture when playing with their daughter since the family activity was a higher priority to them [117]. Limited time and resources were frequent barriers to *reflection/action* in physical activity applications (12 articles).

Physical or cognitive limitations. Twenty-four articles mentioned different physical and cognitive difficulties as challenges for *reflection/action* (e.g., [135, 195]). Participants did not even want to look at the feedback when they were depressed [136]. Similarly, whether children with ADHD would engage with feedback or not would depend on their mood [28, 179]. Further, participants mentioned the challenge of acting on feedback that requires changes to long-term habits or mental models. For instance, it was difficult for participants to adopt new running techniques since they had used their own technique for a long time [37]. *Physical and cognitive limits* were more often reported as barriers in physical activity applications (12 articles, see Figure 4).

4.4 Situational Contextual Factors

In everyday life, users work through different situational barriers beyond their control. As we observed, different real-life circumstances like job loss or medication reactions frequently limit *collection* and *reflection/action*.

4.4.1 Factors for Collection. In many real-life situations, individuals are unable to engage in *collection* even when they wish to collect. Lack of awareness of data, being away from tracking tools, and situations where participants are unable to carry or use devices are some examples of such scenarios. The following discussion presents such observations based on synthesizing the literature.

Traveling. Twenty articles reported traveling as a barrier to *collection*, ten of which were focused on physical activity tracking. While some people deliberately did not track while traveling (e.g., [41, 67, 97]), others forgot to carry the charger or the tracking device (e.g., [38, 54]). Articles mentioned that carrying an extra device while traveling is a burden for users [192]. Lee et al. found that participants took medicine from a different pillbox which did not include the tracker when they were traveling [118]. Consequently, though the participant adhered to medication, their tracking data could not show that. Again, a few articles reported that tracking is challenging when people travel across different time zones [39, 107].

Diverse life circumstances. Different circumstances of real life (e.g., job loss, a reaction from medication) frequently limited people's data collection for self-tracking applications (reported in 39 articles). Changes in life's priorities temporarily or permanently influence tracking (e.g., [12, 86]). In many cases, a tracking device was forbidden at places participants needed to go daily (e.g., school, office) [28, 197]. These situations limited tracking even when the participants intended to track. The diverse life factors impacted self-tracking in most application domains; however, it was more frequently reported in physical activity tracking (11 articles).

Unawareness. In many situations, people could not track data since they were unaware of the data (reported in 13 articles). Examples of such situations include limited or no information about ingredients of restaurant meals [34] and meals prepared by someone else [33], performing some action unconsciously [44], complicated measurements performed by experts [30], and a distorted cognitive condition due to bipolar disorder [157]. Two articles reported that users did not respond to self-report prompts when they did not notice them in time [2, 76].

No access to tracker. Participants reported an inability to track when they were not near the tracking tool in 31 articles (e.g., [54, 151]). This issue was most often reported for physical activity tracking (16 articles). Such temporary inability frequently resulted from lost or broken devices [97, 179]. Articles also reported situations where a bed-based sleep monitor was deployed in a bed; however, the participants had different sleep arrangements [101, 139], or when participants did not carry the tracking device while traveling [195]. In applications

like indoor air-quality tracking [143] or tracking for childcare [76], participants could not report data when they were at work (i.e., away from home or child).

Ingrained Perspectives. Three articles reported natural contextual factors that impact users' estimation of data for tracking. For instance, biases in the users' perceptions [35, 36] influence their data estimation, especially in subjective data tracking. Similarly, the gender of the person collecting data can influence their estimation [11].

4.4.2 Factors for Reflection/Action. Similar to the discussion about *collection* above, users often perceive that *reflection/action* in response to feedback is beyond their control in various real-life scenarios. For example, professional workload and hierarchy of job roles in a workplace can also limit individuals' ability to reflect/act on feedback. Living conditions, particularly in low socioeconomic status communities, can also restrict *reflection/action* in response to reminders. This section discusses such situational contextual barriers for *reflection/action*.

Lack of control over situation. Articles frequently cited practical life scenarios when users perceived *reflection/action* in response to feedback was beyond their control (reported in 20 articles). For instance, when healthcare providers (HCPs) received feedback to support their psychological health, they could not do anything in response to the feedback, even though they knew the need for sound psychological health. They explained that in a global pandemic, everyone is anxious, and improving the situation is beyond their control [91]. Again, people's position in the social hierarchy sometimes dictates their ability to reflect/act on feedback. For instance, articles reported that people who perceive themselves at a lower position in a hierarchy do not always have the power to act (e.g., employees receiving feedback on the quality of the office environment) [134]. 'White-collar workers' (i.e., people who perform professional, managerial, or administrative work) mentioned that they could not respond to reminders to increase steps since their job requires them to sit for prolonged periods [55, 84].

Living Condition. Twelve articles reported that people's living conditions limited their actions in response to feedback (e.g., [51, 91, 123, 160, 180]). In low socioeconomic status (SES) communities, the living condition and crime rate around their neighborhoods significantly limit the likelihood of their action in response to reminders to walk [180]. Again, in families with children with chronic health conditions, people may ignore feedback with generic health guidelines due to the circumstances around the child's health condition [160]. Living condition was reported as a barrier more frequently in sleep tracking applications (5 articles, see Figure 4).

Unawareness. In many cases, people might be unaware of the feedback delivered to them. Eight articles report situations where participants were unaware of the feedback delivered to them. Such situations may arise when the user is away from the device [42, 62, 130, 151], the device is in 'silent' mode [154], or when the user mistakenly removed the notification [198]. Since the user is not aware of the feedback, there is expected to be no reflection/action in response to it in these situations. Unawareness was an issue more often in physical activity applications (5 articles, see Figure 4).

Receptivity to feedback. The users' receptivity influences their *reflection/action* in response to feedback (reported in 13 articles). As reported in four articles, the timing of receiving or interacting with feedback may impact reflection/action in response to feedback. As we discussed earlier, people may receive feedback at a delayed or wrong time due to technical issues limiting timely responses from users. Additionally, people may look at feedback later rather than when they receive it [155], which may limit proper response. Some people may be reluctant to engage with feedback every day [94, 117] or prefer personalized timing to receive feedback [10]. Furthermore, it was difficult for participants to adopt new running techniques while they were already running [37]. Similarly, receiving feedback on estimated sugar consumption at meal time is not actionable since once prepared, the meal cannot be changed [43]. Receptivity is also limited when *reflection/action* is perceived as an interruption to the routine of users' lives [39, 87].

4.5 System-Caused Harm as a Barrier

PI tools are designed to support users in achieving their goals (e.g., monitoring behaviors, behavior change, and supporting health and well-being). However, many articles reported that users perceived the PI tools as harmful and abandoned or limited their usage.

4.5.1 Barriers for Collection. Self-tracking using PI tools is often seen as detrimental to health and well-being. Many individuals avoid tracking to prevent becoming obsessed with the data, while others find symptom tracking depressing. Fear of seeing negative results or being judged for their condition also deters people from tracking. This section discusses these perceptions of system-induced harms as barriers to *collection*.

Tracking causes harm. Self-tracking is often perceived as harmful to health and well-being (reported in 42 articles), especially in application domains like physical activity or chronic condition management (see Figure 4). Eleven articles reported that people avoided tracking to prevent becoming obsessed with the data (e.g., [46, 84]). In chronic condition management, people found symptom tracking depressing (e.g., [5, 145]). Six articles reported that participants did not track for fear that the data would show something 'bad' (e.g., [4, 97]). A few articles reported that people did not track for fear of being judged for their condition [128, 196]. Again, monitoring pain during exercise for rehabilitation could draw additional attention to pain and limit engagement with exercise [58]. Some people reduce involvement in new activities to reduce the burden of tracking them [33, 121]. Again, in some application domains like substance use, tracking could lead to relapse [153, 188].

Distraction. Seven articles reported that people ignore self-tracking prompts when the prompts disrupt their ongoing tasks, for instance, meeting or driving (e.g., [2, 91]). Another seven articles reported that participants could not track during exercise since tracking distracted them from the activity [3, 155] or spoiled the enjoyment of an activity [43, 119]. Tracking was often perceived as a distraction in applications for health and well-being (see Figure 4).

Discomfort. Twenty articles reported that the discomfort of tracking limited people's engagement (e.g., [37, 85]). This issue was more frequently observed in physical activity (10 articles) and sleep tracking (7 articles, see Figure 4). Daily tasks (e.g., manual labor, childcare) sometimes limit wearing a tracking device [169]. Some people reduced engagement when they had physical harm from the tracking device (e.g., a scratch on the skin) [169]. In chronic condition management, the unpleasant feelings (e.g., poking a needle) of measurement limited tracking [4].

4.5.2 Barriers for Reflection/Action. Feedback based on self-tracking data can induce negative emotions and hinder engagement. Some people may avoid interacting with feedback if it does more harm than good, such as triggering eating disorders or leading to relapse. This section sheds light on the perceived system-induced harm that contributes as a barrier to *reflection/action*.

Negative emotional reaction to feedback. Thirty-two articles reported that when people perceive a lack of improvement in their condition, feedback based on their data causes anxiety [11, 147, 153], shame/guilt [51, 188], or feelings of judgment [34, 145] for them. For instance, feedback about higher heart rates worried participants and exacerbated the situation [11]. Participants in three studies reported that the feedback did not appreciate their effort, which reduced engagement for them [25, 107]. Children with ADHD stated that reminders to focus on tasks felt like they were being judged as 'cheating' when they became distracted [28]. People with disabilities or older-age reported that the feedback reminded them about their limitations when they could not improve their data [6, 17, 195]. Negative emotions due to feedback were reported more often in chronic condition management (7 articles) and physical activity tracking (6 articles, see Figure 4).

Fearful content. People may ignore feedback notifications when they fear the feedback's content. This observation was reported in six articles. For instance, fear of surgery can translate to the fear of engaging with

surgery-related notifications [11]. Similarly, some people tended to ignore notifications after the experience of having a bad health condition [4].

Harm from reflection/action. Sixteen articles suggest that people may avoid interacting with feedback when they cause more harm than improving the condition. Some people became obsessed with the feedback about their diet, which triggered eating disorders for them [30]. In some cases, feedback about avoiding certain behaviors led to relapse and repeating those behaviors (e.g., [124, 152, 188]). Three articles reported that people took detrimental actions in response to the feedback (e.g., experimenting with medication without prescription) [163, 170, 182].

Distraction. People ignore feedback notifications when engaged in other tasks, and feedback is perceived as distracting (e.g., [65, 68, 178]). The issue of distraction was reported in sixteen articles, with more often occurring in physical activity applications (8 articles, see Figure 4). In physical activity applications, people ignored feedback messages even when relevance was high, like during exercise, since the feedback felt like a distraction (e.g., [18, 119, 155]).

4.6 Fluctuating Motivations

In our synthesis, we also observed that some factors contribute to fluctuating motivation for *collection* and *reflection/action* rather than leading to complete abandonment or limiting usage. In such scenarios, people track with differing frequency and granularity depending on the situation. The urgency of a situation, progress toward the desired goal, and novelty of information are some of such scenarios that contribute to fluctuating motivation. In this section, we discuss these factors in detail.

4.6.1 Factors impacting Collection. Users' motivation to engage in *collection* fluctuates due to various factors, leading to lapses in tracking. Lack of sufficient reason, feeling inactive, or reaching behavior goals can reduce motivation. The following discussion presents such factors based on our literature synthesis.

Situational lapsing. Twenty-three articles reported situations where users have fluctuating motivation due to different factors resulting in lapses in tracking. People may be reluctant to track with a particular tracking technology when they believe they do not have enough reason to track. Some participants did not track when they believed they were not physically active enough to track activity meaningfully [17]. Tracking was also reduced when participants reached their behavior goals [25, 96]. Furthermore, some people have low motivation to track when they believe that they can manage their conditions without tracking [27, 89] or when they know enough about themselves [51, 161]. Situational lapsing was more often reported in physical activity (6 articles) and chronic condition management applications (6 articles).

Tracking only when needed. In *intermittent tracking* (see Section 4.2.1), users self-track in their usual conditions; however, they take breaks from tracking to balance diverse priorities in their lives. In contrast, some users do not track in their usual scenarios; however, they may track for some period when they perceive a need. As thirty-one articles reported, users track only for a short period when they have visible health problems (e.g., elevated blood sugar, symptoms of migraine) [11, 201], or when they engage in activities they wish to track [85, 106]. This strategy was most frequently adopted by people who track to manage chronic health conditions (10 articles, e.g., [4, 150]). While it may help balance their burdens, it could lead to missing data when the participant has no visible problems.

Lack of novelty. Twenty-four articles reported a lack of novelty influencing people's motivation to track. Thirteen of these articles reported that people had reduced tracking when the tracker's novelty wore off (e.g., [63, 99]). Moreover, participants did not track when they thought they knew what the data would show [117]. People were also reluctant to track repetitive measures since they were not novel [19, 91]. On the contrary, Epstein et al.

found that participants perceived tracking routine things as easier [54]. Reduced engagement after the novelty wore off was more frequent in physical activity tracking (8 articles, see Figure 4).

4.6.2 Factors impacting Reflection/Action. Users' motivation to reflect/act on feedback also fluctuates depending on diverse factors. Users' progress toward goals, the current level of adherence, the urgency of health conditions, and their anticipation of the outcome influence motivation. Next, we discuss these factors that contribute to fluctuating levels of motivation to reflect/act on feedback from PI tools.

Progress toward goal. Eleven articles reported that people's progress toward goals impacts their motivation to reflect/act on feedback. People need personalized feedback when they need support to change their condition. Consequently, ten articles reported that people ignore feedback notifications when they believe that they are already adhering to the recommended behaviors or have reached their goals (e.g., [45, 62, 84, 148]). Articles also reported that people are more likely to reflect/act on feedback if they are already in action (e.g., already walking) or are closer to meeting a goal [39, 68, 69]. Progress toward the goal impacted motivation for *reflection/action* more frequently in physical activity applications (6 articles, see Figure 4).

Urgency of situation. Eighteen articles reported that people respond to feedback more when they have any visible health issue or feel an urgency to act. For instance, participants with diabetes did not act on feedback when they did not perceive enough risk associated with their condition. However, the same population engaged with feedback more when they were concerned about their health and safety and believed that the feedback could be helpful [166]. Participants also ignored feedback when it did not match their perception of their condition [78, 87, 124, 145]. Interestingly, two articles reported that people perceived voice-based feedback as more urgent and felt pressured to reflect/act immediately [113, 130].

Expectations of novelty. Eighteen articles reported people's tendency to ignore reflection/action notifications when the information is not novel or when they can predict when the feedback will be delivered, e.g., at the same time every day (e.g., [52, 152, 168, 188]). Unpredictable prompts were reported as more acceptable to users [152]. This barrier was more frequently reported in physical activity applications (7 articles, see Figure 4).

Anticipation of outcome. People's reflection/action in response to feedback is largely motivated by their perceived outcome of the reflection/action (reported in 20 articles). They tend to reflect/act on feedback with a more immediate impact, especially when the impact is a positive one [16, 152, 171]. On the contrary, people limit reflecting/acting on feedback when they do not achieve desired progress or positive outcome according to their expectations [95, 136, 156]. This issue was more frequent in physical activity applications (7 articles, see Figure 4).

4.7 Interpersonal Contextual Factors

Humans are subject to diverse interpersonal contexts in everyday life as social beings. In the meta-synthesis, we saw barriers and facilitators for engagement with PI tools that arise from such interpersonal contexts. Examples of such contexts include collaboration among people, multiple users of PI tools, different social scenarios, the impact of the tools on friends and family, and privacy issues.

4.7.1 Factors for Collection. In a social context, people sometimes collaborate in data collection, especially when the user cannot track data fully independently. However, social contexts also create situations where users perceive barriers to track. This section discusses such interpersonal contextual factors for *collection* based on our literature synthesis.

Aspects of collaboration. People collaborated in tracking with different motivations, especially in chronic condition management (7 articles) and mental health applications (5 articles, see Figure 4). In these applications, when users cannot track due to physical or cognitive limitations, friends or family members can fill in the

data [154, 178] or remind them to track later [99, 145]. While collaboration can reduce the burden on the actual tracker, articles reported potentially problematic issues like all stakeholders might not be equally motivated to track [128, 143], or they might fail to accurately estimate the internal experiences of the patients [81, 189]. The relationship between the patient and the caregiver could also lead to over- or under-estimation of data [142], and there can be conflicts among collaborators regarding the data [82].

Power dynamics. When HCPs are involved in reflecting on the self-tracked data with users, the obligation toward the HCPs increases the frequency of collection for the users [109, 146]. Participants felt obliged to take measurements and log them since the HCPs would see them [146]. Children [102, 159, 160] and people with chronic conditions [17, 100] perceived tracking as surveillance on them. Children particularly mentioned wanting to be in charge of their data [159, 160]. Since HCPs and caregivers already dictate many of their actions, they perceive tracking as policing them. The participants in one study described it as feeling like being a '*wild animal being tracked*' [190]. This perception limits their engagement with self-tracking. The impact of power dynamics was most common in chronic condition management applications (4 articles).

Multiple users of a PI tool. Six articles reported that multiple users used the same tracking tool. In a shared living or work space, it is expected that users will share some devices (e.g., screen [176], music device [204]). However, in one study, a couple shared one fitness tracker for tracking their physical activity [191]. This is a barrier for the PI tool since it poses a challenge in identifying which data comes from which user.

Social contexts. The most frequently reported (36 articles) social issue was that the different social contexts limited the extent of self-tracking by the users (see Figure 3). While articles reported this issue for most application domains, it was more frequently reported in diet, physical activity, and sleep tracking applications (see Figure 4). In some situations, people felt awkward tracking in front of others (e.g., due to social taboo [140], during a family dinner [33]), and in some other situations, they could not track due to explicit objections from family or friends during a social event [169]. Sometimes, others who share the same space requested to delete the data captured about them [24]. Again, in some cases, collocated people or pets impacted the data (e.g., sleep quality data was impacted by other people's movements who share the same bed [126]).

Privacy concerns. Thirteen articles reported explicitly on users' privacy concerns. People paused tracking when it violated the privacy of other people (e.g., [24, 68]) or completely abandoned tracking (e.g., [51]) when they were concerned about their privacy. As Yarosh reported, participants fear committing personal data to a computer, thinking everything typed into a computer lasts forever [207].

4.7.2 Factors for Reflection/Action. Similar to *collection*, social contexts may limit *reflection/action*, especially in situations where action impacts other people or the presence of other people impact *reflection/action*. This section discusses interpersonal contextual factors that limit *reflection/action*.

Social contexts. Fourteen articles reported that the social setting around people can limit their responses to the feedback they receive. Many people find it annoying to get reminders [48, 62, 87] and ignore notifications [117, 131, 167] when they are in a meeting or class, engaged in a conversation, or other similar social activities. People ignored notifications in a social setting when they drew unintended attention of other people [28]. One article also reported that health conditions of other family members may limit *reflection/action* for users [160].

Impacts on friends and family. Four articles reported that people limit acting on feedback if their action affects their roommate or partner who shares the space [40]. In some situations (e.g., caregiving), *reflection/action* might require participation from multiple stakeholders, which can also limit *reflection/action* [160]. This is especially true in applications where caregivers in chronic condition management or childcare are already burdened with caregiving responsibilities [59, 179].

Role of experts. Six articles reported that people's perception of their expertise on a topic limits their *reflections/actions*. Some participants depend on expert feedback even when they receive personalized feedback from PI systems. This perception is more common in chronic condition management applications (see Figure 4). Participants explained that they need experts' advice in conditions that involve high health risk [146, 184]. Another study noted that people do not reflect/act based on feedback since they believe that 'doctors are the decision makers' and they should act only on a doctor's approval [11].

Privacy concerns. People turned off feedback notifications due to privacy concerns in social settings. They disabled notifications when they were too personal to appear on their smartphone's homepage [53]. Similarly, some participants wanted to avoid a noticeable notification in front of visitors about their private information [181]. Disabling or ignoring notifications due to privacy concerns was reported in three articles (see Figure 4).

4.8 Individual Perspective-Induced Factors

Every user has their personality and perspectives about using technology. In our literature synthesis, we saw a set of user perspectives (e.g., fashion choice, levels of expectations from themselves and technology) that serve as a barrier to their engagement with PI tools. These perspectives limit their usage of PI tools without any external limiting factors. As Figure 3 shows, this is the least frequent category of barriers.

4.8.1 Factors for Collection. We observed that people abandon or limit PI tool usage in the *collection* stage due to their internal resistance or personal choices. The following discussion presents such individual perspective-induced barriers for *collection* in PI tools.

Abandonment by choice. People sometimes do not track owing to their personal choices [116, 121]. A few articles reported the reasons for such choices, for instance, not wearing a tracker for better comfort at home [192], when the tracker device does not match their clothing style [169], or when tracking felt boring [52]. Some users also ignored the prompts when they felt overwhelmed by several subsequent prompts [2, 76]. Abandonment by choice was most frequently reported in physical activity tracking (11 articles, see Figure 4).

Resistance toward tracking. Thirteen articles reported participants' resistance to self-tracking. While some participants mentioned resistance to replacing primary healthcare with technology (e.g., [196]), others reported reluctance to approach behavior change systematically (e.g., [161, 207]). In chronic condition management applications, participants did not want to think about health outside a hospital setting (e.g., [141, 173]). Articles also reported participants' lack of willingness to use smartphones for tracking [8, 130] and desire to reduce phone usage [44, 154]. Interestingly, resistance toward tracking was reported in most self-tracking applications for health and well-being.

Unrealistic expectations. One article noted that participants sometimes have unrealistic expectations from PI systems, and they tend to abandon tracking when that expectation is not immediately met [26]. For instance, patients focusing on chronic condition management wished to see immediate positive impacts of self-tracking on their health, and when they did not see such benefits in the near term, many abandoned tracking with the tool.

4.8.2 Factors for Reflection/Action. We also observed that people limit *reflection/action* based on data in PI tools due to habitual ignorance, deep-rooted resistance toward technology, or lack of interest in change. We discuss these individual perspective-induced barriers for *reflection/action* next.

Willingness to change. Six articles reported that people's willingness to change their behaviors influences their *reflection/action* on the feedback. For instance, participants were reluctant to accept suggestions since they were not psychologically ready to accept changes [59]. This observation is similar to the *'precontemplation'* stage of

the transtheoretical model of behavior change [165]. This is a common challenge for applications for reducing substance abuse (e.g., [153, 188]).

Personal resistance to technology. Two articles reported that people exhibit explicit resistance toward notification from technology. In productivity and performance monitoring applications, participants wanted to avoid further notifications from technology since they perceived technology would provide them with negative feedback (e.g., [77]). Some participants also mentioned a desire to reduce their usage of smartphones and, therefore, ignored notifications from PI systems [154].

Ignorance and procrastination. Ten articles reported that people often ignored or procrastinated on feedback from PI systems as a personal choice without citing any particular barrier to *reflection/action* (e.g., [45, 117, 210]). Interestingly, some people purposefully limited their *actions* based on feedback to limit the system's expectations of them. They did not aim for the complete achievement of a goal, so the system did not increase the goal for them. For instance, bus drivers did not want to achieve a perfect driving score. They believed that it would increase their employer's expectations and that if they could not maintain that performance, it might pose a risk to their ongoing employment [164].

5 DISCUSSION

PI literature is proliferating, with over 70 articles published every year since 2015 [50]. While these articles offer an enormous amount of novel knowledge, they also pose a challenge in effectively capturing and disseminating this knowledge. We synthesized 214 PI articles to categorize the barriers and facilitators for PI tools in the *collection* and *reflection/action* stages to build towards an aggregate understanding of these factors. The following sections discuss gaps in the current literature and inform directions for future research explorations. We also discuss ideas for keeping such syntheses current with the ongoing proliferation of research results.

5.1 Inadequate PI Research Focusing on Specific Communities

We observed that PI research is heavily focused on educated and solvent or white-collar populations in North America and Europe. This meta-synthesis indicates a gap in PI research on other underprivileged communities. We found only two papers [179, 180] explicitly exploring the usage of PI tools in low-SES communities and only one paper [169] discussing the usage of such tools by people who perform manual labor jobs. These observations indicate that more research is required focusing on these marginalized populations. However, there are specific challenges for HCI and UbiComp research with marginalized or vulnerable populations. The difficulty of recruiting participants [13, 90], risk of coercion, undue influence of compensation [70], or other challenges specific to these populations may emerge while working with low-SES communities or manual labor workers. For instance, Holten Møller et al. explicitly reported that they had to be cautious about 'job placement regulations' and 'non-coercive remuneration' while deciding the compensation for their unemployed participants [79].

Similarly, we found only one paper [11] that investigated the health-tracking behaviors of people with cardiac diseases in the global south. While they indicate that several cultural factors may impact people's health-tracking behaviors, more research is needed in this direction. We did not find any paper that explicitly mention a focus on developing countries and/or rural regions. In health informatics, Luna et al. noted a few barriers to e-health programs in developing countries: lack of reliable and low-cost infrastructures (e.g., internet, smartphone), lower levels of tech-savviness and adoption of digital tools [129]. While similar barriers may be expected for PI tools in these regions, there is a need for more research that identifies such barriers and accommodates the different needs in the design and implementation of PI tools. These observations open another path for more inclusive research focusing on these communities.

5.2 Directions for Further Research Exploration

One motivation for this synthesis was to capture the enormous volume of the PI literature and help researchers to map what to expect in a particular application domain. Figure 4 summarizes the application domains, the relevant barriers and facilitators for user engagements, and their frequency for those application domains. However, this synthesis may also help inform the research hypotheses of future studies. We identify some such paths for future research exploration based on this meta-synthesis:

- *Collaboration* could be useful for "workplace environment tracking" since multiple people using the workplaces could share the tracking burden and/or improve the accuracy and granularity of the data. However, Figure 4 shows that such collaboration has not been reported in the literature. It would be interesting to explore if such collaboration happens and, if it does, what such collaboration might look like in the presence of a workplace's organizational hierarchy.
- Barriers and facilitators for *reflection/action* in general for domains like indoor air quality, phone usage, screen time, and childcare were minimally explored or not explored at all. Intuitively, these domains could be supported with personalized feedback; however, we do not know much about these engagements based on existing literature. For instance, how does *living condition* impact *reflection/action* to feedback on indoor air quality? How would people *reflect/act* on the feedback that they have had high phone usage levels?
- *Skills barriers* for *reflection/action* or *individual differences in tracking* were not as frequently reported in the literature as a seasoned PI researcher might expect. Are they not being reported because they are 'expected'? Should researchers report such findings to confirm their external validity? Are there domains where people overcome these barriers due to the urgency of the condition, like chronic health disease or mental health? Or should the PI domain in general conclude that these issues are expected regardless of the application domain, even if they were not explicitly reported in the past for each domain?
- *Timing of feedback* was reported as a barrier for *reflection/action* in physical activity and diet applications. We do not know if this issue is not reported in other domains because there were not observed or if they were not asked about. Is *timing of feedback* an issue for 'chronic condition management' applications or does the urgency of the health condition reduce or eliminate it? Or are people more receptive to feedback when they have chronic health conditions? How would *timing of feedback* impact *reflection/action* in 'screen time' applications when people are at work; would *power dynamics* or the perception that *action is harmful* for their employment (e.g., reducing screentime perceived as less work done) play a more significant role in their *reflection/action*?
- The significance of *relevance* in PI tools is a crucial area for future research. Throughout our analysis of the literature, the recurring theme of "relevance" stands out as a crucial factor influencing users' engagement in the *collection* and *reflection/action* stages. The tool's perceived relevance directly impacts users' willingness to use the PI tool, as evident from cases where users refrained from engaging with PI tools when they found the data or the feedback irrelevant. The urgency of situations and visible health issues also enhanced the responsiveness to feedback, highlighting the importance of relevance in driving user actions. However, the complex nature of relevance is evident from instances where even in high-relevance scenarios, users chose to ignore feedback messages, considering them distracting. Despite the challenges, the frequent reappearance of relevance and the surrounding nuances underscores its significance in designing PI systems. Future work should delve deeper into its multifaceted implications to develop more effective and user-centric PI tools.
- *Nuances in sleep tracking* is another interesting topic for further exploration. Participants were interested in tracking the environmental factors (light, sound, temperature, and air quality) that impact their sleep to learn how these factors impact their sleep and about their sleep behaviors [101]. Note that these particular environmental factors are more controllable for the users than many other life factors that impact sleep. For instance, Pina et al. discussed [160] how the health condition of one family member may cause other

family members to think that generic health guidelines do not apply to their families, and as a result, they start to ignore feedback about their sleep quality. They further noted that feedback on poor sleep could cause tensions with other commitments and negatively impact them overall. The most commonly reported category of barrier for PI systems focusing on sleep was 'situational contextual barriers' that are beyond the users' control. Future research could investigate how the interplay of these controllable and less- or un-controllable factors impact the users' sleep behaviors.

We also compared the different application domains from Figure 4 with the list of 'domain of study' in the *PI paper browser*. We observed that the corpus of papers that reported on different barriers and facilitators for *collection* and *reflection/action* that we reviewed does not include application domains like sustainability, gaming, books read, solar radiation, and words read. While the *PI paper browser* also shows that these are, in general, less explored application domains in PI, we emphasize that barriers and facilitators for *collection* and *reflection/action* specifically in these application domains should be further explored.

5.3 Generalizing PI Research Findings

This meta-synthesis brought a broad range of participants' experiences and engagements in various contexts together. Subsequently, the synthesized categories provide an understanding of the barriers and facilitators for user engagements with PI tools in the *collection* and *reflection/action* stages beyond the findings of the individual studies alone. We discuss these generalizable insights in this section.

5.3.1 Barriers Applicable Across Application Domains. PI research encompasses a wide range of application domains, from health and well-being to personal finances, driving quality, and work performance. In the meta-synthesis, we found that some barriers for *collection* and *reflection/action* are common in most PI applications irrespective of their application domain (e.g., *technical issues*, *forgetfulness*, *tracking integrity* and *burdens of tracking*) as a barrier to *collection* (see Figure 4). Based on the synthesis, other applications may also expect to encounter these barriers. However, we also observed specific barriers that are more commonly observed in health applications. For instance, *'perceived harm'* (see Figure 4) was observed in all applications for supporting health and well-being.

5.3.2 Barriers Specific to Chronic Condition Management and Mental Health Applications. Based on the synthesis of the literature, some barriers for *collection* and *reflection/action* are observed specifically in chronic condition management and mental health applications, for instance, the issues of *'power dynamics'* and *'perceived harm'* (see Figure 4). One reason for this could be the involvement of informal caregivers and HCPs in managing these conditions. Moreover, their vulnerability due to their health conditions could make them more cautious about the potential harm and consequences.

Again, there are nuances around *'collaborative tracking'* from different perspectives and for different contexts. However, it can be helpful in chronic condition management or mental health applications when people need caregivers' support. Figure 4 shows that *'collaborative tracking'* was frequently reported in these domains. Collaboration between target users and their caregivers in tracking can generate more complete data and balance the burden for the caregivers, especially when the target user cannot track due to physical and cognitive limitations (e.g., in critical health conditions). However, it may also result in errors in data estimation [81, 142], privacy concerns [82] and an increased burden for caregivers [160]. These insights encourage further research to understand the different aspects of collaborative tracking and identify their applicability in different contexts.

Similarly, each sub-category in Sections 4.1-4.8 discusses the different barriers for *collection* and *reflection/action* from participants' real-life experiences and the application domains that more often encounter those barriers. Figure 4 further provides the frequency of these barriers and facilitators for each application domain. Thus, this

meta-synthesis expands the understanding of different barriers and facilitators for *collection* and *reflection/action* and their generalizability beyond the scope of an individual article.

5.4 Thinking Beyond 'Barriers to Engagement'

A prior literature review indicated that PI articles predominantly focus on the everyday challenges to engagement with PI tools (e.g., abandonment, not tracking due to social or physical limits) [50]. This meta-synthesis indicates challenges for PI tools beyond the barriers that limit *collection* and *reflection/action*. We observed situations where people engage with *collection* (i.e., no explicit barrier), however, in ways that may result in misleading or imperfect data. For instance, Section 4.1 discussed that people altered the data to portray the desired image of themselves or force a particular diagnosis of their health conditions. In these situations, a PI tool may fail to serve its intended purpose even though participants did not abandon or lapse.

Similarly, Section 4.1.1 presents a generalizable challenge of estimating subjective data consistently. The context at the moment of tracking and prior experiences can influence the estimation of subjective data. While retrospective tracking can help fill in for data that the user could not track earlier, collecting subjective data in retrospect can be subject to recall bias. Thus, even when people collect data, their context at the moment, prior experiences, and biases in recalling past events may influence their subjective data. In such situations, there might be no barriers to data collection; however, data collected may be subject to different interpretations from the baseline for comparison. While this meta-synthesis also identifies and categorizes barriers to engagement, it indicates that further investigations are required beyond just the barriers.

5.5 Supporting Scalable Synthesis for the Future

While meta-synthesis can capture growing bodies of literature and open new paths for research exploration, conducting such meta-synthesis is laborious and time-intensive. The rapid growth of the literature makes the task even more challenging for researchers. The synthesized knowledge may soon become outdated if it is not revised with new discoveries. It is not realistic to expect that one researcher or even one research group will maintain the synthesis of such an enormous volume of literature. Therefore, a challenge for meta-synthesis is: how do we support an ongoing, scalable synthesis of empirical research as it is produced?

One possible solution that we propose is introducing an additional *'Design Statements (DS)'* block in research papers similar to the 'ACM computing classification system' block [60] used by ACM venues. Authors could include the DS block representing their core findings to provide an easily readable structure. For instance, the DS could have the following structure:

> [PI stage]: <primary category> → <sub-category> (*List of barriers and facilitators*);

Since this article focuses on the PI literature, we demonstrate the DS block for supporting the synthesis of PI literature. A DS block for a PI article could identify the key barriers and facilitators for user engagement from the list we synthesized in this article or introduce new categories and keywords. For instance, based on our synthesis, the article [91] could have the DS block written as the following:

1. [Collection]: Threats to data integrity → Timing of tracking (*a: Could the user's lifestyle impact when they log the data?*), Questionable accuracy (*a: Can the user reliably report subjective data?*); Design & implementation factors → Retrospective tracking (a: *Should the system allow retrospective tracking? b: How would the system deal with retrospective data? c: If the data is subjective, what would be the accuracy of the data in retrospect?*); System-caused harms → Distraction (*a: How would the tracking prompt impact other higher priority tasks?*), Tracking caused harm (*a: What would be the impact of tracking the data on users' mental health?*); Fluctuating motivation → Novelty (*a: Would repetitive data reduce engagement or make tracking easier?*);
2. [Reflection/Action]: Situational contextual barriers → Living condition (*a: How does the users' life factors (e.g., workload) impact adherence?*), Action beyond control (*a: How do they perceive their ability to act on feedback?*); Personal contextual factors → Time & resource limits (*a: Do they have the time and limit to act on feedback at a given time?*);

Authors across HCI and UbiComp disciplines could report similar DS blocks in their papers. Creating this block could help authors and peer reviewers to evaluate the contribution of the work. However, it would require the peer-reviewers to check if the findings reported in the article inform the design questions listed in the DS block to verify their rigor.

Accurate reporting of the DS block could support synthesizing the literature and expanding existing syntheses without requiring a laborious process of reading every article. It could help readers quickly glance through the key findings or design recommendations reported in the paper without requiring them to read the entire paper, especially if they have limited time (e.g., industry practitioners). However, such a concise representation of the key findings or design suggestions may also lose much contextual information about the study's setting and the different design trade-offs that might be critical to understanding the findings. The perception of the individual researchers may also influence such summaries of the findings. Nevertheless, such a DS block may open an opportunity for readers with limited time to sift through critical research findings while also allowing any reader to read further details from the articles depending on their specific needs.

While we propose a first structure of the DS block, the research community might collaboratively refine the structure for the broader applicability of the block. However, adopting a DS block requires more meta-synthesis work from UbiComp and HCI disciplines. The research community focusing on these disciplines needs to collaboratively create the first set of key categories that authors may use and expand upon. This article takes the first step toward that goal by synthesizing barriers and facilitators for *collection* and *reflection/action* in the PI system from the literature.

6 CONCLUSION

The gap between academic research and design practice is well-acknowledged in the research community. The challenge of capturing the proliferating body of literature in different research disciplines contributes to this gap. This article takes the initial step to offer a meta-synthesis of the existing literature focusing on barriers and facilitators for user engagement with personal informatics technology. However, the broader research community must collaboratively develop approaches to make their research discoveries more accessible to researchers across disciplines and, more importantly, beyond academia. While this paper is focused on synthesizing PI knowledge, our methodological approach could be adopted for other sub-fields of UbiComp and HCI and to inform the design of human-centered systems in real-world applications.

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