Habilyzer: Empowering Office Workers to Investigate their Working Habits using an Open-Ended Sensor Kit

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Figure 1: Habilyzer is an open-ended sensor kit, empowering office workers to investigate their working habits

ABSTRACT

Office work presents health and wellbeing challenges, triggered by unhealthy working habits or environmental factors. While technologies for vitality in the office context gain popularity, they are often solution-focused and fall short in acknowledging personal needs. Building on approaches from personal informatics, we see value in opening up the design space of tracking and sensing technologies for office workers. We designed and deployed an open-ended sensor kit and conducted two complementary studies to investigate the value of empowering office workers to investigate their own working habits. Findings show that Habilyzer triggers curiosity about working habits, and wireless sensors contribute to inquire into those habits, possibly supported by additional tools. We contribute new insights into how an open-ended sensor kit can be designed to support self-tracking practices and underlying reflections in the underexplored context of office work. It is an alternative approach to workplace vitality, moving from solution-oriented technologies to inquiry-enabling tools.

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CCS CONCEPTS

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

KEYWORDS

Office work, Working habits, Open-ended sensors, Self-tracking, Self-Experiments

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1 INTRODUCTION

Office work presents health and wellbeing challenges, triggered by unhealthy working habits or factors linked to the work environment. Literature offers a myriad of recommendations to improve office workers' health and vitality. Sedentary behavior and sitting time [6, 32] are often emphasized as a main concerns, leading to various design interventions both traditional [7, 10] and speculative [8, 9]. The effects of several characteristics of the physical work environment (e.g., noise, air quality, temperature, light) on the users is also widely acknowledged, on both the well-being and productivity aspects [1, 27, 33, 38]. Despite the strong trend of smart buildings, including sensing capacity to optimize energy efficiency or improve the health, safety and comfort of building occupants through automation, employees are rarely given access to this data and its meaningfulness for them is under-researched. Overall, most health-related design interventions in the office context have a narrow use case, focused on solving a single problem without many options for the users to gain insights into their personal working habits or ability to personalize the intervention. What if we rather empowered office workers to research their working habits? Habilyzer is a set of open-ended sensors which facilitate curiosity-driven inquiry into working habits. The plug-and-play sensors can be deployed freely, driven by the area of interest of the user.

Li et al. define personal informatics as systems that "help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge" [30]. Epstein et al.'s model for personal informatics [16] divides the tracking process into several stages: deciding to track and selecting tools, tracking and acting, and lapsing of tracking that may later be resumed. Noteworthy, reflection often occurs during collection rather than being a separate stage [3]. As self-tracking continues to expand into mainstream practice, self-trackers usually start tracking with a specific goal in mind, like weight loss or fitness. Another common motivation is curiosity to learn more about one's behavior. The prevalence of tracking differs per domain with a dominance of private areas of life (e.g., health, fitness or the home environment), with little research done in office work environments [15, 16]. Rooksby et al. [34] identify five (overlapping) styles in which personal trackers can be used: directive (goal-driven, the dominant style), documentary, diagnostic, collecting rewards, and fetishized tracking. Interestingly, people in diagnostic tracking seek to answer a specific question about themselves [23], looking for causal relationships between several variables in a process of personal scientific discovery.

If traditional public health interventions seek generalizable effects that can be disseminated to the public in terms of generic guidelines and intervention models [4], self-experiments in the context of personal informatics are relevant personalized approaches: "The goal of personal informatics is not to discover knowledge about a broad population, but to help people learn about what affects them, specifically for the parts of their lives that matter to them the most. (. . .) Beyond passive monitoring, the next step towards better understanding one's self is to perform self-experiments: to create and test hypotheses on the effect of small behavior changes" [11]. Recent studies have investigated how to lower the barriers and support the practice of self-experiments [11–13, 22, 23]. Self-E app [12] for instance provide step-by-step guidance into setting up a self-experiment.

Sensors with no pre-defined application are prevalent in educational contexts to learn about electronics and programming. Examples include the Lego® Mindstorms ecosystem or the samlabs.com platform. Totem Pop [2] is an open-ended health tracker that can be re-programmed to fit new use cases. The Sensorstation by Denefleh et al. [14] consists of simple sensors that can be placed anywhere in a home context. It includes a screen to link sensor measurements with custom notifications, and a screen to display a constant live feed of all sensor notifications. Although not a sensor kit per se, I/O Bits [37] is a button-based prototype exploring user-driven situated self-tracking. Van Kollenburg and Bogers [26] identify different levels of flexibility in data trackers: open, closed and hybrid approaches. According to them, the closed approach makes it easier for the intelligent solution (the data tracker) 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. Cila et al. [5] identify three roles for IoT products. The present research dives into Things as Collectors, used for understanding and making invisible patterns visible. If Collector products can inform on environmental factors they also reveal people's behavioral patterns and can serve as "co-ethnographers". The main challenge is to find ways to use the collected data as creative design material, rather than using the data solely for optimization or validation of design. This is for instance what Denefleh et al. [14] pursued through the deployment of *Sensorstation*, which enabled residents in a shared housing context to co-design and co-speculate on smart sensors and services. The present study follows a similar goal of empowering people through the use of simple sensor data to eventually support the co-design of innovative and meaningful solutions. We contribute new insights into how an open-ended sensor kit can be designed to support self-tracking practices (user-driven data collection) and underlying reflections in the underexplored context of office work [15].

2 HABILYZER

Habilyzer is a set of plug-and-play, open-ended sensors that facilitate curiosity-driven inquiry into working habits (Figure 1). It offers office employees a way to become explorers of their own habits. The Habilyzer kit 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. Participants receive a stand-alone plug-and-play kit along with brief instructions. The sensors can be immediately deployed in any way the user wants to, driven by their areas of interest. Habilyzer is delivered to participants in a box (Figure 2) that contains everything they need to get started: an instruction booklet, the base unit with a user interface that aggregates and displays sensor data, an ultrasonic distance sensor, an accelerometer, and some accessories (e.g., self-adhesive velcro, clipping straps) to facilitate attaching the sensors to objects, individuals or building infrastructure in the working environment.

The choice of a distance sensor and an accelerometer was based on the openness of the data they collect. Where for example the data from a decibel sensor more intuitively relates to the environmental noise level, one-to-one mapping of data for a distance sensor or accelerometer is less obvious. We assume that the more open-ended a sensor is, the more diverse its possible application areas, and thus the more creative the deployments could be (see [17] for insights into openness and ambiguity in design or [31] about discovery-driven prototyping). Other sensors could of course be relevant (some have been included in an ongoing v2 of Habilyzer [18]) yet it was wise to limit the scope of our initial deployment. The implementation of Habilyzer's data review functionality is rather rudimentary, only allowing data to be filtered by time interval and sensor, displayed on a line graph. This choice stems from the objective of the kit: investigating whether putting the user in a researcher role triggers curiosity on their habits and insights into

Figure 2: Habilyzer, an open-ended sensors kit including two sensor units and a base display

the role of technology in this process. The evaluation of this kit can lead to insights in how Habilyzer might enable reflection on the collected data.

2.1 Technical Specifications

The Habilyzer Office Vitality kit consists of a base unit that visualizes the data coming from two wireless sensors powered by 1000 mAh Li-Po batteries: a distance sensor (Wemos D1 Mini Wi-Fi enabled microcontroller, HY-SFR05 ultrasonic distance sensor) and an accelerometer (NodeMCU V3 Wi-Fi enabled microcontroller, MPU-6050 accelerometer and 3-axis gyroscope). The base unit contains a Raspberry Pi 3B microcomputer and a 5" TFT capacitive touch screen. The display unit runs on Raspberry Pi OS Lite with a Node-RED instance. The Raspberry Pi hosts a wireless access point to which the sensors connect. The sensors send their data to the base unit using the MQTT protocol. The base unit stores the data in a SQLite database. All sensors have a 3D-printed enclosure and come with an on/off switch and micro-USB charging port. A revised version of the Habilyzer toolkit is presented in [18].

3 METHOD

Our research objective was assess the efficacy of Habilyzer as an open-ended sensor kit in triggering curiosity on working habits and a researcher mindset in office workers. We conducted two complementary studies: an in-situ deployment with the exploration of the sensors as a starting point, followed by an online study starting this time from potential inquiry questions into working habits. The research was approved by the Ethical Review Board of the University, and informed consent was collected amongst participants.

3.1 Study 1

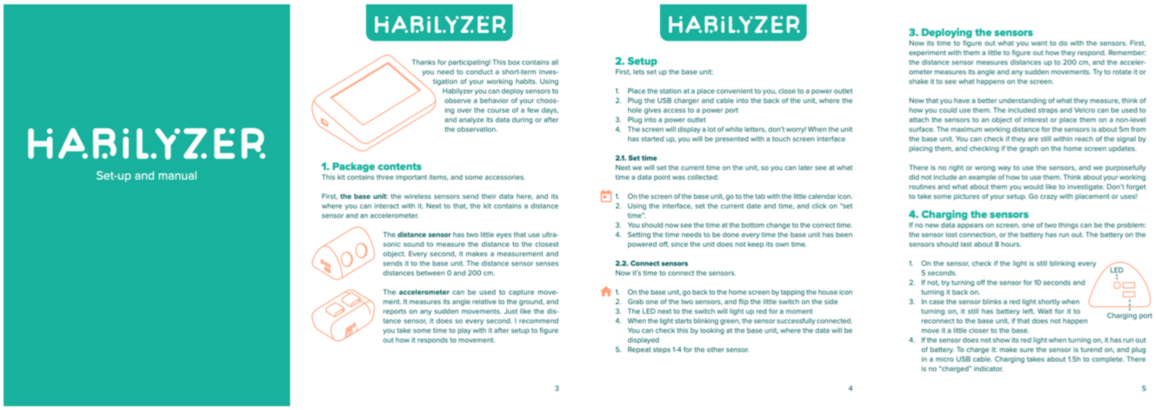
We deployed the Habilyzer kit with 3 participants (2 women, 1 man) for a period of 2 days each. All participants were knowledge workers under the age of 30, with a university degree. Due to Covid-19, they all worked from home at the time of the study. They declared spending an average of 32h (P2, P3) to 40+h (P1) per week sitting at their desk.

We provided the Habilyzer box to participants with the instruction to open it the evening before their 2-days investigation. The instruction manual guided them (Figure 3). First it explained the package contents (sensors, base unit, accessories) and how to set up the base unit, connect the sensors and charge them. No instructions were included for the specific usage of the kit or how to interpret their data, since this was up to the participant. The manual only included the following instructions: *"Now it's time to figure out what you want to do with the sensors. First, experiment with them a little to figure out how they respond. (. . .) Now that you have a better understanding of what they measure, think of how you could use them. The included straps can be used to attach the sensors to an object of interest or place them on a non-level surface. There is no right or wrong way to use the sensors, and we purposefully did not include an example of how to use them. Think about your working routines and what about them you would like to investigate."*

A debriefing semi-structured interview was conducted at the end of the study, with a focus on: (a) when and how did the participants use the sensors and the base display unit, (b) what did they attempt to research and which insights they got into that area of interest (c) how they experienced the use of the sensors and what influence it had on their working habits, (d) envisioned future uses of the sensors and suggestions for improvement.

3.2 Study 2

Study 2 iterated upon the Habilyzer instruction manual, and investigated how participants would deploy the sensors, without actually executing the deployment (thus focused solely on the Preparation stage of Li et al.'s model [30]). Where Study 1 first introduced the sensor kit and then asked participants to use the sensors to investigate their habits, Study 2 first asked about working habits to investigate, and then introduced the Habilyzer kit and asked participants to envision possible sensors deployment ideas that could satisfy their curiosity. The overall research question is similar to Study 1, but we additionally aimed to understand the influence of participants' starting point on their inquiry experience. Six participants (3 women, 3 men) were involved in Study 2, including two design students and four office workers. They declared spending



HABILYZER
Set-up and manual

HABILYZER

Thanks for participating! This box contains all you need to conduct a short-term investigation of your working habits. Using Habilyzer you can deploy sensors to observe a behavior of your choosing over the course of a few days, and analyze its data during or after the observation.

1. Package contents
This kit contains three important items, and some accessories.

First, **the base unit**: the wireless sensors send their data here, and its where you can interact with it. Next to that, the kit contains a distance sensor and an accelerometer.

The **distance sensor** has two little eyes that use ultrasonic sound to measure the distance to the closest object. Every second, it makes a measurement and sends it to the base unit. The distance sensor senses distances between 0 and 200 cm.

The **accelerometer** can be used to capture movement. It measures its angle relative to the ground, and reports on any sudden movements. Just like the distance sensor, it does so every second. I recommend you take some time to play with it after setup to figure out how it responds to movement.

3

HABILYZER

2. Setup
First, lets set up the base unit:

1. Place the station at a place convenient to you, close to a power outlet
2. Plug the USB charger and cable into the back of the unit, where the hole gives access to a power port
3. Plug into a power outlet
4. The screen will display a lot of white letters, don't worry! When the unit has started up, you will be presented with a touch screen interface

2.1. Set time
Next we will set the current time on the unit, so you can later see at what time a data point was collected.

1. On the screen of the base unit, go to the tab with the little calendar icon.
2. Using the interface, set the current date and time, and click on "set time".
3. You should now see the time at the bottom change to the correct time.
4. Setting the time needs to be done every time the base unit has been powered off, since the unit does not keep its own time.

2.2. Connect sensors
Now it's time to connect the sensors.

1. On the base unit, go back to the home screen by tapping the house icon
2. Grab one of the two sensors, and flip the little switch on the side
3. The LED next to the switch will light up red for a moment
4. When the light starts blinking green, the sensor successfully connected. You can check this by looking at the base unit, where the data will be displayed
5. Repeat steps 1-4 for the other sensor.

4

3. Deploying the sensors
Now its time to figure out what you want to do with the sensors. First, experiment with them a little to figure out how they respond. Remember: the distance sensor measures distances up to 200 cm, and the accelerometer measures its angle and any sudden movements. Try to rotate it or shake it to see what happens on the screen.

Now that you have a better understanding of what they measure, think of how you could use them. The included straps and Velcro can be used to attach the sensors to an object of interest or place them on a non-level surface. The maximum working distance for the sensors is about 5m from the base unit. You can check if they are still within reach of the signal by placing them, and checking if the graph on the home screen updates.

There is no right or wrong way to use the sensors, and we purposefully did not include an example of how to use them. Think about your working routines and what about them you would like to investigate. Don't forget to take some pictures of your setup. Go crazy with placement or uses!

4. Charging the sensors
If no new data appears on screen, one of two things can be the problem: the sensor lost connection, or the battery has run out. The battery on the sensors should last about 8 hours.

1. On the sensor, check if the light is still blinking every 5 seconds.
2. If not, try turning off the sensor for 10 seconds and turning it back on.
3. In case the sensor blinks a red light shortly when turning on, it still has battery left. Wait for it to reconnect to the base unit, if that does not happen move it a little closer to the base.
4. If the sensor does not show its red light when turning on, it has run out of battery. To charge it: make sure the sensor is turend on, and plug in a micro USB cable. Charging takes about 1.5h to complete. There is no "charged" indicator.

LED
Charging port

5

Figure 3: Instruction manual included in the Habilyzer kit (extracts)

between 20-40h per week sitting at their desk. This study took the form of a digital interactive workbook based on the instruction manual from Study 1. Besides the distance sensor and accelerometer from Study 1, this protocol included the possibility to deploy a pressure sensor, sound sensor, or another sensor of their liking to further open up the types of inquiry possible with the kit. They filled out the booklet in their own time without active participation from the researcher. The instructions from the booklet guided participants to think of habits to track and change, and ways to do so, following a diagnosis self-tracking approach [34]. Parts were hinting at self-experiment but did not mention cause and effects as [12].

4 RESULTS

Due to the similarity of the research questions investigated and space constraints, we present aggregated results from Study 1 (participants P1 to P3) and 2 (participants P4 to P9), by emphasizing the contrasts between both samples when relevant.

4.1 Investigated Areas of Curiosity

The majority of participants (7 out of 9) investigated a work habit related to bad posture or sedentary behavior. *"I am curious how inactive you actually are during your working day [from home] compared to before [at the office]." (P1).* Other notable habits included routines related to working from home, for example eating in front of the screen during work (P4), or not brushing teeth every morning breaking normal routine (P8). Participants to Study 2 were also curious about their productivity and how it differs when working from home vs. the office. *"I'm curious how long I can work with a focused mind. When to stop and continue again with an efficient brain." (P8).* Two of them mentioned their co-workers, curious to check if their colleagues are as productive as they say (P7) or highlighting that sensors deployed within a team could lead to exchanges and challenges (P7). These curiosities were absent in Study 1, where all 3 participants focused on physical activity and sedentary behavior. Most participants in Study 2 mentioned a pre-existing awareness of bad working habits, but said that filling out the booklet triggered deeper reflection on the issue.

"I was already aware of what my working habits were, such as the bad posture and drinking too little. I had not considered yet to track and measure my behavior, but it made me curious to do so. ... I usually felt too busy at work to feel curious about these habits. They feel like something that stands in the way rather than something to focus on. The questions triggered curiosity and made me feel like I could prioritize my health a bit more."(P5)

4.2 Deployment of the Sensors and Insights Gathered from the Data

Every participant was able to come up with a way to use the sensors to inquire into their habits. Table 1 presents an overview of the sensors for each participant. As a reminder, participants in Study 1 had access to a distance sensor and accelerometer whereas participants in Study 2 had additionally (hypothetical) access to a sound level sensor, pressure sensor and an option to use another yet-to- be-defined sensor. The variables of interests indicated in parenthesis in Table 1 are transcribed verbatims: several of them could have been classified under the same label (e.g., posture could include head/leg position) but it is interesting here to stay true to the way participants envisioned these sensors.

In Study 1, participants deployed the sensors and documented their investigation (Figure 4). P1 placed the distance sensor under her monitor to see when she was typing, sitting, or away for lunch. The accelerometer was wrapped around her wrist, she hypothesized it could see when she was typing and wondered if it would be visible from the data. P2 stuck the distance sensor to the edge of his desk, to understand how much time he spent in his chair. The accelerometer was put on his headset to detect when he was in a call. P3 initially wanted to put the distance sensor at head height to assess if she was sitting upright, or leaning her head forwards. Because she was unable to find a way to place it at that height, she used books to raise it to chest height. The accelerometer was attached to her ankle in order to assess if her legs were at 90°. She also made notes in the booklet when she had breaks, in order to know what data could be filtered out. Some participants felt limited in their investigation by the sensors possibilities. P3 would have appreciated a way to measure neck position and steps, and P1 could have used a sound

Table 1: Overview of the use of sensors by participants of study 1 and 2 by location and (variable of interest) as expressed by participants

	Distance	Accelerometer	Sound	Pressure	Other
P1	On desk (presence)	On wrist (typing)	(Type of work)	Unavailable in study 1	
P2	On desk (presence)	On headset (calling)	Unavailable in study 1	Unavailable in study 1	
P3	Under screen (posture)	On ankle (leg position)	Unavailable in study 1	Unavailable in study 1	
P4	(posture)	On head (head position)	Not used	Mug or chair (sitting time)	Smiling sensor
P5	Not used	On water bottle (drinking frequency)	Not used	Under water bottle (drinking amount)	Option for gathering qualitative data
P6	On desk (presence)	On feet (movement)	Not used	On chair (presence)	Camera (presence)
P7	On desk (presence)	Not used	On desk (disturbance)		-
P8	On monitor (presence)	Not used	Not used	On seat (presence)	Activity sensor in every room
P9	On monitor (posture)	On upper body (posture)	On desk (sound)	On chair (posture)	Screen content

a Note that P1 to P3 corresponds to actual use in-situ, P4 to P9 to self-reported envisioned use. P1 envisioned use of a sound sensor is a speculation as there were no sound sensor in study 1.

Figure 4: In-situ deployment of the sensors as documented by P1, P2 and P3 in Study 1

sensor to gain insight into the type of work she was doing (meeting or working).

In Study 1, P1 and P3 made an attempt to review the data they collected using the base unit. P1 noted that no surprising insights had emerged, since the sensors were too sensitive which made it hard to see patterns in the data. P3 tried to engage with the data before the interview. She mentions that a graph showing the entire day is too broad to make any discoveries. New insights for P3 mainly emerged from the presence of the sensor, noticing for example that during meetings she would move to a position where the sensor could not see her, giving insights into her posture change. Insights that participants in Study 2 would like to gain from the data pertained to quantities (water drunk), time (spent sitting, on a break), and moments (when they move from good to bad posture, or when they tend to forget to drink water).

4.3 Taking the Role of a Researcher of One's Habits

The role of autoethnographic researcher was difficult, "I found it very hard to come up with a research question, why am I going to measure this?" (P1). Looking back at the lack of insights she gained from the study, she mentioned that a better formulated question or idea of what you want and can measure would have helped. She would be able to create a better question and setup now that she knows how the sensors react. P3 noted that she came up with something to measure for the purpose of the study, yet in a natural setting the use of a sensor kit would stem from a problem that needs to be solved. Very important to P3 is intrinsic motivation in changing habits, and involvement in their own habits like with Habilyzer could stimulate motivation. If one can decide for themselves what they will measure, it forces people to think about their habits, and because they made up their own research there is a sort of "psychological trick" due to involvement and investment, and because you can decide everything yourself you have influence on the insights you gain.

P1 and P3 tried not to let the presence of the sensors influence their behavior. They wanted to establish a baseline measure before adapting her routines. Most of Study 2 participants also wanted to collect information on their status-quo, with only P5 specifically investigating their success in changing the bad habit. The amount of time that participants of Study 2 expected to need to gain the insights they were looking for ranged from 3 working days to 3 weeks.

Although they did not gain many new insights at this stage, all three participants in Study 1 saw value in a product like Habilyzer to gain insight into their working habits. Participants from both studies reflected on the functionality of the kit and its possible applications. Stating that she would track her drinking consumption but not her posture, P5 explained, *"I don't want to gather data on something I won't be able to improve on. The kit works when the problem you have is something you cause yourself (as not drinking enough), not when it is caused by external factors (a bad office chair, in case of the posture)" (P5).* P3 and P4 saw value of using tools like this in preventive and diagnostic health too, receiving a sensor kit like this from your doctor to first gain insights into the cause of your symptoms to allow a better fit for remedies.

P2 envisioned an ecosystem of sensors, and an online platform where others could share their setups for inspiration. P4 also notes that "it takes quite a bit of creativity to use the sensors. Some examples of what you can do with it, both sensible and funny ways of use can help you on your way". Suggested functionalities, besides the additional sensors shown in Table 1 pertained to gathering qualitative data next to quantitative: "Since I want to track how I feel (in terms of headaches, fuzziness) after drinking enough vs. not enough water, I would like to add comments to my quantitative data" (P5). Finally, P8 mentions the need for implementing notifications based on the data you collect, beyond just reviewing it. P1 believes that to effectively change a habit, the nudges (e.g., notifications) should be proportional to the problem.

5 DISCUSSION

In this research, we explored the effects of enabling office workers to research their own working habits using an open-ended sensor kit. Previous research [26] identified that open data trackers allow the user to define relevant data. The Habilyzer kit, and especially the research booklet, triggered curiosity in participants into their working habits and tend to support a deeper layer of reflection in participants beyond simple awareness of a habit. The use of Habilyzer also triggered reflections on the efficacy of current vitality interventions and technologies for behavior change. Interventions like notifications to get up or computers locking up to force you to take a break were named as examples of existing solutions that do not work. The notifications are ignored, would come at the most inconvenient times, or are oblivious of context. P3 noted that to effectively trigger behavior change, one needs to have intrinsic motivation to do so. Enabling office workers to set up their own research or intervention could be effective in creating ownership over their habits, possibly leading to more impact than the abandoned smart technologies described by Lazar et al. [29]. Following Gaver, Beaver and Benford's tactics for using ambiguity as a resource for design [17], the 'narrative of use' in Habilyzer creates ambiguity, possibly spurring people to approach our artefact with an open mind and eventually questioning their own values. Habilyzer hence does not provide expected functionalities or an expected solution to a problem, as much products currently do, and also offers unaccustomed roles to encourage imagination and exploration.

In our studies, many participants deployed the sensors for diagnostic tracking, one of the four styles of personal tracking identified by Rooksby et al. [34]. This is in line with the Habilyzer instructions to investigate their bad working habits. In [34], only 10% of participants tracked diagnostically, a directive goal-driven motivation for data collection being more prevalent. Most of our participants deployed the sensors to gain insight into the frequency, moments, and context in which their behaviors emerged. Possibly, when our participants would have those insights, they would turn to a directive mode of data collection to assess the impact of their behavior change attempts.

5.1 Limitations and Future Work

This contribution is a work-in-progress and entails several limitations. First, besides the relatively low sample size involved in our preliminary user studies, our sample was composed almost exclusively of highly educated participants. As using the kit, and especially coming up with questions to research about one's working habits proved to be challenging, investigations on a more representative sample are needed to adjust the material or instructions. Second, participants of Study 1 got first introduced to the sensor kit, before being invited to find habits to investigate. As seen in the results, this made them look for things in the environment that moved or could be interesting rather than thinking about a personal motivation to research their working habits: P1: "*I thought by myself, I need to attach the acceleration to something that actually moves, otherwise the fun of measuring acceleration is a bit lost*". Openness was facilitated in a limited scope by Habilyzer, since both sensors measure change in physical environment (moving objects). No tools to assess environmental factors were included, directing the investigations in Study 1 to the relation of the person to the space (posture) or frequencies of movement. We flipped the order in Study 2 and saw more diversity and creative uses of the sensors - but still limited to habits with a physical manifestation. Indeed, due to its nature, the Habilyzer kit did direct users towards certain habits which could be tracked by the available sensors. As noted by P9, *"It filters out habits that don't have a clear physical manifestation, this made me decide to go into the bad posture instead of distraction"* In future work, we thus want to explore the inclusion of input mechanisms (e.g., smart buttons) to report subjective feelings or events without a physical manifestation, similar the uGrow kit by [25]. A deeper reflection on the components to add to the sensor kit to really support open-endedness in explorations - without being overwhelmingly complex - is necessary. On this topic, the provocative Office Agents kit [35] researched which sensor (out of 5 provided) was more meaningful to office workers by looking at which bossy agents they would obey. Similar sensor kits or open-ended physical computing devices [14, 19, 31, 37] designed for other application areas can be used as inspiration. Finally, if participants envisioned gaining insights from their chosen way of data collection, it was beyond the scope of this study to test if this holds true, and many possibilities are left unexplored.

Our next step is to deploy a revised version of Habilyzer [18] during a 6-weeks longitudinal study in a collective office environment, in order to reflect the collective nature of work and see whether and how social dynamics plays a role in the tracking of working habits. With this longer timeframe, we hope to move beyond the initiation and experimentation stage described by [24] to reach the integration stage. Additionally, we intend to move from facilitating an inquisitive mindset to enabling creative exploration of the gathered data. Which kinds of tools and visualizations do office workers need to be able to answer their questions? Is the physicalization of data [21] similar to Stamhuis et al. [35] a way to go to trigger meaningful data explorations? Could people construct their own physicalizations to engage more deeply with their data [20, 36], possibly by using cost-efficient and fun material to do so [28]? How can we facilitate insights gained from combining several variables (e.g., influence on environment distractions on productivity)? Finally, Habilyzer can be expanded to include outputs (e.g., reminders, notifications) or to inspire interventions co-designed with the participants, in order to make the step from insights into habits to changing the habits.

6 CONCLUSION

In conclusion, our findings have shown that the Habilyzer kit triggers curiosity in office workers into their working habits, enabling reflections that would not be considered without it. Overall, our explorations confirm the need for a dissenting voice to existing system-driven technologies for office health and wellbeing. The present contribution provides a case study of a different approach where office workers are empowered to take ownership over health interventions.

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