Personal Informatics at the Office: User-Driven, Situated Sensor Kits in the Workplace

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ABSTRACT

Workplaces are increasingly leveraging data-driven technological interventions to optimize employee productivity, health, and wellbeing. Yet employees are rarely involved in designing these initiatives, nor have access to the data collected to act upon it. Building on approaches from personal informatics, we investigate the use of user-driven, open-ended sensor kits in an office context. We conducted a 3-week field study, deploying a research probe at a workplace (N=5). Findings show that users explored aspects meaningful to them yet highlight discrepancies between the envisioned self-tracking goals and participants' practices. Regarding sensors' open-endedness, a balance between the burden of data collection and the value derived from it appeared critical. We contribute new insights into how an open-ended sensor kit can be designed to support self-tracking practices in the underexplored context of office work. We discuss implications for the use of personal informatics at the office and highlight opportunities for future research.

CCS CONCEPTS

• **Human-centered computing**; • **Human computer interaction (HCI); Interaction techniques. Human computer interaction (HCI); Empirical studies in HCI.**;

KEYWORDS

Office work, Personal Informatics, Sensing technology, Data-enabled design, Self-tracking

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1 INTRODUCTION

An ever-increasing amount of sensor technologies surrounds work environments, collecting data about building performance, human activity, or workers' wellbeing. This expanding practice presents critical opportunities and challenges for researchers and organizations alike [10, 28, 47]. On the one hand, sensors can help generate a nuanced and detailed understanding of patterns of employees' behaviors, work conditions, and social interactions. Systems such as wearables trackers also might help in raising awareness or stimulate reflection on work routines or healthy behaviors [8]. Design work in this area aims to leverage this data to find novel ways to stimulate healthy behaviors, increase productivity or reduce stress [10]. On the other hand, the ubiquitous use of data-collecting (IoT) systems can create a position of power imbalance, where employees lack control over what is being collected and for what purposes [23]. Data-tracking is hence sometimes used to 'optimize' employees towards often problematic, normative standards of productivity and wellbeing [18, 48] (see also Selke [58] for a good discussion on this). While quite some studies in corporate research and change management have put forward experiments in quantified workplaces [47], most feature productivity-focused interventions ordered by management.

In the domain of health, the Human Computer Interaction (HCI) community has put forward an array of workplace health promotion designs, that translate this somewhat 'intangible' or 'invisible' data into actionable interventions for end-users [10, 25]. They range from break-taking interventions [43], integrated health promotion systems [11], or walking meeting facilities [12]. Many of these interventions rely on researcher-curated or data-driven health promotion prompts [27]. These messages are however often either too generic [11] or do not match the user context [52]. Specifically in a sensitive context such as the workplace, these interventions fall short in informing how end-users might use the data (if they had access to it) to explore their own subjective needs, or how it might give space for users to be curious without imposing a researcher-primed purpose.

The field of personal informatics (PI) focuses on self-tracking systems that "help people collect personally relevant information for self-reflection and gaining self-knowledge" [40]. Self-tracking offers a way for people to gain control over what questions they want to answer, the type of data to collect, and the ability to enrich data with qualitative input. Beyond a "cold quantification of practices", self-tracking devices can be integrated into and support the subjective everyday experience [55]. Meissner [58] argues that data-tracking approaches are not only seeking an optimum, but rather allow the potential of "the discovery of new opportunities for man". In Epstein et al.'s systematic review listing the most frequent metrics in the personal informatics literature, only performance or productivity refer explicitly to the workplace (representing 5% of studied populations) [18]. They found that most of the work investigates workplace wellness programs, or wellness with the goal of increasing productivity. We find that these studies often make the assumption that people *want* to work on their health or

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productivity, and set up their study designs and artefacts in such a way that study participants are, to a certain extent, primed into exploring only health or productivity-related factors. But, specifically for an interpersonal, professional context such as the workplace, where personal health might have a different priority, we argue that Personal Informatics approaches must meet different criteria and should build upon material practices that explore our relationship to tracking activities, within “a constellation of habits, cultural norms, material conditions, ideological constraints” [54]. Despite an increase of datafication of the workplace, the office environment remains an underexplored area in open-ended self-tracking [5, 22, 23, 29]. Workplaces are dynamic, social environments, home to complex relationships and dependencies between people who assign different values and meanings to different parts of the work environment. PI practices such as self-reflection and quantifying the everyday lived experience thus take on different forms, requirements and ethics when moving into the work context. Hence, it is important that HCI researchers gain a better understanding of how Internet-of-Things (IoT) systems may support employees’ own self-tracking goals, values, and work practices.

We build on prior research that explored the opportunities of using open-ended, user-driven self-tracking devices (e.g., sensor kits) to support users’ agency [5, 16, 45] and values. The design and evaluation of such workplace-based artifacts can support the HCI community in demonstrating what interactions new artifacts might support [39] as well as understand how and why these systems are used (or not used) in shorter evaluations [34]. With this study, we expand the body of knowledge on the design and implementation of personal informatics systems in the office context by exploring how office workers use and adopt open-ended sensors. Our contribution is twofold. First, we present Habilyzer as a design exemplar of a personal informatics system for the office, embedding principles of open-endedness to enable office workers to investigate their own work habits and environment. Second, through a 3-weeks field study, we contribute insights into how such systems get appropriated in the office context and what challenges and opportunities emerge around the application of personal informatics tools in the workplace. We discuss design implications for the development of personal informatics systems in the workplace to improve engagement and integration in daily work practice.

2 RELATED WORK

2.1 Personal Informatics at the Workplace

Due to a growing presence of ubiquitous sensing technologies on our bodies, in our homes and offices, the field of personal informatics has become a fertile ground for HCI researchers [28]. Self-tracking technologies have shown potential in a large variety of application domains to support “fostering insight, increasing self-control, and promoting positive behaviors” [18]. In their lived informatics model, Epstein et al. divide the tracking process into stages: deciding to track and selecting tools, tracking and acting, and lapsing of tracking that may later be resumed [19]. Importantly, reflection (i.e., the process of examining one’s own data) often occurs during collection rather than being a separate stage [41]. Rooksby et al. identify five (overlapping) styles in which personal trackers can be used: directive (goal-driven, the dominant style), documentary, diagnostic, collecting rewards, and fetishized tracking [55]. Interestingly, people in diagnostic tracking seek to answer a specific question about themselves [40], looking for causal relationships between several variables in a process of personal scientific discovery.

While self-tracking practices slowly expands to areas beyond the private sphere, the workplace is currently an under-explored context in personal informatics, mostly focused on the tracking of productivity [17, 18, 38, 46]. According to Nappi and Ribeiro [51], technology at the workplace follows an “employee-centered perspective”, involving the use of IoT technology to identify employees’ social, physical, or emotional states in relation to productivity. In the past, researchers have used sensor-badges to investigate these relations [4, 26], mostly focusing on business value rather than using data for the benefit of employees. Recent work presents a similar Sensorbadge [3], arguing instead for a ‘human-data interaction’ perspective [50], where users are involved in data sensemaking via a researchers’ data dashboard.

Wearable sensor systems at the workplace allows for situated sensing, yet they require users to always carry them. Such wearables are thus hard to use for longitudinal place-based data collection when one wishes to unveil hidden patterns in both the personal and environmental experiences at work. There is an opportunity to explore a middle-ground, where user-driven sensor designs are both flexible and portable, similar to concepts such as I/O Bits [61] and Sensorstation [16], yet for the workplace. Researchers have shown empirical insights can be gained by using such systems as open-ended probes, triggering users to explore their habits and work conditions [35].

2.2 Open-Ended Sensor Systems

Recent studies have investigated how to lower the barriers and support the practice of self-tracking. Of particular interest are systems following an open-ended and user-driven approach. They can take the form of digital applications or platforms, wearables or physical sensing solutions, each of these having pros and cons. Applications such as KeepTrack [64] offer flexible tracking, allowing people to build their own trackers. Their downside is to mostly support manual tracking, which costs effort and might cause people to lapse in their self-tracking. Omnitrack [32] similarly allows people to dynamically create their own tracker, leveraging the semi-automated tracking approach from Choe et al. [7]. The DataSelfie app [31] enabled people to determine the representation of their data, using more custom visuals and collaborative sensemaking. However, while such apps are relatively simple ways of collecting a variety of personal data, they require frequent attention and effort, which can compromise data collection. Wearables (e.g., smartwatches, activity trackers) provide a hands-on solution, offering at-a-glance data, but require the user to continuously wear them, and sensor capabilities are limited to on-body measurements. Other applications such as the Self-E app [14] provide step-by-step guidance into setting up a self-experiment (i.e., creating and testing hypothesis on the effect of behavior changes [15]).

Several studies put forward a more tangible self-tracking approach, highlighting that the physical presence of data trackers and visualizations can support people in exploring their own routines

Table 1: Overview of sensor kits or open-ended systems following a PI/user-oriented approach

Design	Context	Sensors	Data Visualization	Deployment
I/O Bits [61]	Individual, Home	Buttons	Embedded e-ink display (personalized graphs)	Field study, 4-21 days, N=6
SensorBadge [3]	Individual, Office	Temperature, humidity, light, physical activity, sound	Researcher data dashboard	Field study, 2 days, N=7
SensorStation [16]	Household, Home	Temperature, light, humidity, air pressure, movement	Shared tablet withgraphs	Field study, 19 days, N=4
Zensors [37]	Individual, everywhere	phone camera + ML + online crowd workers	Mobile app	Technical field test 10-21 days
Smiwork [6]	Social, Office	Wearable	Shared smart mirror screen with graphs and prompts.	Field Study, 1 week, small office
Quantified Workplace [45]	Social, Office	Smartphone microphone, light sensor, environment sensor, mood indicator	Large, shared screen with dataviz, tablets with controls, RGB Lamp	Field Study, 4 months, N=120 employees
IoT Un-Kit Experience [2]	Household, Home	various smaller sensors	None	Workshop, N/A
Physikit [24]	Household, Home	NO2, CO gases, sunlight, noise pollution, temperature, humidity	Cubes with actuators (light, vibration, airflow, movement)	Field Study, 2 weeks, N=5 households
AffectiveWall [63]	Social, Office	Stress (HRV) with wearable	Stress visualization on laptop screen	Lab Study, N=24

[21, 33, 49, 59]. 1 presents a non-exhaustive overview of such systems in recent literature. Van Kollenburg and Bogers [36] identified different levels of flexibility in data trackers: open, closed and hybrid. According to them, the closed approach makes it easier for the intelligent solution to gain a detailed and nuanced understanding of the data, as it is clear beforehand what will be collected. The open approach allows the user to define what data is relevant and supports more openness to adapt the ecosystem of products to their needs. An example of such an open system is I/O Bits [61], which is a prototype exploring user-driven situated self-tracking. They present generic tracker designs that also integrate co-created data visualizations. While their tracking technology (push buttons) is relatively simple, the design is quite effective in allowing for customization and appropriation by users. In a similar fashion, Denefleh et al. used open data trackers and a Sensorstation to provide residents in a shared housing context with the data and tools to co-design and co-speculate on smart sensors and services [16]. The use of open data trackers with a device for visualization in the work context is proposed by van Bussel et al., whose design explored open-ended sensor systems that can be appropriated in a variety of ways towards work routines [5]. The Physikit design from Houben et al. shows that a sensor-kit combined with user-programmable ambient data-physicalisation can open a new kind of physical entry points to support users' interest and understanding of the data streams [24]. Provoking the PI community with a more playful and critical approach, Stamhuis et al. show Office Agents, an ecosystem of sensors with intent engaging employees in a negotiation around their work values and priorities [60].

The review of prior literature has shown that access to open-ended sensor systems and accessible data visualization can empower people in exploring their own interests, and can provide researchers with a richer understanding of employee's experience in a variety of contexts. There is however a dearth of research on the appropriation process of such open-ended systems by employees in the underexplored context of the workplace.

3 RESEARCH OBJECTIVES

The aim of this research is to explore how user-driven, open-ended sensor systems can be designed to enable users to explore their own routines and work conditions. We investigate how such systems get appropriated in the office context and what challenges or opportunities emerge around the use of workplace PI tools. Additionally, such probes might complement more traditional approaches (survey, logbook, interview) that are aimed at envisioning self-tracking goals. This helps in confronting the reality of actual goals and interests when working with an actual self-tracking toolkit. The goal is to use these probes for feedback on early-stage design considerations around open-ended, situated IoT kits at work.

4 DESIGN & IMPLEMENTATION

We designed Habilyzer, a research probe to create an awareness and presence that can support people in using sensor data to explore their own goals, interests, needs and work habits. Habilyzer is a research probe consisting of a set of four distinct sensors and a base display showing data visualizations (1). The Habilyzer probe is designed in such a way that it is usable with a minimal understanding of the underlying technology and can easily be placed around the office environment. Habilyzer is an open-ended toolkit, that participants can immediately deploy in any way they want to, driven by their areas of interest (e.g., insights into their sitting time, water intake or noise levels). The four sensors were designed in a neutral shape and aesthetic to support an open or generic use scenario, in part inspired by work from Denefleh et al. on their Sensorstation

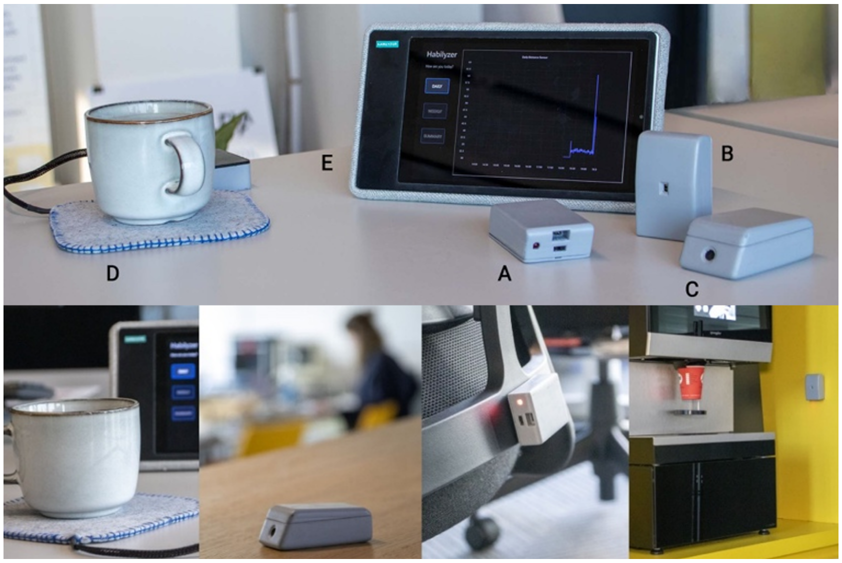

Figure 1: The Habilyzer sensor kit with the four sensor modules

[16]. Habilyzer comes with removable accessories (Velcro, tape, magnet, suction cup, hook) that allow the sensors to be attached to objects or building infrastructure. We chose to use these four sensors because of their understandable nature and because similar types of sensors had been used in related PI work on sensor kits [16, 49]. Users deploy their own Habilyzer kit in any way they want to. Sensors automatically connect to the base unit, which visualizes data real-time. There is no user setup required. Each (timeseries) datastream from a sensor is visualized in a timeline graph, showing trends per day, week and as a summary. Habilyzer is 'always on' and automatically cycles through various views of the data. This was chosen to counter Balestrini et al.'s findings that such a kit became 'invisible' after a while, resulting in people losing interest [1]. Following Gaver et al.'s tactics to use ambiguity as a resource for design [20], the narrative of use in Habilyzer creates ambiguity, possibly spurring people to approach the kit with an open mind and questioning their own values.

4.1 Technical Realization

The Habilyzer kit consists of a base unit that visualizes the data coming from four wireless sensors. The Base Unit (E) contains a Raspberry Pi 4, a Lenovo M8 tablet, and a 4G Router (1). The Raspberry acts as the main server, hosting the database (InfluxDB) and visualization engine (Grafana) (2). Data from the sensors is being ingested via MQTT and preprocessed in Node-Red. Data is then saved to the database and sent to Grafana-panels that are configured in a Playlist that cycles Daily, Weekly, and Summary data for all sensors. A React app embeds Grafana-iframes with buttons for the user to switch views. The tablet loads the application via a Kiosk app that prevents other interactions with the tablet. The 4G router allows the sensors to retrieve NTP time to timestamp data. We chose a 4G module, since we did not want to ask for WiFi credentials or deal with WPA2-Enterprise encryption. Each Habilyzer kit has four sensors, which are ESP32's (Wemos D32 Pro) with an SD-card for local data-storage and powered by a 2000mAh LiPo battery. The four sensor types are (1): (A) Movement (MPU6050 9 DoF IMU), (B) Distance (VL53L1X Time-Of-Flight sensor), (C) Sound (MAX4466 microphone module) (D) Pressure sensor (Velostat-based variable resistance sensor encased in a felt-like fabric mat). All sensors have a grey 3D-printed enclosure and come with an on/off switch, USB-port and a status LED. All modules have a sleep function to preserve battery life. WiFi connection is only established after a significant change in measurement values has been observed. Due to the 'always on' nature of the sensors, battery life is around 2-3 days.

5 METHOD

Our research objective is to empirically investigate how open-ended, user-driven PI systems are used and appropriated in the office context. To address these questions, we used a mixed-method approach combining a preliminary survey, a one-week self-tracking logbook, an intake interview followed by the use of the Habilyzer kit in-situ for three weeks, and final semi-structured interviews. The use of complementary data collection techniques provides a rich picture of the everyday experience of office workers. First, the survey provided baseline information about participants and their views on self-tracking and work. Second, the logbook, situated and longitudinal, provided additional points of interest that participants encountered at work. Using this data, the intake interview addressed detailed questions into the personal needs and routines of the participants. Finally, the 3-weeks deployment of the Habilyzer research probes, along with the debriefing interviews, contributed to in-depth insights into self-tracking practices in the office context. Initially, 7 participants were recruited, but due to drop-out, 5 participants remained, hence numbering of participants lacks P1, P5.

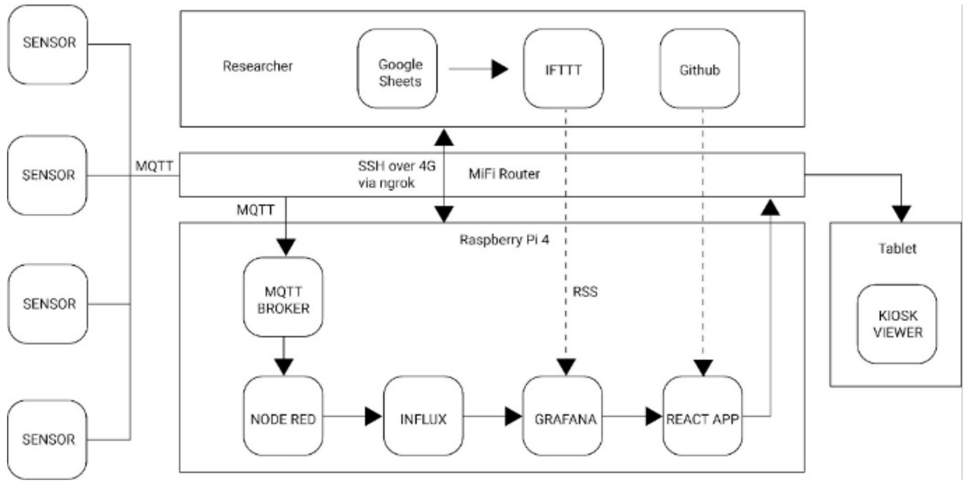

Figure 2: Diagram of the technical architecture of the Habilyzer system.

5.1 Participants

We conducted a three-week field study with 5 participants (5 men, aged 25 to 29, M=27.4, SD=1.8) at an engineering company in (anonymized). Participants were all engineers working in the electronics lab or in the office. They were recruited via non-probability (voluntary) sampling, with no personal or professional relations with the researchers. The inclusion criteria for our sample were having a mostly sedentary job and working at least 0.8 full-time equivalent on-site at the company throughout the study period. The deployment period varied between 19 and 21 days, depending on the availability of the participants for the introduction activities and debriefing interview. Most participants used self-tracking technologies such as smartwatches and phone apps like Google Fit. They declared looking often at the data they collect using their smartwatches or apps (e.g., step counts, sleep time), but few reflect on- or attempt to change their behaviors. The research was approved by the Ethical Review Board of the University, and informed consent was collected amongst participants.

5.2 Procedure

The study (3) consisted of (1) introduction and distribution of the logbooks and survey, (2) semi-structured interviews on work routines and the logbook outcomes, (3) the use of the Habilyzer kit and (4) semi-structured debriefing interviews.

Two weeks prior to the study, participants received an instruction email. During the introduction session, participants were briefed on the study and privacy policy, before signing the consent form. We provided them with a survey to fill out as soon as possible and a logbook to use during 5 workdays. The survey and logbook output were compiled and used as a support during the onboarding interview. The three-week field test started with an 'onboarding' meeting, where the sensor kit and its main functionalities were explained. Little information was given on possible use-cases to avoid priming the participants. The researcher installed the Habilyzer units at the participants' workplaces. The researchers emailed the participants two times during the study period to motivate them to use the kit and be creative in exploring their habits or environment. After using Habilyzer for three weeks, participants were interviewed. The interviews focused on the user experiences and perceived values of using the kit. The open-ended question "how did you experience the use of Habilyzer?" was followed by questions about sensor usage, use of the visualizations, values that participants recognized in such systems and improvements for future versions. The interview also included a discussion using a print-out of the collected sensor data.

5.3 Materials

Preliminary survey and logbook. To prepare the participants for self-tracking, we elicited elements of interest in a survey, using the sentence completion format with items such as "To improve my working habits or wellbeing at work, I would like to know more about my...". This stage was followed by a logbook with space for notetaking (4).

Habilyzer kit & manual. The sensor kit was accompanied by a user manual, describing the system, its setup and how to charge the sensors. One example use case was provided for each sensor. Privacy and ethical concerns were also addressed. The material and documentation were open, but some elements were priming participants towards the topic of healthier office environments.

Data visualization. Simplified visualizations of the sensor data were created, highlighting the points where the sensor values were above baseline level for each sensor (5).

5.4 Data Analysis

The data gathered in this study consisted of 1) survey data, 2) logbook data, 3) audio recordings of the start and exit interviews, 4) sensor data, 5), field notes of Habilyzer positions and environments. All interviews were transcribed verbatim. The transcripts were coded and analyzed using NVIVO [42] by thematic analysis using an inductive approach. First, two researchers used independent initial open coding to analyze a first exit interview, after which they formed a consensus on the coding scheme.

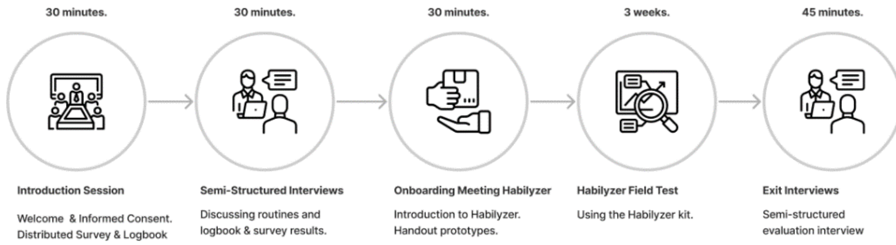

Figure 3: Overview of the process of the study

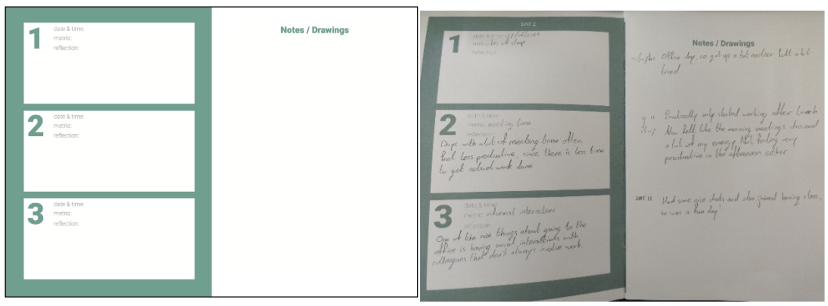

Figure 4: Example page of the logbook used by participants to elicit metrics to self-track.

Figure 5: Data visualization of P4, used in the exit interview

6 RESULTS

Based on the surveys, logbooks, the field study, and interviews, we have gathered a picture of the benefits and limitations of user-driven, open-ended sensor kits in the workplace. Combining the themes extracted from the thematic analysis of the interviews with field notes and observations, we gained insights into the experience of using Habilyzer, participants' emergent behaviors and interesting outcomes.

6.1 Self-Tracking Preparation through a Survey and Logbook

Participants completed a preliminary survey documenting what aspects of their work they were interested in knowing more about. Metrics of interest were mostly focused on personal routines (e.g., beverage consumption, screen time, sleep) or environmental factors (e.g., noise, temperature). Most participants wished to pay more attention to taking breaks and avoiding sedentary activities. Participants then used a logbook for 5 days to track and reflect on metrics they deemed relevant. Some metrics from the survey did not appear in the logbook. Logbook entries were very diverse, ranging from simple notes to keeping track of personal goals, e.g., "*Count: 12 switches from sitting to standing. I was at the office and moving quite a lot between desk and lab. I felt pretty good at the end of the day.*" (P2). During the onboarding interview, participants mentioned looking for correlations between the metrics and their perceived productivity or energy level. None of the participants defined 'productivity' or 'energy' itself, rather, they describe it as a feeling: "*Days with a*

Table 2: Overview of the use of sensors by participants by location and variable of interest.

	Distance	Accelerometer	Sound	Pressure
P2	desk: presence	did not use	desk: office noise	desk: water intake
P3	desk: passersby	did not use	desk: lab noise	desk: amount of tea
P4	desk: presence	pocket: physical activity, chair: chair use	desk: office noise	desk: drink intake, phone presence
P6	shelf: passersby	pocket: physical activity	desk: lab noise	Did not use
P7	desk: presence, gate: passersby	did not use	desk: lab noise, on machine: noise	Did not use

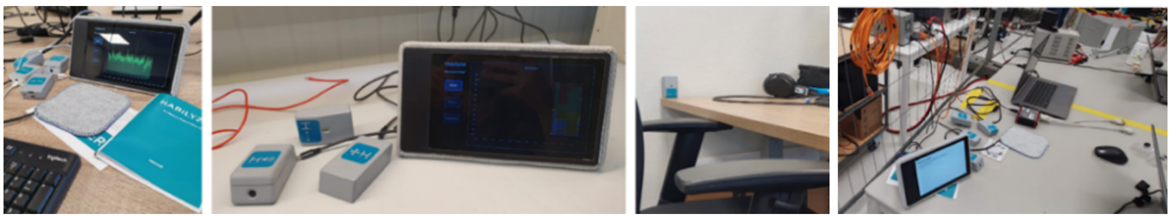

Figure 6: Examples of placements of the Habilyzer kits during the field study.

lot of meeting time often feel less productive, since there is less time to get actual work done." (P2). The longitudinal nature of the logbook triggered participants to describe more metrics after their initial ideas.

6.2 Field Study: System Usage

Almost all participants were able to use the sensor kit for the three-weeks duration of the study period. Some kits however suffered some issues (e.g., auto-updates, internet outages) that participants did not immediately report, ranging from hours to a few days. Additional gaps in the data are due to participants forgetting to charge the sensors. Findings show that most participants hardly moved the sensors beyond their personal desk, and none moved the base unit. Only the movement sensor was used by walking around. Every participant found a way to use Habilyzer to track something about their behavior or work. 2 shows the use of sensors by location and (**Fig.6**) variable of interest.

While some participants did not try and follow up goals they noted in the logbook prior to the field test, some tried to use a Habilyzer sensor to track a specific goal. P2 and P6 did not track any goals from their logbook. P3 used the pressure sensor to track his tea-drinking habits, but stopped after a while, saying that tracking all these things made him obsessed with the data. He would prefer someone else to make sense of it: "*Yesterday I drank 3 cups of tea, today only two...should I get one more? You know it will put me under too unnecessary pressure. It will make my mind busy, but I think someone else can interpret it.*" (P3). P4 tried to track some of his initial interests from the logbook, e.g., presence at his desk, water intake and physical activity, but did not set any goals with Habilyzer and quickly realized that systematically keeping track of his routines would cost substantial effort. P7 had a well-filled logbook, tracking various metrics such as feelings of anxiety, productivity, positivity, water intake, meeting times, and after-work activities. When given the kit, P7 only tracked noise: "*...but the audible [sound sensor] yes because that was one of the big things in the lab, I mean the traffic thing was also..., But nothing personal. I couldn't use the kit for coffee. Then I have to do my own efforts to understand... because there is no correlation between (drinking coffee and my environment).*" (P7).

In the interviews, participants often mentioned the effort they were willing to put into working with such user-oriented IoT systems. While all participants were initially enthusiastic and interested in trying out the kit, we observed a split within the participant group in how they kept engaging with the sensors and the collected data. The use of the sensors seemed highly influenced by the work environment of the participants, with a difference between those working mainly at the lab (P3, P6, P7) and those in the open office (P2, P4). The two participants in the regular office mainly focused on their individual productivity and wellbeing. Working in an almost isolated manner at a fixed desk within a relatively quiet space, they reduced their active use of Habilyzer quickly: "*it started with what I thought were interesting things to measure. But this changed a lot more to whether I found it effortless enough to measure.*" (P4) The ratio of effort versus benefits became a key consideration: "*It's about the balance between the amount of effort and the value of what you get from tracking.*" (P2). The three participants working in the lab had a more social environment. They were more actively seeking valuable information to improve their collective workspace. They could sometimes better integrate the use of Habilyzer in their daily routines. They mostly used the toolkit to quantify sources of annoyance or lab safety issues. Although here the value of the collected data seemed more meaningful, they had a hard time reflecting on what the data meant. The fine-grained, low-level nature of the Habilyzer visualizations was one of the causes of the difficulty all participants had in interpreting the data: "*every time we run the test, I could see there is higher noise or higher data, but I could not really say that was relevant.*" (P7).

6.3 Creative Use and Data Sensemaking

Most participants struggled with making sense of the data they collected. They expressed doubts on the interpretation of the data visualization and the use of the sensors. Several participants emphasized that they underestimated the amount of effort required to attach meaning to the data (e.g., through counting peaks or connecting several types of data). They put the amount of effort into perspective with engagement: "*You really need to systematically use it, if you want to discover patterns. That costs too much effort to remain engaged.*" (P4). Some participants gave up throughout the study and 'delegated' the task of sensemaking to the researchers: "*There were like 3 windows for three sensors, but I gave up on it because my understanding was that I will not be able to interpret the data. And it will be you [the re-searcher] who will have the data and you can interpret it later so like there's no point in looking into it.*" (P7). Both participants in the office (P2, P4) placed the distance sensors on their desks to monitor their time at their desks, but when reflecting on the data, found the patterns not that meaningful. They expressed a wish to see it correlated with productivity trends rather than a unique measure. They were both curious about impactful factors towards their wellbeing, but after discovering that relating the data to productivity was difficult, they quickly became less interested in using the kit.

The Habilyzer probe was open-ended in functionality and appearance by design, to investigate whether this would stimulate or restrict appropriation and creative use. Overall, participants understood the open-ended nature of Habilyzer, which they could use to explore their self-defined metrics. Participants did not use the Habilyzer kit to explore metrics beyond the more obvious one supported by the sensors. Most participants used the sound sensor to measure overall noise or the distance sensor as a counter for passersby. When asked about their uses of the probe, they often mentioned that they did not think beyond the first application they used the sensors for. Similarly, only two participants changed the use of the sensors throughout the experiment. Enquiring if the participants experienced any hesitations in moving the sensors outside their desk or direct work environment, most mentioned not having thought about it. Illustrated by P4: "*I don't want to spend all day readjusting the sensors, I just want to set them up and put them down and not having to look at them.*" (P4).

While participants did not explore much beyond their initial conception of what the sensors could do, they were able to tailor its use to their own situated work context. We again observed a difference between the office and the lab context. The participants in the lab focused on environmental factors, diagnosing problems they experienced. P7 mentioned his goal to investigate the burden he experiences from continuous exposure to loud noises. "*For me the most interesting one was the audible [sound sensor], ... that is the one thing that is bothering me in the lab, and we wanted to collect some data, so that was a good opportunity.*" (P7). Further in the study, P7 adjusted the use of the sensor towards diagnostics; "*The audible was there next to the machine 3 because we really want to see the effect at that position.*" (P7).

The other participant working in the lab (P6), had similar ideas yet interestingly was not aware others had the same issues: "*I think it only affects me, I guess, ... usually there's just the guys on the other side of the lab and they're like comfortable with the noise, so I think it's just personal*" (P6). They also suspected that the noise might be detrimental to their health, prompting them to use the sound sensor to find correlations. "*There must be a level of too much exposure to too much loud noise for this duration. So, if there is a machine and I would expect that machine to do it, that this lab has been too loud and it's not safe for human experience anymore, so we stop the machines...*" (P7). Collecting this noise data and reflecting on its impact, participants also considered potential solutions, e.g., proposing to the lab manager a better scheduling of machine-usage. "*I'd like to see at what time the noise peaked ...compare that to our tests at that time to see what's causing it. And... trying to figure out how we could work without having that noise around us because sometimes the machines are just running for no purpose and there is the background noise you show.*" (P7). The office-based participants were not bothered by sounds, as they use noise-canceling headphones. The lab-based participants used the distance sensor to analyze busyness in the lab, placing it on the edge of a desk, shelf or attaching it to the gate. When they run tests, distractions can be annoying or dangerous: "*that's the objective... we put that proximity sensor to see if there are too many people out there.*" (P6). New use cases emerged during the study: "*So for example in the middle of the experiment, I put it on the edge of the table, so it gives more data. And we can track how many people pass by my table*" (P3).

6.4 Personal Informatics at the Office as a Collaborative Effort

Most participants wished to have influence on what, how and where to use sensors, but would like to be provided with those tools by the company. P7 values this agency because it allows users to adjust the use-case of the sensors to their own curiosities or changing work conditions. "*if you like, give us the features and we'll use it however we want to, this is something that we did with Habilyzer.*"(P7). This was echoed by P6: "*I think I'd want a kit from the company directly. Yeah, I'd rather not have like...A big list of choices. Just give me four things and I will, like, try to find a way to use them to my own benefits.*" (P6). Yet, if a company were to ask users to track things in the workplace, participants point out that it must have a perceivable value to them. "*it has to be interesting for me, if I don't see the use, I'm not going to spend effort on this.*" (P4). Similarly, P7 highlights that the use of such sensors cannot be prescribed by the company, "*What [colleagues] would do with this, will not work with me, even if they will be in the lab or not. . . Like I do not want somebody telling me track your footsteps because everybody is doing it.*" (P7).

P3 envisioned collaborating with a dedicated person to improve working conditions. "*if there is someone that is dedicated to this work, that (person) would know much better than anyone else. And would interpret the data in a better way.*" (P3). "*It should be more like advice rather than a conclusion, that the person who analyzed it may say that, OK, this sensor notices too many people passing by... Maybe you may consider changing location of your table then.*" (P3) Most lab-based participants wanted to collect data to act as 'proof' of their suspicions on noise levels and busyness in the lab and use that proof to discuss potential changes with the manager, "*My idea* *was if we could collect data, I stick it to the team lead that we need a system in place.*" (P7).

P4 would prefer occasional reflections in a group retrospective or social gatherings, to discuss what they found using sensor kits, and propose adjustments or ideas for the work environment. "*Every once in a while, we have a retrospective. That's a nice moment to bring such a thing to the group.*" (P4). Participants hence considered the alignment between employees. In collective environments such as the workplace, you cannot always decide yourself on what is the most impactful factor in the office, or the work routine that might need adjustment, especially if these adjustments impact others: "*I think we're not all aligned on what we think is a nice work environment.*" (P4). P6 argues that it is important to also look at larger trends in the data, not just his own. He envisions that employees could collaborate or contribute to a larger company-wide analysis. "*You will see only your data so..., you may see your data in small view. You will not have, like, a big picture, so I think...an individual analysis of the data and like a company analysis of the data is needed.*" (P6).

7 DISCUSSION

Our study reveals insights into how five employees used an open-ended sensor kit at the workplace. Their use depended on context, personal needs and curiosity towards their behaviors and environment. Participants instrumented their workplace to quantify sources of annoyance, diagnose health conditions and discover work routine patterns. The results indicate that all participants could tailor the use of the kit towards their interests and goals but were not always able to uncover patterns or lessons from the data. It is explained by a combination of difficulties in interpreting the data and extracting meaningful information from the use of Habilyzer. The efforts of collecting the data were frequently put into perspective with the insights gathered, this assessment playing a key role in the acceptance and use of the sensors. All participants envisioned some form of collaboration with colleagues or management in using such an open-ended, user-driven system. They advocate for agency in the use of such tools, but also in support or even shared responsibility with the company. In this section, we discuss our findings, focusing on three main themes. Reflecting on the opportunities, challenges and limitations of using a user-driven sensor kit at the workplace, we suggest implications for design and avenues for future research.

7.1 Open-Endedness as a Quality and Limitation

First, our study suggest that simple and open sensor-based trackers can support a variety of tasks, goals and applications. All participants were able to come up with ideas to use Habilyzer, at the start and during the study. Similar to the I/O Bits [61], we find that such general-purpose trackers with "task-agnostic interfaces" enable a diverse array of uses for PI, in our case in the work context. However, the gap between imagined use-cases participants wanted to explore and the realities of using raw sensor information to extract meaningful knowledge is large and holds many challenges. Participants were aware that the system would need more contextual information on how they placed the sensors and with what purpose, to tailor data visualization or notifications. Mathur et al. found that sensing and visualization of raw environmental metrics was not found useful by most of the employees, primarily because they felt they had little power to act on the results of the quantification [45].

Epstein et al. describe three main self-tracker motivations: behavior change, instrumentation, and curiosity [19]. Our results show that the office-based participants leaned towards a 'curiosity' tracking motivation whereas lab-based participants adopted an 'instrumental tracker' perspective. Noteworthy, none of the participants started tracking to change behavior. Reflecting on how the open-endedness of our research probe has been instrumental to both perspectives, we observed that it did not support the curiosity trackers adequately. After their initial curiosity had been satisfied or delivered unsatisfactory results, office-based participants did not decide on a new self-tracking goal. They lapsed their tracking because they no longer had strong motivations to select new sensors, nor were interested in acting upon their newfound curiosity-driven insights. The ratio between efforts and interest in the outcomes was perceived as too high. Conversely, for the participants who used Habilyzer to instrument their workplace, open-endedness was perceived as a quality, which allowed them to decide to track a variety of issues they observed at work. Having specific problems that users want to diagnose is a strong motivator, aligned with Kollenburg & Bogers, who found open-ended trackers very valuable in the healthcare context [36]. As commercial products in self-tracking tend to adopt a one-size-fits-all approach supporting predefined and rather narrow scenarios of use, they might not support individuals interested in diagnostic-tracking very specific individual issues not covered by the use scenarios proposed. We hypothesize that open-endedness can account for interindividual differences in that regard.

Limitations of open-endedness are nevertheless non negligible. For our participants, it increased both the difficulty of making sense of data, and the effort required to imagine how to deploy or combine them to gain meaningful insight. As compared to self-tracking in a private context, the work context has a different connotation regarding the acceptable amount of effort to make data meaningful, or to conduct self-experiments [13] with such sensor kits. Participants mentioned that time to invest in such efforts is limited because of their work duties. We see this back in participants' reflections from the participants, suggesting to outsourcing the data analysis or by offering tailored, easy-to-use tools based on their experiences. Interestingly, the desire for coaching or support might paradoxically coincide with the concerns on privacy or feelings of autonomy, echoing findings from Moore et al. [47].

Future work could explore how solutions can address this need by providing onboarding guidance on how users could better leverage the sensors to answer their questions (similar to tracking apps like [14]) or a first analysis of data.

The evaluation also showed that besides the difficulties around data sensemaking and managing effort to use Habilyzer, participants had preconceived notions of the functionalities of the sensors. When presented with the sensors, they assigned a certain function (sometimes based on the onboarding presentation or user manual) and did not explore much beyond that. Prior work suggests opportunities to provoke participants to leverage the open-ended nature of Habilyzer and move beyond these cases. Hence, Denefleh et al. relied on social dynamics and the ability to program thresholds and customized notifications to sustain use and trigger explorative behaviors [16].

7.2 Lived Informatics at Work

With the advent of sensing technologies, discussion on self-tracking at the workplace is important. Although the lived informatics model [19] provides a worthwhile framework, its application to the work context has been limited.

In the previous section, we discussed the interdependencies between the motivation to track and the open-endedness of the research probe. In selecting tools, we saw that participants were less interested to track individual wellbeing and showed more engagement to track environmental factors. Understanding or improving a professional environment had a larger commitment from participants. This resonates well with [56], who argued that self-tracking technologies should be considered more social and collaborative. Here, their motivation was stronger to solve a problem, or at least to empower them in collecting data about an issue before going to management. Saukko & Weedon observed that self-tracking fostered a discontent with working conditions, and we can wonder whether this was also exacerbated in our case [57].

Noteworthy, researchers often make the assumption that people want to work on their health or productivity and set up their study and designs in such a way that study participants are, to a certain extent, primed into exploring mostly such factors. This is also the case to some extent in our study. Especially for an interpersonal, professional context such as the workplace, we would argue that personal informatics approaches must meet different criteria and should build upon material practices that explore our relationship to tracking activities, within “a constellation of habits, cultural norms, material conditions, ideological constraints” [53]. We invite other researchers to further explore the balance between encouraging use of such systems and allowing for more organic development.

The cycle of Tracking and Acting, is an ongoing process of collecting, integrating, and reflecting. Our study showed that collecting data is facilitated by the simplicity of the sensors. The Habilyzer kit does not capture personal data, making it more suitable for a privacy-sensitive environment such as work. Some authors [63] have proposed anonymized, collective data-tracking and visualization to create collective reflection. Mathur et al. in their *quantified workplace system* [45] for instance found that a sense of inclusion triggered by participatory sensing can act as an initial incentive for engagement and that anonymous participatory sensing could lead to sustained user engagement.

The Habilyzer data was not integrated into other services. Supporting situated sensor data in the future with other sources such as work schedules, machine usage or company activities might make the data more meaningful to employees. Reflection happened not only on the collected data, but also on the practice of using sensors to track data in the workplace. Participants often had difficulties extracting meaningful knowledge from the collected data but had good reflections on how they used the sensors or what they learned from the experience. By engaging with such tools, they were confronted with questions like “Can I take this data to my manager to foster change?” or “Can we discuss the results of my explorations in the group biweekly retrospective?” People lapse in their self-tracking efforts due to a myriad of reasons [19]. Our participants got sometimes frustrated by the limitations of the sensors [9] or that they were perceived as not working as intended. Research by Moore et al. saw something similar, seeing high exit rates due to difficulties in using the technolog, quoting uncertainty about the validity and usefulness of their project [47]. Furthermore, if data interpretation is difficult, the perceived value of using the system decreases and usage stops. Recent work is exploring engaging data visualizations and user-defined features that might provide options to prevent lapsing or promote resuming of self-tracking [16, 61].

Reflecting on our study findings through the lens of the lived informatics model is worthwhile, yet we see also ways to challenge the model by applying it to interpersonal and collaborative contexts of use, where a new light can be shed on steps like Selection of tools or Integration with other data sources. In a work environment, data collection through sensors can present risks for individuals. Previous work highlighted the direct influence of privacy concerns on the intention to use tracking device [23, 29]. Risks of self-censorship [44], data dissemination, or the misuse of metrics beyond their intended purpose (e.g., as performance indicators) should be carefully weighted, and prevented as much as possible, in the design of such systems.

7.3 Designers’ Insights on The Use of Open-Ended Research Probes

Deploying the Habilyzer research probe in the field yielded insights for participants and designers alike. Exploring how users appropriated Habilyzer and how they reflected on its use gave us, as design researchers, a better understanding of the full complexity of the design space. As a result, we identified how self-tracking systems might support users in investigating their own habits and working conditions as well as detailed pointers towards the future design of interventions in the office context.

While self-tracking in and of itself is not a solution to mitigate the effects of sedentary lifestyles or unpleasant workplace experiences, its application provides insights otherwise not available through traditional forms of data collection. In this study, we triangulated multiple sources of information to paint a rich picture of everyday experiences or behaviors of employees in the workplace. The survey provided a snapshot of participants’ intentions, mental models and envisioned goals. The logbook provided insights into what goals they could realistically track and what new goals emerged over time. The interview uncovered reasons why users wanted to pursue certain goals or use self-tracking. As envisioned goals and intentions are often different from reality, the deployment of Habilyzer as a situated artefact revealed patterns of behavior that were more subtle or ungraspable.

Throughout the study, participants often struggled to find a direction for the use of the open-ended data-trackers. However, regardless of the accuracy of the gathered data or the preciseness of their goals, the experience of gathering and reflecting upon data inspired not only the employees in how they might improve their work environment, but it also helped us to see the possibilities and pitfalls of using self-tracking technologies. We can envision going beyond self-tracking solely, towards collaborative sense-making with a designer.

This approach follows the principles of Data-Enabled Design [35], whose framework describes a two-step process; the contextual step and the informed step. Rapid iterative cycles between these steps do not only increase the designers' understanding of the everyday experience of users in order to design more informed interventions, but it also provides users themselves with novel insights into their own behaviors. Habilyzer could similarly be the foundation for an infrastructure, enabling an iterative and user-driven approach towards more informed interventions in the office context.

7.4 Limitations and Future Work

Our study entails several limitations. First, besides the relatively low sample size in-volved, we sampled participants from a unique work environment and with a high level of tech savviness. Their workplace was also perceived by employees as supportive and trustworthy. Participants had no issues with sharing data with the company. Although we collected in-depth insights, from different sources and in a longitudinal manner, our sample limits our results' generalizability. An opportunity is to involve future samples with less technical knowledge or less supportive cultures. Second, participants encountered some issues using our research probe. Beyond a few gaps in the data, battery life and reliability have impacted the user experience. Similarly, the choice of presenting rather raw data has been questioned by the participants, who expressed the need for more insightful or intuitive data visualizations. In future work, we aim to take inspiration from [62] using co-design to tailor visualizations. Our study showed much diversity in the participants' outlooks, practices and needs, which also points at the potential of co-design to unveil the values and needs of employees prior to implementation of such systems or interventions within a company [16].

Finally, our participants did not move beyond the experimentation stage of relationship between users and self-tracking devices described by [30]. Longer deployments are needed to investigate the integration stage. In future work, we aim to improve scaffolding, providing scenarios of use for the kit, supported by an interface that more actively guides users towards their self-tracking goals. Inspired by [16, 45], we see potential in leveraging social dynamics to make personal informatics at work more fun, collaborative, and useful. We also aim to provoke creative use of the probes by giving recommendations on interesting datapoints and supporting self-experimentations [14].

7.5 Implications for Design

While we do not claim generalizability of our results, the insights gathered through our study complement the few studies on personal informatics in the office environment and on open-ended sensing solutions. Building on our data and prior work in the area, we summarize some take-away messages and implications for design, which we encourage the community to consolidate in future work.

Scaffold the practice of self-tracking. Guidance can take the form of guidelines, tutorials or use scenarios, or use features to balance the open-endedness of sensors, such as the ability to select a specific goal which tailors the way sensors collect data.

Support participants in setting up self-experiments. For individuals or teams interested in diagnostic tracking, technologies integrating principles of self-experiments are relevant to find correlations between phenomena of interests.

Promote collaborative tracking and sensemaking. Away from individual practices, self-tracking at the workplace requires negotiations between stakeholders. Co-design methods can support collective data sensemaking and follow-up actions.

Design for privacy, control and inclusivity. Non-individualistic or normative contexts such as the workplace calls for a critical integration of ethical perspectives in the conception and use of open-ended systems, anticipating potential adverse uses or unintended consequences.

8 CONCLUSION

The workplace is an underexplored context in the personal informatics domain, specifically in user-driven, open-ended systems, and challenges arise with the development of new technologies for such dynamic and open contexts. There is no 'best' solution or approach to account for the complexity, diversity and tensions in work habits, cultures and working conditions. Through the design and field study of Habilyzer, we explored what user-driven sensor systems mean at the workplace and what are the benefits and limitations of an open-ended approach to self-tracking. We expand the body of knowledge on the design and implementation of personal informatics systems in the office context by exploring how office workers use and adopt open-ended sensors.

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