Exploring Opportunities for Data-Driven Wellbeing Support through Positive Reinforcements

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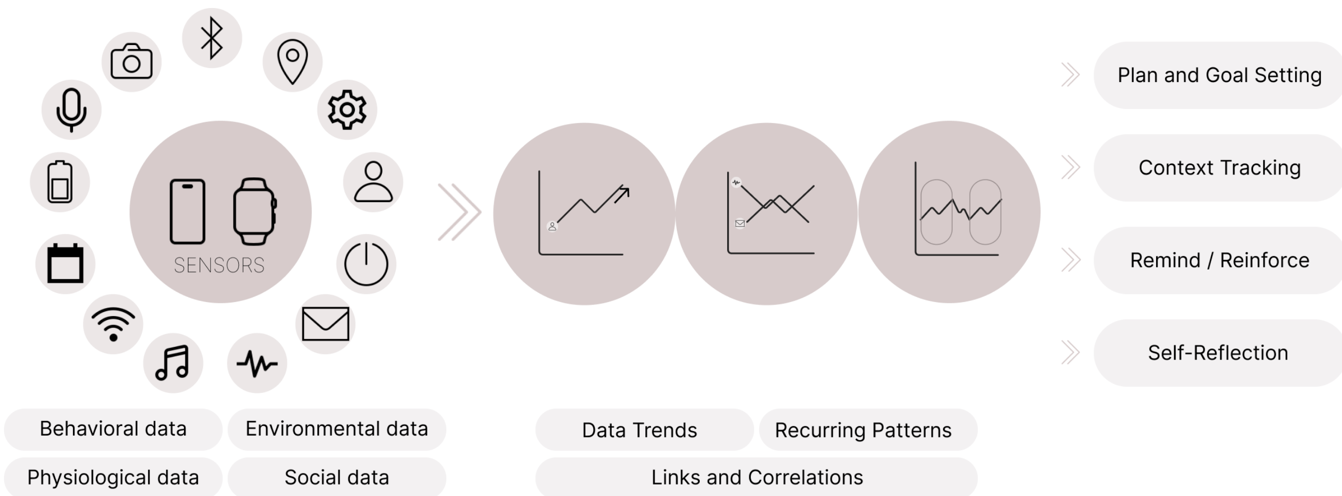

Figure 1: Mobile Sensors offer behavioral, physiological, environmental, and social data that allow for user quantification of wellbeing. Identifying data trends, links, and correlations between sensor data or recurring patterns enables tailored and smart technology to support the user and promote wellbeing. This lays the data foundation to design for wellbeing maintenance and implementing positive computing systems enabling their four main scenarios: plan and goal setting, context tracking, remind/reinforce, or self-reflection [18].

ABSTRACT

Modern technologies support users' wellbeing, enabling the quantification of user behavior to allow for holistic insights into mental health in its multifaceted nature. Current research leverages personal data gained through mobile sensing for problem-oriented support of poor health conditions. We argue that data-driven approaches can also be used to craft positive user support on the broader mental health continuum. Moreover, artificial intelligence offers novel opportunities to design positive technology that identifies complex behaviors, contexts, and user wellbeing interplays. These insights can be helpful for self-reflection or positive reinforcement. It can foster designs that promote healthy habits, supporting users in structuring their days accordingly and expanding interventions to embed into daily experiences to adapt to specific contexts and situations in situ. In this work, we highlight the potential of context-aware user support, which is driven by artificial intelligence coupled with mobile sensing. In detail, we present four examples to underpin the support potential.

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CCS CONCEPTS

• **Human-centered computing** → **Collaborative and social computing**; *Human computer interaction (HCI).*

KEYWORDS

Positive Computing, Wellbeing

1 INTRODUCTION

Mental health can be viewed as a continuum from optimal wellbeing to severe distress [15]. This perspective, known as the *mental health continuum*, highlights the diverse range of experiences individuals may encounter. At one end, individuals flourish, enjoying high life satisfaction and positive emotions. In contrast, some may languish in the middle, grappling with mild symptoms of depression or anxiety. At the opposite extreme, individuals may suffer from diagnosed mental illnesses or severe distress. This continuum emphasizes promoting wellbeing across all levels and implementing support that fosters resilience and positive functioning. Adopting an approach that considers this complexity is essential to effectively promote wellbeing, enabling a nuanced understanding of the factors influencing mental health outcomes. However, today, we typically see that support, notification, and interventions are given only when a "decline" in wellbeing is detected; thus, they are not used to promote stability or increase wellbeing positively.

Wellbeing is a multifaceted construct [19] encompassing psychological, social, and environmental dimensions. Effective wellbeing promotion requires an approach that acknowledges this complexity. With the lens of intelligent systems, we argue that human-computer interaction can support adapting and adjusting to the user's needs by understanding the user's context. Here, integrating mobile sensing technology into mental health research offers new avenues for comprehending and addressing the complexities of wellbeing, e.g., [36]. By capturing diverse aspects of behavior, context, and social/environmental factors, mobile sensing provides a comprehensive lens to examine mental health's multifaceted nature [7, 33]. Recent studies demonstrate the potential of leveraging Mobile Sensing data to monitor mental health symptoms, predict conditions like depression severity [25], and therapeutic outcomes [13]. Additionally, passive sensing technologies have shown promise in detecting mood states in everyday life [10, 17, 22]. However, traditional approaches often focus solely on identifying deteriorating mental health, neglecting the significance of positive moments in preventing relapse and reshaping individuals' perceptions. Our research emphasizes identifying and reinforcing positive trends within digital markers indicative of mental health conditions. By harnessing these indicators, derived from moments of wellbeing captured by mobile sensing technology, we aim to promote resilience and prevent relapse.

We argue for leveraging positive trends to craft data-centric interventions for mental health and wellbeing, see Figure 1. Tailoring interventions to individuals' needs and preferences and leveraging technology to identify and amplify factors contributing to wellbeing can lead to more effective outcomes. Our research explores the potential of data-driven technologies in addressing mental health issues, particularly focusing on depression and its symptoms [30]. As mental health comes on a spectrum [15], the pure absence of illness does not necessarily mean that no support or internal work is needed to promote wellbeing (e.g., Terzimehić et al. [37]), and insights valuable for the treatment and support of mental disorders can be beneficial for the broader spectrum of mental health.

By infusing positive psychology and human-centered design principles into computing systems, we aim to develop tools and environments that foster human flourishing and unlock individuals' full potential [4]. Moreover, we seek to initiate discussions on the future trajectory of technology in promoting and preserving mental health, shifting the paradigm from solely addressing poor mental states to embedding everyday life with designs that uphold positivity and wellbeing.

2 MOBILE USER QUANTIFICATION OF WELLBEING

In HCI research, there's a trend towards developing systems that quantify user behavior to enhance wellbeing, particularly focusing on digital mental health support tools. In recent years, there has been a surge in interest in self-tracking and reflection among HCI researchers, leading to the evaluation of various personal informatics systems. These increasingly popular systems are evident in movements like Quantified Self and the proliferation of commercial self-tracking apps. Particularly, the rise of affordable wearables has spurred research in fitness tracking. However, personal informatics extends beyond physical activity to domains such as tracking mood [3], sleep [35], and social interactions [31] to promote mental health.

Self-tracking mood helps users to improve their awareness and proactive self-regulation of their emotional wellbeing [6]. However, people are sometimes unaware of their mood and the various aspects that might influence it [39]. Due to these factors and the direct impact of mood on individuals' subjective wellbeing, investigating the contextual aspects of mood becomes particularly interesting [2].

Self-management involves applying self-regulation techniques to effectively handle health-related conditions and their associated risk factors [11]. In particular, individuals learn techniques to treat disorders in the long term. At the same time, many self-help approaches include techniques from Cognitive Behavioral Therapy (CBT) that focus on symptom treatment during depressive episodes [11]. Therefore, self-management goals involve empowering individuals to recognize early signs of deteriorating health conditions, formulating action plans for relapse, and understanding available resources [14]. Caldeira et al. [3] showed that users want features that help them better associate mood data with contextual information to manage their emotional wellbeing and health conditions.

Nevertheless, the fluctuating trajectory of depression raises significant challenges, as individuals do not perform self-management consistently [16]. Individuals aware of symptom fluctuations prefer self-management during episodes with fewer symptoms [16]. Therefore, integrating technology-based methods into everyday life may be a viable solution for self-tracking to understand patterns in symptoms and behaviors [16, 20]. Since they prefer to engage more during episodes with fewer symptoms, these windows can motivate and empower users to focus on the positive to keep them engaged and hopefully prevent symptoms from deteriorating again.

Another thread of research explores how to make use of digital behavioral markers to automatically track, monitor, and detect the behavior of users leveraging mobile sensing data, such as GPS, or machine learning [24, 26, 32]. The available data from sensors embedded in smartphones or wearable devices can capture a wide range of information, such as physical activity levels, sleep patterns, heart rate, and location data. These factors impact mental health and wellbeing, highlighting the importance of considering a diverse range of contextual information in applications to understand better and support users' wellbeing. Promising mobile sensing data to predict depression or its severity include GPS for mobility or location, smartphone usage behavior, activity, sleep, and heart rate variability [5, 21, 29, 38]. Digital phenotyping through features such as time spent at home, sleep duration, and activity have statistically significant and consistent correlations with depressive mood [28]. Moreover, tracking attributes such as spatial trajectories, mobility patterns, social interactions, and audio can be beneficial in identifying relapse in depressed patients [23].

Summary. Utilizing this data to quantify user behavior helps identify advantageous behaviors and contexts to highlight positive experiences and helpful connections in the data, ultimately supporting users' wellbeing. Thus, this can prove beneficial for addressing mental disorders and for enhancing overall mental health. Therefore, we argue that future AI systems should use mobile sensing data to promote wellbeing through tailored support.

3 PATTERNS AND TRENDS IN PERSONAL DATA

The wealth of data gathered through various sources, such as smartphones and wearables, relates to an individual's behavior, environment, social interactions, and mood. AI introduces a huge potential for technology as mental health support by identifying correlations and patterns within user data to help uncover the complex interplay between different factors and their impact on users. It can provide valuable insights into how various environmental, social, and behavioral factors influence an individual's mood and overall wellbeing. For instance, interventions can be tailored to reinforce these positive influences if a person's mood data consistently correlates with specific environmental factors or social interactions, such as spending time outdoors or engaging in meaningful conversations.

The integration of AI can further play a crucial role in identifying outliers within datasets, which can serve as indicators of shifts in emotions or significant events. By leveraging AI algorithms, such as anomaly detection techniques, subtle deviations in data can be highlighted, potentially signaling changes in mood or circumstances. However, while much attention is given to detecting and addressing negative trends in personal data streams [34], it's equally important to recognize and reinforce positive patterns that contribute to wellbeing and mental health. Leveraging AI to analyze interconnected data streams and identify the beneficial behaviors and routines contributes to the design of positive technology. However, this aspect is often understudied in current literature.

Mental health and wellbeing are often influenced by long-term habits and various factors beyond isolated events on which current technology and personal informatics tools typically focus on tracking and reflecting. It is not just about one night's sleep but the sleep hygiene maintained over weeks, which may intertwine with regular physical activity. These contextual factors are crucial for fostering wellbeing and contribute significantly to overall mental health, emphasizing the importance of routines over singular events. However, identifying and communicating these connections to users through visualizations is not straightforward. A significant challenge lies in providing appropriate feedback to users and presenting information in a supportive and insightful manner without overwhelming them. This demands a delicate balance to ensure users benefit from self-reflection while avoiding information overload, particularly regarding long-term habits and routines that are more challenging for users to reflect on and comprehend. Despite this awareness, integrating and analyzing insights identified through technology into self-tracking remains daunting for users, underscoring technology's potential role in providing support. Technology can alleviate this burden for users, yet users' design requirements, preferences, and perceptions are still not fully explored. Unanswered questions also persist regarding determining the optimal timing and format for displaying such information, whether during moments of distress to help improve the situation or rather during positive experiences to amplify positive feelings further.

4 DESIGNING FOR WELLBEING MAINTENANCE

We believe that AI is a powerful tool for uncovering complex relationships within personal data, offering support in understanding and improving wellbeing by identifying trends, correlations, and opportunities for intervention. Its ability to process vast amounts of data and uncover subtle patterns makes it an invaluable asset in mental health and self-management.

Yet, there are numerous challenges facing HCI research and the design of future applications. While detecting negative trends or designing interventions to help users in distress is a clear objective, there is a lack of research on designing for positive reinforcement. Leveraging the concept of possibility-driven design [8], technology holds the potential to nurture wellbeing in a daily or habitual manner. Shifting the mindset of both developers and users to see technology as more than just problem-solving but rather to enhance life and promote positive change and personal growth [8]. Enhancing and solidifying positive experiences and moments for users can be instrumental in promoting stable and healthy mental conditions, not just during poor mental health. Riva et al. [27] introduce the "Positive Technology" approach as the scientific and practical methodology for utilizing technology to enhance the quality of personal experiences through its organization, enhancement, and/or substitution. Positive Technology focuses on three key variables: emotional quality, engagement/actualization, and connectedness that can transform personal experience into a tool for building new and enduring personal resources [1]. Positive technologies, based on their impact on three aspects of personal experience, can be (1) Hedonic Technologies designed to elicit positive and enjoyable experiences, (2) Eudaimonic Technologies aimed at aiding individuals in attaining fulfilling and self-actualizing experiences, (3) Social/Interpersonal Technologies intended to enhance and facilitate connections among individuals, groups, and organizations [1]. Similarly, Hassenzahl et al. [12] argues for promoting wellbeing through the concept of Experience Design, which prioritizes the creation of enjoyable and meaningful moments as the focal point of all design efforts. However, building technology for positive experiences comes with questions yet to be answered for HCI research. How can technology support the preservation of those joyful moments and healthy behaviors for easy access whenever needed? How can users or technology effectively record these positive moments to relive them later? What aspects do users desire to preserve in this regard? Photos, audio, or videos might serve as more suitable mediums than text, as they can better capture the moment's essence. More and more memories also happen or are shared in the digital space [9]. Additionally, certain places may carry particular significance. What defines a "good" moment or habit, and how can its emotional essence be preserved? And how do users desire to capture content? Is it through user input or passively collected routines and habits, considering that positive experiences often manifest in recognizable patterns and regular routines [12]?

Lee et al. [18] propose a general-purposed platform architecture describing data handling, analysis, and applications to build such intelligent, positive computing systems. The main scenarios they identified are *Plan and Goal Setting*, *Context Tracking*, *Remind/Reinforce* and *Self-reflection*. We discuss possible applications for each scenario based on our vision of leveraging mobile behavior and context markers.

Plan and Goal Setting. By analyzing data, technology can pinpoint healthy behavior patterns and identify positive contexts influencing wellbeing. This data-driven approach enables users to align their daily routines with these beneficial patterns and establish realistic, measurable goals based on their current wellbeing status and desired outcomes. Moreover, users can set individualized goals, with technology offering personalized interventions tailored to their unique needs. These interventions dynamically adapt to changing circumstances, such as mood fluctuations, stress levels, or environmental factors detected through mobile sensing data. Seamlessly integrating into daily life, these interventions support user wellbeing, monitor progress, and provide mechanisms to achieve set goals. This holistic approach empowers users to manage their wellbeing and cultivate sustainable lifestyle changes proactively.

Context Tracking. In particular, crafting uplifting experiences and cultivating joyful memories through a data-driven approach facilitates the creation of personalized interventions, which presents a challenge with unclear design requirements. While identifying real-time connections and patterns, context tracking enables dynamic interventions that adjust to the user and the surrounding situation, location, and context. These interventions should not solely rely on reactive measures but also endorse proactive strategies seamlessly integrated into various contexts and situations to sustain wellbeing. The technology has the potential to learn to recognize significant cues, offering context and location/event-based feedback to users, seamlessly embedding positive experiences into their everyday routines.

Remind / Reinforce. AI systems can analyze user data, including habits, preferences, and schedules, to provide personalized reminders for wellbeing-related activities for positive reinforcement. Further, LLMs can consider contextual information such as time of day, location, recent activities, and past interactions to generate context-aware. For example, if a user has just completed a workout, the system can offer positive reinforcement and encouragement for their efforts. The system can consider the user's goals, interests, emotional state, and past behaviors. AI systems can continuously learn from user feedback and interactions to refine the effectiveness of reminders and positive reinforcement strategies over time. This adaptability ensures that interventions remain relevant and impactful as users' needs and circumstances change.

Self-Reflection. Data-driven approaches enable the analysis of vast datasets, uncovering nuanced patterns and trends that might enhance individual perception. By inspecting data about behaviors, emotions, and experiences, AI offers invaluable insights beneficial to self-reflection and introspection. Moreover, it can deliver tailored feedback derived from individual data profiles. This continuous data gathering empowers users to monitor their progress longitudinally, identifying patterns and drawing connections between present and long-term behaviors. Additionally, AI can seize opportune moments for reflection, seamlessly integrating self-reflection into everyday experiences and prompting users when most supportive.

5 FUTURE WORK

Mobile user quantification can provide a comprehensive understanding of the multifaceted nature of wellbeing and user context. Therefore, we can uncover relevant influences, trends, and patterns, enabling a new generation of personalized technology support tools tailored to individual needs. Prioritizing positive influences and favorable contexts for user wellbeing and crafting proactive and opportunity-driven interventions to promote and amplify positivity can play a crucial role in safeguarding mental health and nurturing human flourishing. We believe the vast amounts of personal data and advanced technological analysis of key indicators in user trajectories hold immense potential for shaping positive technological advancements.

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