Tensions in Personal Informatics: Considering Product Design and Academic Responsibility

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Abstract

Research in Human-Computer Interaction (HCI) and Personal Informatics (PI) has largely focused on how design elements influence user behaviour, yet little attention is given to the strategies of commercial PI device manufacturers. This creates a tension: researchers aim to support users' wellbeing while also working within existing commercial ecosystems that prioritise engagement, as the ultimate goal of fitness trackers is to convince the user to buy the next tracker. This workshop paper highlights the need for critically evaluating the studies we conduct in the PI space. We argue that PI researchers have a dual role: studying current use to identify what promotes wellbeing and critically examining commercial approaches to propose alternatives. By acknowledging the intrinsic conflict in studying PI technologies, the research community can ensure that design interventions both reflect real-world use and offer pathways toward more ethical and wellbeing-oriented PI technologies.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; *Ubiquitous and mobile computing*.

Keywords

Personal informatics, academic responsibility, commercial products, fitness trackers, tensions, product design

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1 Introduction

With the increasing popularity of Personal Informatics (PI) tools, such as wearables, in everyday life, research on PI has significantly expanded within Human-Computer Interaction (HCI) over the past two decades. PI research has, inter alia, focused on understanding and measuring how users perceive specific design elements (e.g. [18, 20]) and how they adapt their behaviour and routines in response to their data (e.g. [9]). To investigate these aspects, HCI researchers have actively developed PI artefacts across various health domains and settings [8, 14, 24]. PI tools can exert a profound influence on daily life, similar to smartphones, due to addictive qualities. For instance, research has documented the addictive, dependent and compulsive consequences of smartphones [3, 6] due to persuasive design elements. Similarly, commercial PI tools integrate 'dark patterns' [4, 13], encouraging continued use and product dependency, to enhance user retention and future sales. While much of PI research seeks to understand the lived experiences of users, it primarily achieves this by studying design elements of existing commercial technologies through custom-made artefacts. While valuable for ecological validity, this dependence on how market-available tools are designed inherently constrains academic research within the business models of commercial tracker manufacturers. These models likely prioritise continued use over long-term wellbeing, raising questions about the role of addictive and persuasive design strategies in PI technologies.

The HCI community acknowledges the ethical concerns surrounding persuasive technology, with increasing discussions on the responsibility of designers to mitigate harm (e.g. [11, 12]). However, identifying persuasive practices in PI tools specifically has received little attention. Given their influence on behaviour and decision-making, PI technologies warrant greater scrutiny to ensure they do not exploit users' habits or encourage unhealthy levels of engagement (e.g. [5]). As HCI and PI researchers, we observe a lack of critical engagement with the design strategies of commercial PI tools within the field. One possible reason is our reliance on self-developed artefacts rather than using commercial products directly in our studies. As a result, the design principles we generate may have limited relevance to the technologies people use in everyday life. This raises a crucial question: How can we ensure our research has a tangible impact beyond academia? In this provocation paper, we argue for researchers' dual role in PI research through a

discussion of several tensions within the PI space: studying how PI designs can have wellbeing benefits, while critically evaluating commercial approaches to propose alternative, ethically aligned design strategies.

2 Tensions in Personal Informatics

In this section, we discuss three design tensions we have identified in the PI field.

2.1 Balancing Positive and Negative Responses to Personal Data

The first tension that research demonstrates is that PI technologies can foster negative thought processes in users, like rumination [27], and negative feelings. For instance, Niess et al. [20] explored to what extent different types of data visualisations communicating unmet fitness tracker goals induce self-reflection and rumination in users. The follow-up study by Loerakker et al. [18] studied whether differently framed data representations can promote reflection, rumination or self-compassion. These studies show that negative feelings can be induced for a variety of reasons, including failing to achieve fitness and health goals and negatively framed data visualisations. It may be that the tracking technology itself is likely purposefully designed this way, with the hope that somewhat negative reinforcement can motivate users to continue using the device. To illustrate, a typical design element in PI devices that can evoke either positive or negative feelings is progress bars. Their completion often symbolises success in achieving a goal, while failing to achieve a goal can induce negative feelings [20]. Traditional progress visualisations include step counts and 'zone minutes', e.g. used by Fitbit, while newer fitness trackers like WHOOP introduce more dynamic progress bars that update at intervals rather than continuously. The visualisation of these progress bars is arguably 'gamified'. While gamification in PI tools could promote sensemaking and engagement, hence facilitating behaviour change [21], it could also suggest a potential for addictive tool usage.

2.2 Translating Personal Goals to Data through Sensemaking

It is well-known that PI tools assume users have a performance-focused mindset (e.g. [2]). This is somewhat unsurprising, considering these devices tend to have assumptions about the user embedded in them [23]. These goals are mainly visualised in a quantitative way, thereby overlooking the following tension: how do we translate our qualitative health and fitness goals to the quantitative data visualisations with which we are typically presented in our PI tools? In other words, how can data representations aid the data sensemaking process so that we can extract meaningful information from them to achieve our goals? To explore, Strömel et al. [26] evaluated whether narratives of one's personal data can provide meaningful and effective interactions instead of the more traditional kinds of representations, like graphs. They found that unconventional kinds of representations, like textual ones, can complement conventional representations. Similarly, Wagener et al. [28] explored the qualitative representation of personal data through weather scenarios in Virtual Reality (VR), finding that it increased engagement with and in-depth understanding of the data. Both emphasise, though, that the full potential of such uncommon visualisations of data needs to be explored further.

Technologies, both goal-oriented and open-ended, have the potential to shape goal-setting behaviours (e.g. [7, 8]), nudge a user towards new behaviours and, ultimately, new routines, as goal-setting is a key component to achieve behaviour change [17]. Typically, these assumptions are integrated in the form of pre-defined goals that the device sets by default upon installation and account set-up. As such, commercial PI products are predominantly designed with the one-size-fits-all mentality in mind. For instance, one common goal is the 10,000 step goal which many commercial fitness trackers tend to have as a default setting. For instance, the default goals embedded in PI tools may either prompt users to adapt their own potential pre-defined goals or adapt the ones from the tool. In one study, users were prodded to use the PI tool's default step goal as their own 'minimum' goal [19]. Although these nudges towards goal setting and possibly behaviour change can positively influence a user's health routine, there are notable additional risks. To elaborate, the 10,000 default step goal may convince users that this is applicable to them, regardless of their lifestyle and body, showing ageist, classist and ableist propensities of such tools [16, 25]. To this end, we question whether this goal-oriented mindset and possibly never-ending PI tool usage, enforced through commercial product design patterns, will allow users to feel content with their bodies.

2.3 Designing for Manual versus (Semi-)Automated Data Tracking

Many commercial PI tools heavily rely on automated data tracking. For example, users can momentarily glance at their readily accessible data through smartwatch displays. Based on the self-determination theory [22], it can be argued that this constant tracking creates externalised motivation and can lead to compulsive engagement rather than fostering intrinsic motivation to reflect on personal wellbeing. This suggests that such feedback loops can contribute to over-reliance on data rather than awareness, thus representing a form of persuasiveness and addictiveness. Arguably, (semi-)automated tracking might be a solution [15]. Along similar lines, previous work showed that autonomously tracking and making sense of emotions and goals facilitated reflection and mindful awareness [1]. However, previous work also showed that manual tracking is accompanied by challenges such as the difficulty of interpreting self-tracking artefacts during retrospective reflection over a longer period [1]. Additionally, different user groups may have varying amounts of time available for tracking, influencing their preferences for manual or automated approaches based on their specific needs and interests. Based on these findings, we present the third tension: balancing (semi-)automated and manual tracking depending on the use case and user group.

3 Three Open Questions for PI Researchers

Based on our observations in PI research, we set up three open questions to guide PI researchers towards critically engaging with commercial PI products while ensuring research quality and vigour.

Question 1: Are We in Touch with the Multidimensional PI Journey and Commercial PI Device Production? In light of our observations of commercial product designs and the state of the research field, we

wonder what kind of impact PI research aims to make and what kind of impact we *assume* we are making. Considering companies have a business model they need to abide by, our research may not always be as impactful on the commercial product design process as we may think. To bridge this gap between industry and academia, we call for more collaborations between our research endeavours and commercial design processes of PI tools. Such partnerships can provide deeper insights into industry practices while clarifying which aspects of our research influence commercial development. Companies strive for constant PI tool use, but our studies also indirectly adopt this perspective, lacking consideration for the alternative: what if, *temporary* PI use is a more suitable use practice—in certain instances—possibly even more effective, than *continuous* PI use? As shown by Epstein et al. [10], the concept of 'lapsing' from using our PI device is considered a natural part of our PI journey, and should be taken into consideration in PI design.

Question 2: How Addictive are Commercial PI Tools, Really? Arguably, the addictiveness of PI tool usage may be more subtle than smartphone addiction, due to the automated tracking principle, and being able to glance at one's watch in a matter of seconds. While glancing may promote a kind of addiction, it also makes it harder to study addiction: how can we track glancing behaviour? Thus, how can we be sure that glancing does not postulate a form of addictiveness? Furthermore, in PI studies, we tend to conduct short-term studies, possibly limiting our understanding of the long-term consequences of persuasive design elements and how to identify obsessive PI behaviour. It begs the question if we possess the knowledge and the tools to be able to study PI addiction. In our own research, we have tried to uncover design practices that place users' wellbeing at the forefront, while also considering user differences by evaluating how particular design elements in commonly used data visualisations in PI products influence, see [18, 20]. However, we tend to study PI behaviour in an one-dimensional manner, ignoring the fact that many commercial PI tools are not designed to make us more healthy or fit, but instead, to keep users engaged, regardless of the consequences.

Question 3: Can Commercial Needs and Academic Responsibility Co-exist? Our utilisation of custom-made PI artefacts instead of commercial products in some of our studies means we may obtain little insight into what drives corporate decision-making and how our findings could be made relevant to commercial design processes. While PI research primarily focuses on understanding user perception and behaviour with metrics, it rarely addresses purposeful behaviour change strategies, persuasive design, or dark patterns, which are areas that companies actively leverage to increase engagement. If our goal is to shape more ethical and wellbeing-oriented PI technologies, we must consider how to bridge this gap and engage more effectively with stakeholders, and question to what extent we influence metric designs in PI tools. We propose that we should start employing more commercial products in our studies, alongside our custom-made artefacts, while also 'allowing' ourselves to apply a critical lens on the possible addictive and non-health-oriented designs of commercial products.

4 Conclusion

The tensions within PI research highlight the complex relationship between academic inquiry, product design and user wellbeing. As this paper has argued, PI researchers must navigate the competing priorities of commercial engagement strategies and ethical responsibility, ensuring that their work does not inadvertently reinforce persuasive design practices that prioritise engagement over wellbeing. Addressing these challenges requires critically examining existing PI technologies and developing ethically aligned alternatives. Collaborating across industry and academia can provide insights into real-world constraints while fostering more responsible design. We postulate that by recognising and addressing these tensions, the HCI community can help shape a more human-centred approach to PI that prioritises wellbeing.

5 Researcher Background

Meagan B. Loerakker is a PhD student in the research unit of Human-Computer Interaction at TU Wien's Institute of Visual Computing and Human-Centered Technology. Her research focuses on how to design feedback-adaptive technologies for a variety of purposes, like improving bodily awareness and performance, in sport and health contexts.

Nadine Wagener is a postdoctoral researcher at the Max Planck Institute for Informatics in Saarbrücken, Germany. Her research explores the design of XR technologies that support wellbeing, with a focus on autonomy, sense of agency, and ethical considerations. She is particularly interested in how people engage with technology for self-guided support in managing their everyday wellbeing.

Evropi Stefanidi is a postdoctoral researcher at TU Wien's Human-Computer Interaction research group in the Institute of Visual Computing and Human-Centered Technology. Her research seeks to support the wellbeing of both neurotypical and neurodivergent children and their caregivers through technologies that support their diverse needs and interests.

Jasmin Niess is an associate professor in the Design of Interactive Systems research group at the University of Oslo. In her work, she takes on a people-centric approach to the design of technologies for wellbeing and health, and she is passionate about empowering minorities and vulnerable users. With a background in psychology, she has a unique perspective on how to design technologies through user psychology.

Paweł W. Woźniak is full professor and the head of TU Wien's Human-Computer Interaction research group, part of the Institute of Visual Computing and Human-Centered Technology. He has conducted research on a diverse range of topics, and has explored them with a wide range of research methodologies. With extensive experience as a senior researcher in the HCI research field, he has expansive knowledge on the design of technologies for health, wellbeing, and sport.

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