Chapter 5
Smartphones in Personal Informatics: A Framework for Self-Tracking Research with Mobile Sensing

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Abstract Recent years have seen a growth in the spread of digital technologies for self-tracking and personal informatics. Smartphones, in particular, stand out as being an ideal self-tracking technology that permits both active logging (via self-reports) and passive tracking of information (via phone logs and mobile sensors). In this chapter, we present the results of a literature review of smartphone-based personal informatics studies across three different disciplinary databases (computer science, psychology, and communication). In doing so, we propose a conceptual framework for organizing the smartphone-based personal informatics literature. Our framework situates self-tracking studies based on their substantive focus across two domains: (1) the measurement domain (whether the study uses subjective or objective data) and (2) the outcome of interest domain (whether the study aims to promote insight or change in physical and/or mental characteristics). We use this framework to identify and discuss research trends and gaps in the literature. For example, most research has been concentrated on tracking of objective measurements to change either physical or mental characteristics, while less research used subjective measures to study a physical outcome of interest. We conclude by pointing to promising future directions for research on self-tracking and personal informatics and emphasize the need for a greater appreciation of individual differences in future self-tracking research.

Keywords Self-tracking · Smartphones · Mobile sensing · Personal informatics

The tracking of physical (e.g., weight, physical activity) and mental (e.g., mood, stress) characteristics has long fascinated individuals and scientists alike (e.g., Li et al. 2010; Wolf 2010). The practice of self-tracking involves a process of "…collecting data about oneself on a regular basis and then recording and analyzing the data to produce statistics and other data (such as images) relating to regular habits, behaviors, and feelings" (Lupton 2014, p. 1). According to the Pew Research Center, a recent national survey of adults in the United States found that nearly 69% of American adults track at least one health-related physical characteristic or behavior (e.g.,

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weight, diet, sickness symptoms, exercise routine), and that individuals with chronic health conditions were more likely to track such behaviors compared to healthy individuals. Among the self-trackers, approximately half reported recording their histories "in their head" (49%) and reported using notebooks or digital technology to record their physical health behaviors (55%; Fox and Duggan 2013).

The practice of self-tracking is typically associated with the goal of inducing behavior change through self-insight and self-monitoring (Kersten-van Dijk et al. 2017). That is, most individuals track their behaviors with the intention of changing unhealthy patterns and improving upon their general well-being. Today, the advent of ubiquitous sensor-driven technologies (e.g., smartphones, wearable devices) has revolutionized the way individuals self-track their physical and mental characteristics, and how they interact with personal informatics in general (e.g., Swan 2012).

5.1 Personal Informatics and Self-Tracking Technologies

Personal informatics (PI) broadly defines a set of self-tracking technologies that help individuals collect and reflect on personal information (Li et al. 2010). Self-tracking technologies include diverse forms of digital technology, such as web-based applications (i.e. Mint Financial planner), wearables (i.e. Apple Watch, Nike + Band), mobile phone applications (i.e. WeRun; Li et al. 2010). Personal informatics systems operate under the pretext of three interrelated goals (Kersten-van Dijk et al. 2017): (a) to accurately measure the target domain (e.g., physical behaviors, mental states) using data produced from the use of digital technology, (b) to produce meaningful analysis of this data and (c) to communicate this analysis to the user in a comprehensible manner.

Past research has compared two working models of personal informatics (Kersten-van Dijk et al. 2017). The first model is a stage-based model consisting of distinctive consecutive states: preparation, collection, integration, reflection, and action (Li et al. 2010). The reflection stage constitutes periods of self-reflection resulting from the use of PI systems, which leads users to change their behavioral trajectories after self-reflection. The second competing model maintains that the use of PI systems is too continuous to be discretely modeled in a stage-wise manner because participants using personal informatics systems often simultaneously engage in the activities described in the discrete stage model (Epstein et al. 2015). For example, the collection of self-tracking data usually occurs in conjunction with processes of self-reflection, as participants' experience of self-tracking induces them to reflect on their behavioral patterns. Despite their differences, both models of personal informatics (Li et al. 2010; Epstein et al. 2015) converge on the idea that behavior change is the ultimate outcome of an engagement with personal informatics systems (see Kersten-van Dijk et al. 2017 for complete review and comparison of both models).

The use of self-tracking technologies in daily life is likely to continue increasing at a rapid rate in the near future, as digital self-tracking is already becoming a pervasive and ubiquitous phenomenon (Paré et al. 2018). Thus far, the majority of commercial digital technologies for self-tracking target health and fitness as areas of application (e.g., Samsung Gear Fit, Apple Watch). Yet, digital self-tracking applications are accessible for none to marginal costs, and portable fitness hardware such as pedometers are relatively affordable (Rooksby et al. 2014). Moreover, scholars have collectively recognized the growing popularity of smartphone applications, wearable sensing technology, and other digital self-tracking platforms (Lupton 2013; Rooksby et al. 2014; Sanders 2017). And movements such as Quantified Self (2015) have developed a variety of digital technologies that facilitate the tracking of diverse behaviors (e.g., mobility patterns from GPS data; Parecki 2018).

Smartphones, in particular, stand out as a digital technology with much promise for self-tracking and personal informatics because they permit both active logging (via surveys) and passive tracking (via mobile sensing; Harari et al. 2017). Mobile sensing technologies permit the unobtrusive collection of data from mobile sensors and system logs embedded in the smartphone (microphones, accelerometers, app usage logs) to recognize human activity (e.g., sociability, physical activity, digital media use; Choudhury et al. 2008; Lane et al. 2010). By automating the continuous detection of a person's behavioral patterns and surrounding context (Harari et al. 2017b; Harari et al. 2018), mobile sensing is poised to play an important role in the development of effective personal informatics systems that induce positive behavior change. To examine the effects of self-tracking with smartphones in personal informatics, here we review and provide an organizing framework for existing and future scholarship on self-tracking research with mobile sensing.

5.2 A Framework for Self-Tracking Research

We have two interrelated aims in writing this chapter. First, we aim to provide a review of the existing trends, gaps, and directions in the research literature on smartphones in personal informatics. We focus specifically on reviewing the existing literature that uses smartphone-based self-tracking technologies to collect user data (e.g., via self-report questions or mobile sensing), analyze user data, and/or that use the smartphone to communicate results aggregated from a variety of sources to the user. Given the interdisciplinary nature of self-tracking research and the variety of application domains into which smartphones have been deployed in personal informatics systems, we conducted our literature review across three databases selected to represent the primary disciplines engaging in such research: PsychINFO (representing psychology), ACM (representing computer science), and Communication and Mass Media Complete (representing communication). We note that nearly all of the articles that met our inclusion criteria were indexed in the ACM database, while our inclusion criteria yielded few articles from the PsychINFO and Communication and Mass Media Complete databases. We provide a detailed description of our literature review procedure in Table 5.1 (keywords used), Table 5.2 (derivation of keywords and their search arrangement), and Table 5.3 (filtering process). Additionally, Fig. 5.1

Table 5.1 Methodology of literature review

Mobile sensing keywords	Mobile sensing; mobile-sensing; mobile sense; smartphone sensing; smartphone sensing; smartphone sense
Personal informatics keywords	Self-monitoring; self monitoring; self-tracking; self-track; self tracking; self track; quantified self; life-logging; lifelogging; life logging; personal informatics
Behavior change keyword	Behavior change
Categorical keywords	*Physical activities:* Physical health; Activity, walking, steps, sedentary; Running; Exercise, fitness, workouts; Illness, symptoms
	Physiological: Physiological; Heart rate; Blood pressure; Nutrition; Food diet; Calories; Sugar intake; Water intake; Alcohol; Vitamins; Medications
	Sleeping patterns: Sleeping patterns; Duration, Quality, Schedule; Rest
	Productivity: Productivity; Study habits; Laziness; Focus; Time management, time spent working; School-life balance taking breaks; Academics; Class Schedule
	Mood: Mood, Emotions; Depression; Sadness; Anxiety; Stress; Happy; Content; Relaxed; Relaxation; Anger; Curiosity; Kindness; Consideration; Positive Thoughts; Negative thoughts
	Socializing: Socializing; Conversation Quality; Conversation Duration; People Spending Time With; Time Spent Alone; Dating, Romance; Social Media Communications
	Digital Media Use: Digital media use; TV Time; Screen Time; Computer Use; Internet use; Phone use; Gaming; Social Media Use
	Daily Activities: Daily activities; Hobbies; Reading; Learning; Location; Hygiene

shows the number of search results returned at and filtered during the various stages of the filtration process .

Second, we aim to provide a conceptual organizing framework to situate the substantive contributions of past and future smartphone-based personal informatics research. We believe a framework is needed to help situate the contributions of a given self-tracking study within the broader literature with regard to its measurement and outcome of interest domains.

Generally, existing research on smartphones in personal informatics has largely focused on describing the development, deployment, and effectiveness of individual personal informatics systems that measure different behaviors in a variety of contexts.

Less is known about the substantive focus of these different studies, across different measurement domains (tracking of physical and/or mental characteristics) and outcome of interest domains (aiming to promote insight or change in physical and/or mental characteristics). To provide an organizing conceptual framework, we present a two-dimensional space that resembles the Cartesian coordinate plane (as shown in Fig. 5.2) that maps out four different quadrant areas representing the substantive focus of smartphone-based self-tracking research: (1) objective measurement—physical outcome of interest (e.g., measuring accelerometer to infer physical activity levels), (2) objective measurement- mental outcome of interest (e.g., measuring mobility data using GPS to infer depressed mood), (3) subjective measurement—mental outcome of interest (e.g., measuring self-reported experience sampling surveys to assess psychological states), and (4) subjective measurement—physical outcome of interest (e.g., measuring self-reported experience sampling surveys to assess subsequent changes in sensed physical activity).

To illustrate our framework's potential for conceptually organizing domains of interest in self-tracking research, we coded each reviewed article into one of the four quadrants based on its substantive research contribution with regard to its measurement-outcome of interest domains. To verify the accuracy of our framework classifications, a research assistant independently coded the articles using the

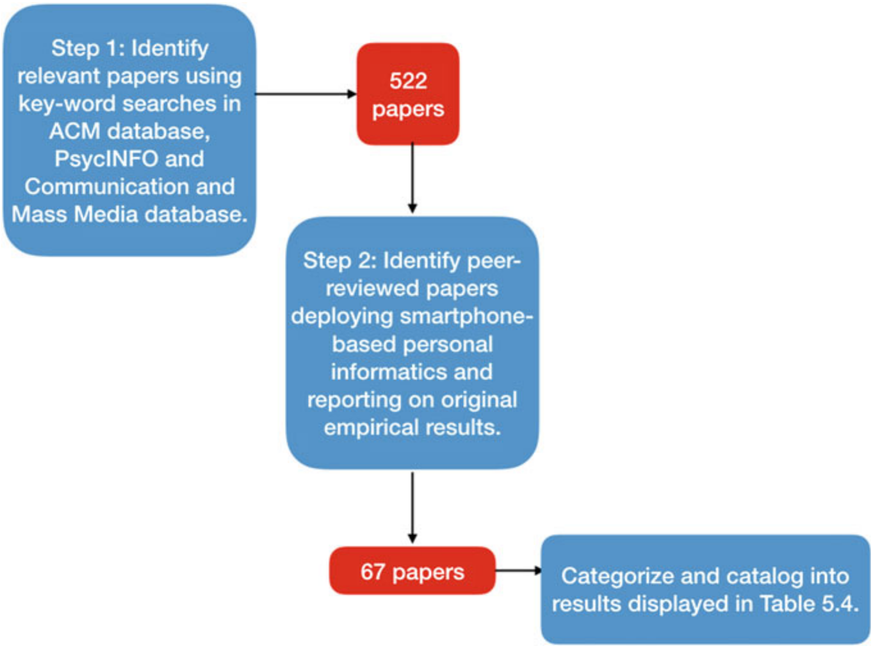

Fig. 5.1 Procedural flowchart and number of search results returned

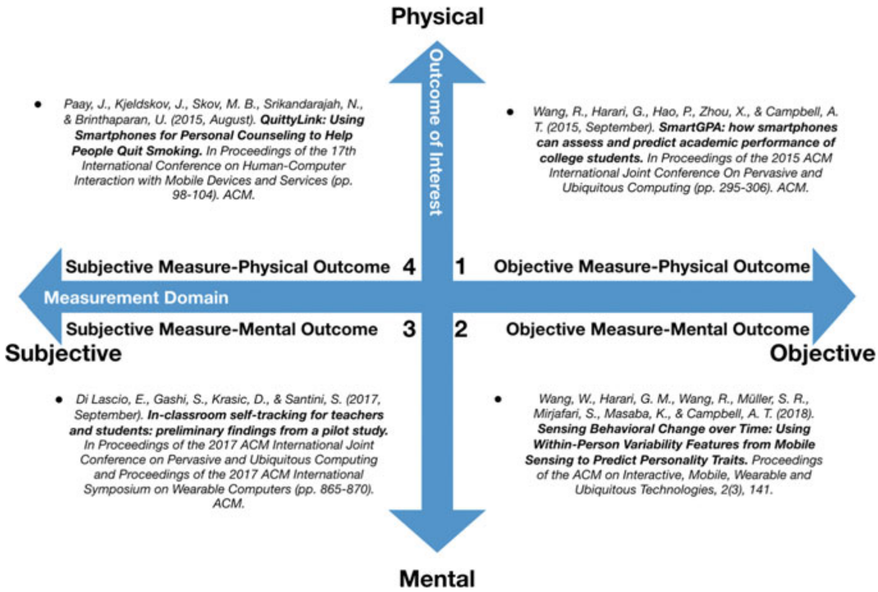

Fig. 5.2 Conceptual framework for organizing the smartphone-based PI literature. To organize the surveyed mobile sensing literature, we present a two dimensional conceptual framework. The conceptual framework resembles the Cartesian coordinate plane, consisting of two axis that encode magnitude relative to space. As shown in Fig. 5.1, the x-axis represents the measurement domain of the surveyed literature—specifically, it identifies the extent to a given article was focused on collecting either subjectively measured data (i.e. experience sampling surveys) or objectively measured data (e.g., mobile sensors). For instance, some papers described collecting physical activity data using the accelerometer (Wang et al. 2015), whereas others were focused on collecting mood or depression related information using phone-based ecological momentary assessments (Di Lascio et al. 2017). The y-axis represents the extent to which the researchers used their measurements to assess either physical or mental outcomes of interests. For instance, while some researchers were focused on using collected physical activity data to categorize various kinds of physical movements and social interactions (Harari et al. 2017b), others were focused on using physical activity data to infer mood or depression scores (Mehrotra et al. 2016)

four quadrants as well. The classifications were then compared, and any discrepancies were resolved through discussion. The full results of the literature review are presented in Table 5.4.

Much of the existing research has focused on the different components or "stages" that are characteristic of personal informatics systems. Some studies were focused on developing high-accuracy activity classifiers from sensors embedded in smartphones and wearables (e.g., Madan et al. 2010), whereas others were anchored around creating optimal feedback systems that were effective at inducing behavior change (e.g., Bentley et al. 2013). Below we discuss the literature on smartphones in personal informatics, focusing our discussion of previous research based on the type of physical and mental characteristics being tracked (Table 5.4).

Table 5.2 Details of literature review

Procedure	Categorical keyword source
In order to determine the extant literature linking the themes of smartphone-based personal informatics and behavior change, we used the following formatting of keywords to return searches in each database: [mobile-sensing keywords separated by OR] AND [self-tracking keywords separated by OR) AND ["behavior change"] AND [coding category keywords]	The coding category keywords were extracted from another study in which student's responded to questions asking them about motivations to self-track different aspects of their lifestyle To conduct our literature review, we utilized categorical keywords that were extracted from qualitative responses that 1706 young adults provided to the following question: "What would motivate you personally to self-track, and which behaviors would you track?" The qualitative responses were content analyzed to obtain an exhaustive list of 75 individual self-tracking categories, which could be described by 8 broader categories (See Table 5.1 for the full list of categories): physical health, physiological, sleeping patterns, productivity, mood, socializing, digital media use, and daily activities Hence, we conducted the full literature review in eight stages, operationalizing one self-tracking category (with all of its individual sub-category topics) through our keyword patterns in each stage

Table 5.3 Steps for filtering literature review results

Step No.	Description of filter
Step 1	The result must be a peer-reviewed paper and report on original empirical work
Step 2	The result must discuss at least one smartphone-based technology that supports a collection of human characteristics and/or acts a mediator of relevant feedback information on behavioral patterns

Note The smartphone or mobile may be involved either in the data collection stage or the feedback generation and communication stage of the personal informatics ecosystem deployed

Physical Activity. Physical activity was the substantive focus of many of the papers we reviewed. The majority of studies on physical activity fell under either the objective measurement-physical outcome of interest or objective measurement-mental outcome of interest quadrants of our conceptual framework. For instance, Harari et al. (2017a) deployed a smartphone sensing application, StudentLife, which measured daily durations of physical activity using data collected from the accelerometer sensor of the smartphone in a college student population. Notably, the authors found that individual differences in ethnicity and academic class were predictive of changes in physical activity. While Harari et al. (2017a) were not focused on the feedback component of personal informatics systems, other researchers were especially interested in developing an effective feedback system developed from the collected physical activity data in order to engage users in self-reflection. Kocielnik et al. (2018) developed Reflect Companion, a mobile conversational software that facilitated immersion in the reflection of activity levels as aggregated from fitness trackers. Their results indicated that mini-dialogues were successful in inducing reflection from the users, on their physical activity levels. Some studies were focused on using the personal informatics system to induce systematic behavior change that increases physical activity levels in individuals. To incentivize higher levels of physical activity, these studies gamified the objective of increasing physical activity by either individual into motivated competing teams (e.g., Ciman et al. 2016; Zuckerman and Gal-Oz 2014) or by tapping into their existing social networks (Gui et al. 2017).

A large majority of studies in this category were single deployment studies that examined the efficacy of personal informatics tools deployed to monitor physical activity. While some studies attempted to situate their work under a theoretical model of behavior change (e.g., Theory of Planned Behavior; Ajzen 1985; Du et al. 2014) virtually no research attempted to integrate with extant personal informatics models of behavior change such as those proposed by Li et al. (2010). Instead, different researchers tended to make use of different theoretical models of behavior change originating from a range of behavioral disciplines. For example, the Transtheoretical Model of Behavior Change (Glanz et al. 2008) and the Social Cognitive Theory of Behavior Change (Bandura 2004) have been employed in physical activity intervention studies (e.g., in the design of applications; Marcu et al. 2018). However, there is a general lack of integration between these theoretical models and personal informatics models of behavior change. Such an approach has led to some studies reporting conflicting behavior change outcomes and high participant attrition, which may be a result of using models of behavior change that are not specifically adapted to the use of personal informatics systems.

Physiological. There were only four studies that we categorized as pertaining to physiology in our literature search. Hwang and Pushp (2018) deployed a system called “StressWatch”, which was aimed towards assisting users in triangulating the sources of their stress in their daily life. Using a concert of smartphone and smartwatch systems, StressWatch monitored the context of users in concert with their heart rate variability. Subsequently, the StressWatch extracted stress levels from the heart rate variability data and “matched” these patterns with the changing contexts of the user in order to suggest possible origins of stress in daily life. In a single subject pilot deployment, the authors refined the design of StressWatch by deciding that stress levels could be accurately detected when eating and working, but not when walking.

In a similar line of work, Bickmore et al. (2018) developed a virtual conversational agent that counseled patients suffering from chronic heart condition atrial fibrillation using data collected from a heart rhythm monitor attached to a smartphone. In a randomized trial with 120 patients, the authors found that the conversational agents led to a significant positive change in the self-reported quality of life scores as compared to a control group who did not receive the agent-based counseling. Cumulatively,

Table 5.4 Overview of literature review results organized according to our framework

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
1. Objective Measurement—Physical Outcome of Interest										
Athukorala et al. (2014)	1								X	X
Bentley et al. (2013)	1	X		X						X
Bexheti et al. (2015)	1	X								X
Brewer et al. (2015)	1								X	X
Chen et al. (2016)	1	X		X				X		
Ciman et al. (2016)	1	X								X
Du et al. (2017)	1	X								X
Fang et al. (2016)	1	X								X
Fujiki et al. (2007)	1	X		X				X		
Gouveia et al. (2015)	1	X								X

(continued)

Table 5.4 (continued)

References	Framework classification	Physical and mental characteristics								
		Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Grimes et al. (2010)	1	X		X						X
Gweon et al. (2018)	1	X							X	X
Harari et al. (2017b)	1	X						X		
Hirano et al. (2013)	1	X								X
Johansen et al. (2017)	1	X								X
Jylhä et al. (2013)	1	X								X
Kadomura et al. (2014)	1			X						
Kamphorst et al. (2014)	1	X								X
Ko et al. (2015)	1			X					X	X
Kocielnik et al. (2018b)	1	X								X

(continued)

Table 5.4 (continued)

References	Framework classification	Physical and mental characteristics								
		Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Lacroix et al. (2008)	1	X					X			X
Lee et al. (2014)	1	X	X	X						X
Lee et al. (2017)	1	X		X	X					X
Li et al. (2017)	1								X	X
Madan et al. (2010)	1	X		X				X		
Mollee et al. (2017)	1	X								X
Muaremi et al. (2013)	1	X		X						X
Pipke et al. (2013)	1									X
Rabbi et al. (2015)	1	X		X						X
Simon et al. (2012)	1								X	X

(continued)

Table 5.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Tang et al. (2013)	1								X	X
Tulusan et al. (2012)	1					X				X
Van Bruggen et al. (2013)	1								X	X
Wang et al. (2015)	1	X								X
Weiss et al. (2012)	1					X			X	X
Zheng et al. (2008)	1									X
Zuckerman and Gal-Oz (2014)	1	X	X	X						X
2. Objective Measurement—Mental Outcome of Interest										
Abney et al. (2014)	2								X	X
Bai et al. (2013)	2				X			X		X

(continued)

Table 5.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Bickmore et al. (2018)	2	X	X							X
Canzian and Musolesi (2015)	2						X			X
Chaudhry et al. (2016)	2	X		X						
Cuttone and Larsen (2014)	2									X
Doryab et al. (2015)	2	X								X
Greis et al. (2017)	2								X	X
Huang et al. (2016)	2						X	X		X
Hwang and Pushp (2018)	2		X				X			X
Mehrotra et al. (2016)	2						X		X	X

(continued)

Table 5.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Meyer et al. (2016)	2	X								X
Wang et al. (2016)	2	X			X		X			
Wang et al. (2018a)	2	X					X			
Wang et al. (2018b)	2	X			X	X		X		X
3. Subjective Measurement—Mental Outcome of Interest										
Barbarin et al. (2018)	3	X		X						
Bentley and Tollmar (2013)	3	X			X		X			X
Di Lascio et al. (2017)	3					X	X	X		
Kuo et al. (2018)	3	X							X	X
Paredes et al. (2014)	3	X		X				X		

(continued)

Table 5.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physiological	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Sasaki et al. (2018)	3						X			X
Springer et al. (2018)	3						X			
4. Subjective Measurement—Physical Outcome of Interest										
Du et al. (2014)	4	X		X						X
Gui et al. (2017)	4	X						X		X
Hsu et al. (2014)	4	X		X						X
Kocielnik et al. (2018a)	4								X	X
Li et al. (2015)	4	X						X		X
Luhanga (2015)	4	X		X						
Marcu et al. (2018)	4	X								X
Möller et al. (2013)	4								X	X
Paay et al. (2015)	4	X								X

Table 5.4 shows the following information: (1) the quadrant of our self-tracking framework that references were categorized under and (2) the categories that were a focus of the specified references, as denoted by an "X" in the relevant columns

studies in the Physiology category provided promising avenues for detecting and modeling feedback based on real-time heart-rate data.

Nutrition. The large majority of studies on nutrition were categorized as objective measurement-physical outcome of interest quadrants of our conceptual framework. For example, Rabbi et al. (2015) developed and tested the efficacy of the MyBehavior application using the Theory of Planned Behavior (Ajzen 1985). MyBehavior was a smartphone application that integrated inferences of physical activity levels and dietary behaviors to produce personalized recommended changes to these patterns in order to promote a healthier lifestyle. The authors found that their personal informatics system led to an increase in physical activity and a decrease in food calorie intake, as compared to a control condition of participants not using the MyBehavior application. Other studies were focused especially on target populations—such as women suffering from obesity (Barbarin et al. 2018). Instead of implementing behavior change interventions directly, these studies were focused on identifying the unique needs of clinical populations.

Sleeping Patterns. The large majority of studies on sleeping patterns were categorized in either the objective measurement-physical outcome of interest or objective measurement-mental outcome of interest quadrants of our conceptual framework. Studies categorizing this theme are focused on assessing sleeping patterns from smartphone or wearable sensors and also on the digitized manual tracking of sleeping patterns, to delineate resulting changes in behavior. The emphasis individual studies place on different components of personal informatics varies. For instance, Bai et al. (2013) assessed changes in sleeping patterns using data collected from a mobile phone and through self-report surveys. They did not provide a feedback mechanism for participants, but instead used parts of the collected data to train their model on sleep-related habit formation patterns.

In contrast to this feedback-agnostic approach, Bentley et al. (2013) were exclusively focused on creating a tool to help individuals derive meaningful feedback from smartphone sensing data. The researchers constructed Health Mashups, a system designed to detect meaningful connections that are stable over time between a variety of behaviors and sensed data. One of these behaviors was sleep—the researchers collected sleeping pattern data from Fitbit. The researchers performed statistical analyses on the sleep data each night and then displayed natural language statements to individuals about observed associations (i.e. "On days when you sleep more, you get more exercise") on their smartphones (Bentley et al. 2013). A comprehensive PI deployment, incorporating elements from both of the previously cited sleep-related studies, was performed by Lee et al. (2017), who developed a wearable and smartphone-based system to manage unconscious itching behaviors that occur while individuals slept. Developed over the duration of two experiments and deployed in a full pilot study, the Itchtector was deemed helpful by many of the participants in the study, as revealed through qualitative interviews.

Productivity. Research examining productivity in personal informatics systems is relatively sparse and focused on the objective measurement-physical outcome of interest, objective measurement-mental outcome of interest, and subjective measurement-mental outcome of interest quadrants of our conceptual framework. Di Lascio et al. (2017) refocused the attention of personal informatics from fitness and personal health onto the “work environment”. The researchers identified broad aims that a Quantified Workplace personal informatics system would need to be designed to address: choosing valuable data sources, deriving insights relevant to the workplace from this data, and driving change from these insights. The researchers then implemented a personal informatics system in a university setting to explore potential answers to their three questions. A metric called the Emotional Shift was developed in order to assess changes in affective states over the course of a university lecture. The authors reported tracking this metric using the PI system to show how emotional trajectories manifest in a real-life productivity-based environment. Since these researchers relied on surveys to collect data to assess mood changes in a work environment, this paper fit into the subjective measurement-mental variable of interest quadrant of our conceptual framework.

Mood. The large majority of studies on mood were distributed over the objective measurement-mental outcome of interest and mental measurement-mental outcome of interest quadrants. Studies categorizing this theme typically relied on self-reported mood information at pre-specified daily frequencies to track individual trajectories of mood over time. For instance, the EmotiCal personal informatics system tracked mood and provided predictive emotional analytics to individuals with the intention of facilitating participant understanding of mood and “trigger events” (Hollis et al. 2017; Springer et al. 2018). The EmotiCal system also implemented a feature to generate remedial plans by recommending new behaviors with the aim of increasing positive emotion. The researchers found that mood forecasting improved mood and emotional self-awareness in comparison to control condition participants, implying that positive behavior change had occurred as a result of using the PI system. In another example, mood-driven PI systems deployed amongst targeted populations—such as bipolar patients—did not result in systematic behavior changes (Doryab et al. 2015). The researchers deployed the MONARCA system, which patients used to report their daily mood scores. Additionally, the MONARCA system was able to sense behavioral traces, and it aimed to identify the effect of specific behaviors on the daily mood scores. While the authors identified sleeping patterns and physical activity as the main drivers of mood, none of the 78 participants in the pilot deployment reported any mood improvements as a result of using MONARCA. The authors used their insights to develop a “mood inference” engine for the existing MONARCA app.

The majority of the studies categorized by this theme did not set out to induce and measure the behavior change resulting from the use of their platforms. This was a concern, as without such an approach, the efficacy of different mood-targeted personal informatics systems cannot be assessed. Moreover, there was a distinct absence of passive mood detection technologies— all the surveyed papers relied on participant input to collect mood-related information.

Socializing. The large majority of studies on socializing were distributed over the objective measurement-physical outcome of interest and objective measurement-mental outcome of interest quadrants. Studies categorizing this theme typically assessed sociability from existing online social networks or from the microphone contained in smartphones and attempted to relate variations in behaviors and traits to the observed variances in sensed sociability. For instance, Harari et al. (2017a) examined behavior change in sociability patterns amongst a cohort of 48 students that participated in a 10-week smartphone-sensing study. The results suggested that sociability was typically high during the initial weeks of a semester but then decreased during the first half of the semester as the midterm examination period approached. In the second half, sociability increased and individual differences in sociodemographic characteristics (ethnicity and academic class) predicted sociability trajectories during the semester.

In a similar line of work across the objective measurement-physical outcome of interest quadrant, Madan et al. (2010) investigated how health-related behaviors spread as a result of face-to-face interactions with peers, by deploying a mobile sensing study that collected relevant data about participant location and ambient conversation using the microphone. The researchers found that the health behaviors exhibited by participants were correlated with the behaviors of peers that they interacted with over sustained periods of time, and this type of sensing could be implemented using just the sensor technology already embedded in a smartphone. This work suggests that future behavior change interventions might benefit from relying on the sensing of social interactions, given the strengths of these technologies for passively and non-intrusively collecting data about interpersonal interactions as they unfold in the course of daily life.

Hence, studies categorizing this self-tracking theme were typically focused on detecting sociability from online social networks or through smartphone sensors, in order to assess how social trajectories manifest in an ecologically valid manner. Some studies were focused on examining the impact of this sociability on real-world habits and behaviors, including fitness and diet. Studies under this theme occasionally attempted to assess behavioral change quantitatively (for instance, see Chen et al. 2016) but a large number of studies did not aim to operationalize behavior change or failed to do so in a quantitative manner.

Digital Media Use. Studies on digital media use were distributed over the objective measurement-physical outcome of interest, and the objective measurement-mental outcome of interest quadrants. For instance, FamiLync is a self-tracking app designed to measure digital media use and abuse in collaboration with one's family (Ko et al. 2015). The app promoted the non-use of smartphones in certain settings, contained a 'virtual public space' which facilitated social awareness on the use of the smartphone and contained tools that discouraged or prevented the use of digital media technologies (i.e., locking the screen and snoozing social media notifications). A three-week user study spanning 12 weeks indicated that the app improved the understanding of smartphone usage behavior and therefore allowed for more efficient parental mediation of excessive digital media use. Such positive changes in digital media use are likely to boost the mental health of participants, as excessive or very frequent smartphone usage is shown to negatively influence mental illness (Choi et al. 2012). In a related approach that went one further step by operationalizing participant predictions of future behaviors, Greis et al. (2017) deployed a PI system that tracked the number of times individuals unlocked their phone on any given day. Participants were required to indicate how many times they predicted to unlock their phone on any given day during each morning of the study. The results indicated that the exercise of self-predicting future behavioral patterns led to the automatic discovery of new insights into patterns of smartphone use (Greis et al. 2017). Hence, while the literature on digital media use trackers is sparse, this is a particularly important area for PI deployment with past research showing that it is possible to obtain behavioral assessments of "smartphone addiction" tendencies from smartphone data (Montag et al. 2015). This seems like a promising direction for behavior change interventions given the adverse risks that excessive digital media use (e.g., smartphone or social media addiction) poses to developing adolescents and adults. The research reviewed here indicates that digital media use tracking PI systems may influence positive behavioral change through increased self-tracking habits that reduced usage through increased awareness of use (Greis et al. 2017; Ko et al. 2015).

Daily Activities. The large majority of studies on daily activities were distributed over the objective measurement -physical outcome of interest, objective measurement-mental outcome of interest, and subjective measurement-physical outcome of interest quadrants. For instance, Wang et al. (2018) investigated how patterns of behavior change in daily activities, as sensed through the smartphone, could be used to predict personality traits of young adults. Specifically, the researchers examined how trends in within-person ambient audio amplitude, exposure to human voice, physical activity, phone usage, and location data predicted self-reported Big Five personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness). Hence, this study fits into the objective measurement -mental variable of interest quadrant because it used data generated from physical measure (i.e., accelerometer data, microphone data) to make mental inferences (i.e., personality traits). The results indicated that personality traits could be modeled with high accuracy from these within-person variations in daily activities.

While Wang et al. (2018) did not overtly focus on administering feedback to individuals, Hirano et al. (2013) deployed a PI system with a focus on providing effective feedback to participants, specifically about their walking behavior. The researchers designed an app that detected participant motion, contained a manual digital logging feature of daily step count, and regularly notified participants to engage in physical activity. The researchers found that participants reported becoming more self-aware of their bodies and were wary of the time they spent sitting.

Some studies examined how daily activities are indicative of personality traits and mental states. For instance, one mobility study, focused on target populations of depressed individuals, succeeded in predicting depression states from mobility data of participants (Canzian and Musolesi 2015). Other studies developed and tested the efficacy of developing feedback techniques that nudge users towards engaging in healthier physical routines during their daily activities (i.e., Hirano et al. 2013). While the reviewed work suggests that daily activity PI systems can induce self-insight and self-awareness (e.g., Hirano et al. 2013), the effects of these systems on behavioral change outcomes remain relatively under-investigated and ambiguous.

5.3 Discussion

In this chapter, we surveyed the existing literature to identify an organizing framework for situating past and future scholarship using smartphones in personal informatics research. Our review findings suggest that a two-dimensional conceptual framework can be used to organize the smartphone-based self-tracking literature. Our review suggests that most of the smartphone-based self-tracking literature is concentrated in the first two quadrants of the conceptual framework: they tend to use objectively collected measurements (e.g., using mobile sensing) to deploy interventions aimed towards influencing mental or physical outcomes of interest. However, research in the other two quadrants was relatively sparse: fewer studies attempted to collect subjective measurements of physical and mental states to assess or influence physical outcomes of interest. Thus, future research should focus on filling in this gap in the literature by evaluating personal informatics systems that collect mental state information using subjective measures and quantify behavior change in relation to changing physical and mental states resulting from the intervention. There is especially a need to develop passive mobile sensing systems that can collect mood-related information unobtrusively from users (e.g., LiKamWa et al. 2013). The growth of mobile sensing systems in the physical domain has been rapid, and there is immense potential for this growth to percolate into the surrounding conceptual quadrants—namely to the subjective measurement-mental outcome of interest and subjective measurement—physical outcome of interest quadrants

Generally, research has prioritized certain components of personal informatics systems over others. For instance, some researchers focused on developing accurate sensing technologies in favor of administering user feedback, while other researchers were entirely focused on exploring optimal ways of generating actionable feedback for the user. Our results indicated that personal informatics work is currently dominated by computer science researchers, indicating a timely opportunity for behavioral researchers to get into the fray. Furthermore, we found limited theoretical integration in most of the extant literature, with findings indicating a shift in behavioral trajectories typically being considered in relation to one or two behavior change theories disciplinary-specific theories. While the use of classical theories in designing personal informatics is valuable, future work needs to further deploy theories developed specifically for the use of personal informatics systems (e.g., Li et al. 2010) in order to directly address the needs and habits of personal informatics application users. Such a consistency in theoretical integration will also ease cross-domain comparisons of the effectiveness of different personal informatics apps in inducing self-awareness and causing behavior change. Future theoretical work should integrate theories of personal informatics (e.g., Kersten-van Dijk et al. 2017) with behavior change theories (e.g., Prochaska and Velicer 1997), in order to develop a cross-disciplinary theoretical framework for designing optimal personal informatics applications.

5.4 Future Directions

The vast majority of reviewed papers in this literature review originated from the ACM database, suggesting that our results are skewed towards research produced by computer science and technically-oriented researchers. Furthermore, we found that an appreciation for individual differences in demographic and personality traits was generally absent from the reviewed empirical work, presumably because these were not variables of interest to technical researchers (e.g., Götz et al. 2017). In order to sustain behavior change interventions using digital self-tracking data, future work should identify how variations in individual differences are related to patterns of behavior change resulting from digitally engineered interventions. Indeed, there is a need for more work in the domain of understanding how an individual's personality and demographic traits relate to their motivations to self-track, and how these then influence the sustainability of the resulting behavior change.

An increase in cross-disciplinary dialogue between technologists and social scientists may facilitate an appreciation for individual differences in psychosocial characteristics (e.g., demographics, personality traits) during the design, implementation, and evaluation of smartphone-based self-tracking systems. Such interdisciplinary efforts are underway in the form of workshops (e.g., Campbell and Lane 2013), conferences (e.g., Rentfrow and Gosling 2012), and research initiatives (e.g., Life Sensing Consortium; lifesensingconsortium.org) that bring mobile sensing researchers from diverse disciplines into conversation with one other. An increase in interdisciplinary collaboration and widespread adoption of personal informatics models are likely to engender the next generation of personal informatics tools that customize their feedback to an individuals' psychological characteristics. We believe that customizing interventions according to individual differences will play an important role in facilitating self-reflection and sustained behavior change for the next generation of personal informatics systems.

It is encouraging to see that there are abundant deployment studies of different types of personal informatics studies in the literature. The diversity of applications of personal informatics system is particularly impressive, as is the commitment of researchers to pilot their proposed systems with real participants. While results pertaining to induced behavioral change vary across studies, we generally find that participants respond favorably to interventions and report increased feelings of self-awareness as a result. This work suggests that the future for personal informatics is bright, as more and more individuals are likely to adopt self-tracking methods as wearables and sensor-laden smartphones penetrate further into the human population. Future work should especially build upon two domains that contained sparse sensing literature: productivity and digital media use. Developing personal informatics systems for productivity tracking can assist organizations in monitoring employee productivity by displaying the times and locations at which an employee is at their most productive, and can further assist employees in maintaining adequate work-life balance by allowing employees to set time-based goals for work and recreational activities (see Mashhadi et al. 2016 for review). Similarly, sensing tools to examine detailed patterns of engagement with digital media can help curb concerns of social media abuse and its resulting detriments on mental health by prompting users to limit their time on the internet if it exceeds some predetermined threshold (i.e. Pardes 2019). More sophisticated applications could sense different kinds of social media use (i.e., active vs. passive use; Gerson et al. 2017) and alert users when they are engaged in types of social media usage that are typically associated with declines in mental well-being.

Moreover, future research should focus on deploying sensing work in non-Western settings. Virtually every cited study in this paper sampled from predominantly Western populations, as has been the tradition in behavioral science (Henrich et al. 2010). However, there are several Eastern social media platforms that rival the size and reach of their Western counterparts, such as WeChat (Lien and Cao 2014, Montag et al. 2018) and Weibo (Sullivan 2014). Similarly, over the last few years, the Quantified Self movement has diffused from the western hemisphere to the eastern hemisphere, especially to China (Yangjingjing 2012). The potential for personal informatics to succeed in the developing world is also bolstered by increasing smartphone penetration rates in fast-growing democratic nations such as India (Singh 2012). Hence, the spread of personal informatics around the world, coupled by the growth of non-Western social media platforms makes it essential for future research to focus on non-Western, multicultural samples in designing and deploying smartphone-based personal informatics systems. By deploying digital self-tracking platforms in developing countries around the world, we can accomplish two interrelated goals: (a) we can make digitized self-tracking a tool used at large by diverse individuals and (b) we can use the generated data to examine how richness in individual differences guides human-computer interaction. We look forward to social scientists and technologists collectively embracing the potential of self-tracking technologies in conducting interdisciplinary research.

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