To cite this chapter:

De Calheiros Velozo, J., Niemeijer, K., & Vaessen, T. (2021). Passive sensing. In I. Myin-Germeys & P. Kuppens (Eds.), *The open handbook of experience sampling methodology: A step-by-step guide to designing, conducting, and analyzing ESM studies* (pp. 251-262). Center for Research on Experience Sampling and Ambulatory Methods Leuven.

CHAPTER 13

PASSIVE SENSING

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Over the past decade, there has been a steep increase in the use of wearables and other means of passive sensing (data collection without immediate active involvement of the user) to capture aspects of real-life behavior and environment. For instance, according to the Web of Science database, there has been over a tenfold increase in the number of published scientific reports annually on wearables (i.e., body-worn devices that measure bodily or environmental signals) since 2010. No doubt, this rise has to do with the technological advances in the fields of microelectronics and software development, but also improvements in esthetic design during the past decade. Likewise, the development of smartphones has taken flight, adding even more possibilities for the passive ecological investigation of daily-life dynamics. The results of these developments on crucial aspects for both general and research purposes, such as measurement accuracy and reliability, battery life, comfort, esthetics, and user friendliness, have led to the utilization of wearables in both science and personal use on an unprecedented scale. These wearables have become particularly popular with eESM researchers who use passive sensing to add to and further develop their traditional protocols.

Commercial wearables such as sports watches and fitness trackers have become mainstream products. In 2019, there were a projected total of 722 million wearables connected worldwide (Statista, 2019); twenty-one percent of American adults owned a smartwatch or fitness tracker, with projections for the next years indicating an increasing trend (PewResearch, 2020). Most commercial wearables can now continually measure physiological variables for days. Whereas even basic wearables are able to estimate heart and respiration rate through photoplethysmography (PPG) and accelerometer-based movement, higher-end wearables complement these measures with electrocardiography (ECG), galvanic skin response (GSR), and skin temperature sensors. The widespread personal use of these wearables has undoubtedly lowered the threshold for scientific data collection – not only in terms of availability, but also of user acceptance – paving the way for large-scale monitoring of physiological and motion variables in everyday life.

Even more so than wearables, the smartphone itself has become a critical tool for passive collection of daily life data, due to its many applications and its global availability. An estimated 3.2 billion people worldwide own a smartphone (Newzoo, 2019), with percentages of >76 for populations of developed countries (PewResearch, 2019). Not only the many built-in sensors, but also the analysis of

smartphone usage make it the richest data source of information on daily living. For instance, location and movement can be tracked using an accelerometer, gyroscope, GPS, and Bluetooth – features that are available in most smartphones today. Social interactions can be monitored through Bluetooth, microphone, or app usage, calls, and text messages. Screen on/off time, typing speed and patterns, and Wi-Fi connectivity are only some of the other possibilities smartphones offer to capture behavioral and environmental markers of daily living. These means of data collection offer unprecedented new opportunities for daily-life research.

Passive sensing is increasingly used in combination with ESM. Although the field is growing rapidly, tangible results have only started to come out recently. Many features of daily life, such as an individual's environment or behavior, can be assessed using passive sensors. Combining passive sensing with ESM potentially holds several important benefits. First, it could add information to ESM measures. Although passive sensing may never be able to assess an individual's personal experience, it can enrich ESM data by adding biological, behavioral, and contextual variables of interest. Second, it could substitute certain ESM measures. In some cases, passive sensing may be able to replace ESM items asking for a description of a phenomenon that can be directly measured using passive sensing (e.g., location, ambient noise, etc.). Third, it could improve the precision of ESM, increasing the sampling of moments of interest by triggering ESM questionnaires when pre-set passive sensor-based thresholds are reached. However, additional sensors and protocols may also increase the burden of participating in ESM research, potentially influencing compliance and the measurements themselves. In this chapter, we will discuss the benefits and potential challenges of passive sensing for ESM research.

13.1 Using passive sensing to enhance ESM research

ESM has garnered a significant following in part because of its unique ability to account for context. Passive sensors are particularly useful to amplify ESM by collecting a wide array of contextual factors that would have not been possible otherwise. Passive sensing encompasses two main branches of data collection: data that is passively collected directly from the participant's smartphone (e.g., microphone, bluetooth, swiping activity, GPS, message and call logs), and data collected from an additional wearable device be that a wristband,

an earpiece, a chest patch, or anything additional that is provided to the participant to wear.

13.1.1 Smartphone sensing

Smartphones have effectively become an extension of the self (C. S. Park & Kaye, 2019) and as such provide a means that may be particularly useful to supplement ESM research, providing more fine-grained information on several well-studied fields. Social behavior, for instance who the participant is with and whether they are actively engaged in a social interaction or not, is a construct that may greatly benefit from the addition of passive sensing as it is oftentimes difficult to capture precisely with ESM items alone. In a standard ESM protocol, participants may be asked whether they are in the company of others and if so, to appraise this company, but little is known about the specifics of their company. This is where passive sensing can come in to augment our knowledge of the social context; while ESM collects information on subjective experience, passive sensing can gather information on behavior and surroundings (Lathia et al., 2013). Together, data from the microphone, Bluetooth, calls and messages, as well as various apps can help identify if the participant is in company or not, with how many people, how close or far, and whether they are actively interacting or not (Bachmann, 2015). In fact, data collected from the smartphone has been used as a complement to ESM in order to estimate not only if the participant is having or is near a conversation but also more specific information such as how long the conversation lasts (Morshed et al., 2019).

Naturally, social behavior is no longer limited to the physical realm but extends to the virtual world as well. Online social behavior is difficult to capture via questionnaires as it comprises a wide complex range of behaviors starting from more direct active forms of online interaction (e.g., messaging, calling) to more passive forms such as liking, sharing, and commenting. Smartphone usage can easily track every aspect of these behaviors without adding any additional burden to the participant and further contributing to the ESM (Morshed et al., 2019).

Smartphone data such as Bluetooth and GPS further work to amplify ESM by providing near continuous measurement on various aspects surrounding the individual that are scarcely captured through ESM unless it is the specific focus of the study. The specifics of an individual's daily trips for example are

generally omitted from ESM even though it has shown to have a direct effect on their affect. A study combining GPS with ESM for example found that it may not be where people are going that affects their mood but how they get there. That is, regardless of where they are going, people generally report a more positive mood when engaging in an active mode of transportation such as walking or biking rather than driving or taking a bus. Likewise, a commute that includes greenery and large water bodies was found to be better for mood than commuting through dense urban areas (Glasgow et al., 2019).

GPS not only informs on the participant's travel patterns (Glasgow et al., 2019; Reinau et al., 2015), but also on situational factors such as weather, daylight, location type, proximity to certain structures (i.e., entertainment, nature, social buildings, offices, shopping centers, etc.) (Mackerron & Mourato, 2013), to name a few examples. Given that people report higher levels of well-being when completing a questionnaire outdoors, and/or on sunny days versus indoors, and/or on cold dark days (Feddersen et al., 2016; Kööts et al., 2011; Messner & Wanke, 2011), access to this type of data offers the opportunity to assess their role in daily life, as well as control for them in more complex statistical models.

These are but a few examples of the possibilities passive smartphone sensors bring. Some researchers have even claimed that solely by tracking patterns in typing or swiping pressure, it is possible to identify when an individual is stressed or not (Exposito et al., 2018). And while promising, we must note that these applications come with several new challenges. For instance, Bluetooth interactions can only be established when nearby devices have this function activated, and it may be difficult to identify the type of interacting device (mistaking a printer for another smartphone may lead to very erroneous conclusions!). Users must have their smartphone on them for the sensors to collect meaningful information at all. At the same time, we can but acknowledge the youngness of this field and even though passive sensing will not allow us to measure everything, it allows us to measure much more than ESM alone.

13.1.2 Wearable sensing

Like smartphones, developments and access to wearable technology has proven a great asset for ambulatory research. For instance, accelerometry derived from body-worn sensors, ideally placed on the torso, provides much more reliable information about bodily movements than do smartphone sensors.

Accelerometry and/or physiological markers such as heart rate and breathing can further inform on the intensity of the participant's physical activity (Treuth et al., 2004). More and more studies investigate the possibility of predicting different experiential states such as affect types through variables acquired through passive sensing. For instance, several studies have tried to predict the experience of acute stress using machine learning models based on physiological and motion parameters that have been collected using passive sensing (Hovsepian et al., 2015; Smets et al., 2018). Although these models as of yet do no not reach desired performance levels, in time they may provide possibilities to estimate experiential states, at least to a certain extent, without active involvement of the participant. However, as these models inevitably are built upon subjective experience as ground truth, the question can always be posed whether passive sensing is a better approach than self-report.

The same applies to sleeping behavior. While ESM studies may include a few items inquiring about sleeping patterns such as length, and quality of sleep (i.e., waking up multiple times, ease falling asleep, etc.), passive sensing can further inform on this by directly tracking the physiology and movement associated with the participant's sleep. By adding passive sensing to ESM, it is possible to investigate the effects of the more detailed aspects of sleep quality, such as the exact moment the participant fell asleep and woke up, how much did the participant move in their sleep (Staples et al., 2017), to name a few.

In short, passive sensing can significantly enhance ESM by expanding or in some cases replacing ESM within the scope of interest. Although ESM already covers a broad range of measures, passive sensing can further amplify them by providing more comprehensive data to complement it.

13.2 Using passive sensing to substantiate ESM research

Passive sensing is not limited to enhancing ESM data, in some cases it can also be used to corroborate or substantiate it. That is, passive sensing can work as a means to check (or confirm) the subjective data reported. While it is not yet widely used in this context it presents enormous potential to better study certain populations or behaviors that are particularly difficult to track precisely otherwise. For example, it is notably challenging to study individuals who suffer from substance abuse as they may be either unable to or unwilling to honestly respond to successive self-reported questionnaires on their substance use. For that reason,

rather than relying solely on their ESM reports, GPS data combined with physiological data can provide further evidence to substantiate their reports. Using GPS allows the researcher to check whether the participant is in close proximity to places where substance is likely to be present such as bars for example, and physiology can help identify substance use by confirming whether there is a physiological response associated with taking said substance or not. In addition, certain tools can further corroborate whether a substance has or not been used, for example in the case of a breathalyzer to check for alcohol intake (Bertz et al., 2018). Needless to say, there may also be ethical objections to certain usage of passive monitoring. Some of these considerations are discussed in chapter 5.

Likewise, young children are also difficult to study accurately as they may struggle to complete electronic surveys. In a study investigating physical activity in children between the ages of five and seven, accelerometers tracking their activity was combined with an ESM completed by the parents (Engelen et al., 2015). The addition of passive sensing worked to confirm children's actual physical activity.

In some cases, it is not the population that presents the challenge but the behavior itself. In fact, there are certain behaviors that we are simply unable to report correctly as we grossly under- or over- estimate them. This is the case of phone or internet usage that are commonly heavily underestimated (Yuan et al., 2019). In these cases, passive data may be more reliable than ESM self-reports, providing a more accurate and timely depiction of the participants' phone usage.

Smoking is another behavior that is difficult to measure accurately with self-reported measures. In fact, smokers frequently underestimate how often and how much they actually smoke. Using Bluetooth e-cigarettes in parallel with ESM to measure the puff count and duration, Pearson and colleagues (2017) found that smokers underestimated how much they smoked 87% of the time, with an average difference of 33 puffs per day.

These are mere examples where passive sensing has and can be used to add value to ESM by either enhancing and/or corroborating certain measures that may not be entirely reliable on their own due to either the demographic or the measure itself. However, there are other potential applications and no doubt these will be further explored and applied in future research.

13.3 Triggering ESM questionnaires based on passive sensors

An important challenge with ESM is when to trigger the questionnaires (cf. event-contingent sampling) so that it is able to capture a wide range of events that are representative of the participant's daily life while also collecting enough of the event of interest (i.e., fleeting experiences or situations). Setting-up a trigger schedule that can fulfil those two requirements whilst also keeping participant burden to a minimum and compliance to a maximum is a delicate balancing act that can be substantially improved with passive sensing technology (Lathia et al., 2013).

One way where passive sensing can facilitate ESM is by triggering beeps in the moments of interest to the study, so a more event-based approach. In fact, certain research questions do not require data representative of every aspect of an individual's life, but more focused data on specific events as is the case for research on eating behavior for example. By using a smartwatch that can trigger a beep when it detects a meal episode it limits probing to the relevant moments only (Morshed et al., 2020). Passive sensing can also help increase compliance by triggering beeps only at opportune times such as when the participant is using the phone, after ending a phone-call or finishing a text (Fischer et al., 2011), or based on activity transitions by use of accelerometers (Pejovic & Musolesi, 2014), rather than in the middle of a sports activity or when driving, where answering a questionnaire would be difficult, and in some cases dangerous. Adjusting the trigger schedule to the participant's lifestyle via passive sensing has shown to not only significantly improve compliance rate, but more importantly effectively improve data quality by as much as 96% and reduce the time between trigger and survey completion (Gosh et al., 2019; Lathia et al., 2013).

In addition to triggering individual beeps, the whole day schedule could be adjusted based on passive sensor data, for instance, to match the participant's sleep-wake rhythm. Based on either smartphone use data or physiological data, it could be inferred when a participant is awake and thus could respond to the beep schedule. Going one step further, the same could be done with the triggering of an entire ESM period. Predetermined passive sensor data could here trigger the initiation of an ESM period, for instance when physiology or smartphone sensors detect a change in functioning (e.g., changes in stress levels, sleeping patterns, social media use, movement, etc.). Although these applications are still

speculative, they have the potential of becoming essential additions to standard ESM studies in the not-too-distant future.

13.4 Participant burden

An important aspect to consider before deciding to implement passive sensing in a study is the impact on participant burden. That is, whether or not adding passive sensing will increase or decrease participant burden and if it does, whether its use can be justified. As mentioned above, passive sensing can significantly reduce the burden on participants in two key ways: first, by replacing ESM items that can easily be monitored passively (i.e., without participant involvement) such as social interactions (Doryab et al., 2019). Second, passive sensing may be able to guide the trigger schedule so that questionnaires appear only at informative moments (e.g., Bertz et al., 2018; Halem et al., 2020). Nevertheless, there are instances where passive sensing can actually increase participant burden.

There are several technical issues that may increase perceived participant burden. Namely, the added battery-drain if a participant's device is used, and/or the burden of having to carry an additional device in the case of research phones or wearables (e.g., chest-patch, wristband, earpiece). The latter case can be especially burdensome as participants need to remember to carry this additional device and, in some cases, occasionally charge it. Some devices such as chest-patches or earpieces may also be cumbersome to use causing an added discomfort to the participant. As mentioned before, privacy issues are another important factor to consider. Depending on what kind of passive sensing is used, it can have an impact on the participants' privacy and may even compromise their anonymity. For instance, tracking GPS information may potentially reveal the participant's home address and consequently their identity. While there are ways to address and thus avoid such ethical concerns, participants may still feel that they are being monitored which can cause uneasiness. If as a result of this discomfort participants either avoid using their phone or adjust their behavior, then this may in turn compromise ecological validity. Finally, the burden on the researcher is also of note. Passive sensing requires an active involvement of the researcher to ensure devices and or software function properly, collect the appropriate data, and abide by GDPR regulations. Subsequent pre-processing and data analysis will also involve more time and energy. The use of passive sensing should therefore

always be carefully deliberated prior to initiating a study so that any challenges do not overshadow its benefits.

13.5 Conclusions

Passive sensing is a new and developing field providing a myriad of opportunities for ESM research. Technological advances will keep driving new developments in hardware, whereas improvement of computational models will determine the possibilities of application.

With this world of new possibilities also come new deliberations. First, we mentioned potential ethical issues related to the monitoring of sensitive or personally identifiable information. In some cases, data may be immediately processed such that the information that is left has lost identifiable features. In the case of GPS data, instead of using an individual's exact coordinates, the data can be processed into a measure of distance to a pre-specified location (e.g., home, work). It may also be tempting to collect data on as many measures as possible when data collection is as easy as some forms of passive monitoring. However, that alone is naturally not a justification. A thorough evaluation of the potential ethical issues of using passive sensing is, however, necessary to determine if its use is warranted. A second point is related to the participant's burden. Although we have advocated that, when used adequately, the addition of passive sensing to ESM may decrease this burden, very often it means that the participant has to perform more actions (e.g., recharge wearables, install apps) and experiences more discomfort (e.g., psychological discomfort form the invasion of their privacy, physical discomfort from the wearables). The researcher therefore must at all times consider the costs and benefits of adding passive sensing to their ESM protocol, not in the last place because an increase in perceived burden may have consequences for data quality and participant compliance. A final deliberation is of more theoretical nature: as stated in this chapter, with passive sensing one can never directly measure an individual's experience and therefore, when the aim is to measure experience, the measurement error will almost always be greater than in self-report measurements. There will be further developments in the field of predicting experiences based on passive sensing data, which will keep improving model performance. However, in the field of *experience* sampling, the most straightforward method of assessment will always remain self-report. For each

variable of interest, a thoughtful consideration between these two assessment methods will be necessary to determine the optimal approach. Passive sensing can be an invaluable addition in the study of daily life by substituting ESM items, enriching ESM data, or triggering ESM sampling schemes or individual beeps. As long as the issues that come with it are taken into consideration, it has the potential to forever change ESM research for the better.