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Chapter 2: Possible research questions that can be answered with ESM research

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Human beings are inquisitive and curious by nature (Kidd & Hayden, 2015; Loewenstein, 1994). In other words, we continuously ask ourselves questions about the world. In positive sciences, questions about the world are answered with experiment or data. While most of this volume is concerned with how to collect data in the most reliable, valid, and ethical way possible [link to chapter on study design, questionnaire development, and ethical considerations] using the experience sampling method, we should not forget that the data are there to answer our questions about the world in the first place. In this chapter we provide a structured overview of the type of research questions that can be answered using ESM data. While the overview is meant to be of a generic nature, meaning that it can be applied to any domain of study, we will give concrete examples of research in order to illustrate how in practice the variety of research questions are being answered.

This chapter is structured as follows. In a first part, we discuss research questions that can be asked (and answered!) in the context of a classic observational ESM study, in which the aim is to simply measure participants throughout their normal daily activities. First, we review research questions that can be asked regarding one single variable measured with ESM. Next, we discuss research questions that can be asked regarding the relation between multiple variables measured with ESM. Next, we review questions that combine one or both of the previous with additional information at the level of the person. Finally, in a second part, we review research questions that can be asked when one goes beyond the classic paradigm and not only intends to measure daily life, but also impact on daily life and examine the consequences, yielding experimental and intervention paradigms.

Research questions in observational ESM research

Most of the existing, classic ESM research can be considered to be of an observational nature. In observational ESM research, one is interested in observing the natural behavior and ebb and flow of phenomena in the context of daily life. These phenomena are typically about how people feel, think, or behave, but can be as varied as ranging from lower order drives such as sex (e.g., Inpett, et al., 2008) and eating (e.g., Reichenberger, et al., 2018), over higher faculties of the mind like morality (e.g., Hofmann, et al., 2014), aesthetic experience (e.g., Nusbaum, et al., 2014) or just letting the mind wander (e.g., Kane, et al., 2007). The phenomena can be common and mundane (e.g., Chin, et al., 2014) or more unusual (Hillbrand & Waite, 1994), and can be studied in relation to harmless (Dickens et al., 2018) or profound contextual events (Monk, et al., 2006).

Regardless of their nature, common to these phenomena is that they unfold over time, and take place in connection to (within, between, or around) individuals. In other words, they show both within-person and between-person variation. Following this common characterization, we introduce a systematic set of research questions that can be asked when observing phenomena in daily life: (1) questions related to the behavior of one time-varying variable under study, (2) questions related to relations between several time-varying variables under study (within-person), and (3) questions about the role of person characteristics in time-varying variables (between-person).

In what follows, we will elaborate on and give concrete examples of these research questions. Of particular note is that this set of research questions follows the same buildup as the chapter about statistical modeling of ESM data, in the sense that they map onto (1) models with one time-varying variable, (2) models with more than one time-varying variable, and (3) models with person-level variables). As such, the reviewed research questions can be readily mapped onto the statistical models laid out in that chapter.[link to stats chapter]

Research questions related to the behavior of one time-varying variable

We start with the most simple example, where a researcher has or is planning the collection of data related to a certain phenomenon of how people feel, think, or behave in the context of daily life. Several basic (but important) questions can be asked about the behavior of this phenomenon:

1. How do people feel, think, or behave on average?

Of course, with ESM data, one is often interested in the changes, dynamics, temporal behavior of phenomena over time (why otherwise do ESM research in the first place right?). Yet, that does not imply that people's average feelings, thoughts, or behavior are not important to consider or study. To the contrary! One important reason is that several core concepts in the behavioral sciences are meant to reflect typical, habitual, "stable" forms of feeling, thinking and behaving and average levels of a variable in ESM data allow to get to these concepts in the context of daily life. Personality is a prime example of such a concept, and indeed prominent theories of personality describe people's behavior as a distribution of behavior of which the average or median is the most typical instantiation (e.g., Fleeson & Law, 2015). Relatedly, average levels are often assessed in standard, trait-like measures of people's feelings, thoughts, and behaviors. An important type of research question therefore consists of examining the validity of these measures by relating them to average levels of people's feelings, thoughts and behavior, obtained in daily life (for an example of such research in the domain of emotion regulation, see e.g., Koval, et al., 2020). Finally, average levels of how people feel, think, and behave, often hold substantial explanatory or predictive power for important outcomes, and thus should not be discarded or overlooked (this is in no small part due to the fact that these outcomes are often themselves intended to reflect average levels). For instance, in recent work we showed that the personality trait of neuroticism, which is often also called emotional instability, does not so much reflect variable or unstable emotions, but mostly the tendency to experience higher levels of negative emotions (Kalokerinos, et al., 2020).
[examining average levels of a time-varying variable is done with random intercept models in multilevel modeling]

2. How much do people differ from themselves compared to how much people differ from each other?

This may sound like a bit of a weird question on first sight, but is actually a crucial question in ESM research. The idea of assessing people's feelings, thoughts and behavior (or any other phenomenon) multiple times during daily lives, starts from the assumption that people's feelings, thoughts, and behaviors vary across time. As you know by now this is called within-person variability, and should be sizeable if ESM research wants to be meaningful (there is not much sense measuring the color of your eyes 6 times a day). On the other hand, people also differ from one another. This is called between-person variability, and is studied in the psychology of individual differences.

The relative proportion of the two, expresses to what extent a certain phenomenon mostly varies within persons, or rather between persons. An often used fraction here is intra-class correlation coefficient, which is calculated between-person variance/(within + between person variance) and thus reflects the between-person variance over the total variance. If this is relatively large (e.g., higher than .5), this means that individual differences in the phenomenon under study are larger compared than within-person differences. Yet, if this is relatively low (e.g., lower than .5), this means that people differ more from themselves than people differ from each other.

Even in domains that study purportedly stable characteristics of the mind, this proportion can be surprising. For instance, personality is considered to be the stable set of characteristics that determines who you are as a person, and to lie at the base of individual differences in how people behave, think and feel. Yet, work by Fleeson and colleagues (e.g., Fleeson & Law, 2015) has shown that when repeatedly assessing personality-related behavior in daily life, the variance observed within persons is as large or even larger compared to the variance observed between persons (and is even comparable to the variance observed within persons in subjectively experienced affect, which is considered to be highly context-dependent and fluctuating in nature).

3. What do moment-to-moment fluctuations look like?

Once you've established that you're indeed studying something that shows within-person variability, the next sensible question to ask is what this variability looks like. Identifying and trying to understand the patterns and regularities that characterize the fluctuations of your phenomenon will without doubt contribute greatly to understand its nature and underlying mechanisms (for an example of this exercise in the domain of emotion or affect, see, e.g., Kuppens & Verduyn, 2017).

The type of research questions that can be asked here are endless, but we will give a set of guiding examples. First, one may want to know whether the fluctuations follow a certain pattern across the day, week, seasons, or over time more generally. For instance, Park et al. (2019) showed how music preferences change reliably over the course of a day (with less intense music being preferred in the mornings versus evenings). As another example, Stone et al. (2012) confirmed our inner suspicion that we feel better on weekend-days compared to weekdays (but the good news is that once you're retired, this difference will disappear!). One may also ask whether the fluctuations are a function of time itself. This function can be linear, like for instance the personality traits of agreeableness and conscientiousness that show a more or less steady increase in the population throughout adulthood (Roberts & Wood, 2006), or non-linear, like for instance the alleged U-shaped relation between happiness and age (Frijters & Beatton, 2012). A particular time-bound pattern for repeated assessment data that ESM researchers should be aware of is the initial elevation bias (Shrout, et al., 2017). This bias refers to the often (but not always) observed tendency for repeated subjective reports of any variable to show higher values for the first set of assessments, followed by a slight decrease that than stabilizes. While the exact reason for this bias remains unknown, it is nonetheless important for researchers to be aware of the possibility of its occurrence in their data. This is often one of the reasons why researchers sometimes shy away from using the first few assessment in the analyses of intensive longitudinal data.

Second, next to being predicted by day, week, or time itself, one may ask whether a particular phenomenon is predicted by itself over time. This refers to the self-predictability, time-

dependency, or autocorrelation of time-varying variables. A very simple example is the weather: if you want to know what kind of weather it will be tomorrow, the weather of today is usually a pretty good predictor. In other words, the weather is self-predictable or autocorrelated over time. The same holds for many psychological phenomena, like for instance emotion or affect (Kuppens, Allen, & Sheeber, 2010; Suls, Green, & Hillis, 1998). The extent to which something is self-predictive, says a lot about the nature of it: If something is highly auto-correlated, it means that it is generated by a system that is not very much impacted by outside influences but is running its own course. If on the other hand, something is not very highly auto correlated, it means that it is very much under control of outside influences. If something is negatively auto-correlated, it means it follows an oscillating pattern at the frequency of measurement (this is also why autocorrelations are being used to detect cyclical patterns in time-series data).

This issue of time-dependency also comes into play in the question of whether the order of the fluctuations matters for understanding the within-person variability. When we say a person is unstable, we are saying that they show large variability in their feelings, thoughts, or behavior. Yet, a person who feels good the first part of the week and bad the second part of the week, shows the same variability yet a very different pattern of fluctuations compared to a person how constantly alternates between feeling good and bad over the week. For this reason, researchers have compared indices of variability (that does not take the ordering into account) with indices of instability (that looks at the size of consecutive changes and therefor takes the order into account) and examined which type of variability is most indicative for instance adaptive versus maladaptive functioning (for a more detailed discussion of this, see. e.g., Jahng, Wood, & Trull, 2008). For instance, Thewissen et al. (2008) examined the importance of this distinction with respect to self-esteem and paranoia. As another example, Koval et al. (2016), examined this question for emotion in relation to depression.

Questions related to the behavior of multiple time-varying variables

Of course, often you are not interested in observing just one single variable, but in observing multiple variables, and how they relate to or even predict each other. After all, any theory that tries to explain something has at least two elements, that what needs to be explained (the explanans) and that what explains it (the explanandum). Finding regularities in the relations between variables is the prerequisite to explaining them, and so examining relations between variables is what much research is about (especially in correlational research like most ESM research). A meaningful distinction in this respect is whether you're looking at concurrent or time-lagged relationships [thesaurus + link to stats chapter] between variables.

In concurrent within-person relationships, you're examining how the fluctuations in one variable coincide with the fluctuations in another variable. For instance, van der Steen et al. (2017) examine the concurrent associations between momentary stress, affective and psychotic symptoms in populations with varying risk for psychosis. As another example, Hermans, et al. (2020) study the relation between activity pleasantness and positive affect. When one has data from other channels than ESM, one can also examine relations between experiential, physiological, and behavioral systems. As an example, Vaessen et al. (2018) described a curvilinear relationship between self-reported activity-related stress and cortisol fluctuations. In principle, the variables do not even have to be from the same individual. When one has data from multiple individuals assessed at the same time points, one can study the relation between a variable in one person and a variable in another person over time. For instance, Sels et al. (2020) studied to what extent the emotions romantic partners experience synchronize in daily life (and found surprisingly little evidence for the existence of emotional interdependence).

In lagged relationships, one is interested in examining how one variable at one point in time is predictive of another variable at a next point in time. For instance, Thewissen, et al. (2011) examined to what extent levels of self-esteem or anxiety were able to predict the onset of a subsequent episode of paranoia. Here, the researchers were interested in whether low levels of self-

esteem or high levels of anxiety were able to predict the fact that soon after a paranoid episode could occur, and therefore tested lagged relations between the former two and the latter (the lagged refers to the fact that for these analyses, the data are lagged such that previous time values of one variable can be used to predict current time values of another variable). Another example can be found in Houben et al. (2017), where positive and negative mood are used to predict the subsequent engagement in non-suicidal self-injury in individuals diagnosed with borderline personality disorder. A special, but often studied type of lagged relation asks the question whether the level of one variable is associated with an increase or decrease in another variable. This is often done in research on reactivity to stressors or context variables, or in research on how emotions, symptoms, etc., change as a function of certain types of behavior or regulation efforts. For instance, Brans et al. (2013) examine to what extent positive or negative emotions increase or decrease in association with the use of a set of emotion regulation strategies. In the associated analyses, emotionality at one time point is predicted by emotion regulation use in between that and the previous time-point, controlling for emotion at the previous time-point (note that this type of model is a simple version of the vector-autoregressive model). The large benefit of this type of analyses over concurrent relations, is that they give an indication of the temporal directionality of the relation between variables, hinting at what comes first and what comes second and therefore patterns of sequences between variables (although causal interpretations still remain unwarranted). Both concurrent and lagged relationships can moreover be studied with respect to not just two but multiple variables at the same time, allowing one to chart a network of the relations between different variables, either concurrently or directional. This network approach has in recent years become very popular to study for instance the organization of symptoms in psychopathology (e.g., Borsboom & Kramer, 2013; Robinaugh, et al., 2020), and has been applied to ESM data (e.g. Klippel et al, 2018; Wigman et al, 2015).

All of the above is in principle strictly concerned with understanding the behavior of one or more variables, how they unfold, relate, and interact over time within one or more individuals (or between individuals as in some examples). Yet how this happens can vastly differ from one person to

the next. To understand this variability, researchers relate individual differences in these patterns, processes, and relationships to person-level variables.

Research questions related to person-level characteristics

Indeed, no two persons are the same, and an intriguing and important set of questions relate to how we can map and understand the individual variation in the above reviewed patterns, processes, and relationships (note that these individual differences directly correspond to the random parameters in the models reviewed in chapter X)[link to stats chapter]. As manipulation of individual differences is difficult or ethically objectionable (however see the next section), researchers often work with natural variation of individual differences. Roughly two types of questions are possible here.

A first question pertains to charting the observed variation and trying to understand the underlying structure and organization. As individuals may differ in so many respects related to the processes and patterns reviewed above, it may be wise to sometimes try to structure these individual differences and see where there is overlap and distinctiveness (just like researchers trying to understand the fundamental dimensions involved in say personality, values, intelligence, and so on). For example, Dejonckheere et al. (2019) examined the underlying dimensionality of commonly studied affect dynamic indices, showing distinct groupings of ways people differ in the patterns and regularities underling the dynamics of their emotional lives.

A second question then pertains to trying to understand the observed variation by directly relating it to third (person-level) variables. The list of individual differences variables that typify and/or shape people's feelings, thoughts, and behavior is endless, but categories or variables that are often studied are for instance age, gender, personality, psychiatric illness (severity), early childhood experiences, trauma and stress exposure, cognitive functioning, genetic constitution and expression, biological substrates or indicators such as peripheral physiology, brain structure, activity, and connectivity, and interactions between all of the above such as for instance gene x environment

interaction studies. In fact, much of the concrete research examples reviewed above often include person-level variables to understand variation in the within-person processes they observe. For instance, Vaessen et al. (2018) examined the relation between perceived stress and cortisol as a function of risk for psychotic disorder. Sels et al. (2020) examined the degree of emotional synchrony between partners as a function of relationship duration and satisfaction. For examples with more biologically oriented individual differences, for instance Collip et al. (2011) examined how variation in the catechol-O-methyltransferase (COMT) Val158Met polymorphism is related to stress reactivity in healthy and psychotic individuals. Provenzano et al. (2018) examined how brain activity in response to social inclusion or exclusion is related to the dynamics of affective experiences in daily life (note that including person-level variables as moderators is also covered in chapter X of this volume [link to stats chapter]).

Of course, here also, it is important to stress that the design or data remains correlational and that causal interpretations of the role of these individual difference variables are unwarranted. Experiments are needed for causal interpretations, which calls for deliberately manipulating factors so to change people's feelings, thoughts and behaviors in daily life.

Research questions involving non-natural variation

As ESM is quintessentially about studying people's normal daily lives, most research is concerned with recording and observing their object of study during the normal daily routines that make up our lives. With as much as can be learned from that, it is limited in the sense that sometimes researchers may be interested in the effects of particular type of events on people's feelings, thoughts, and behaviors, and in daily life these may be difficult to predict, let alone control. It is also limited in the sense that normal daily life may more often than not be rather ordinary, and may not always elicit very much of the feelings, thoughts, or behaviors we are interested in. Moreover, when studying the effect of interventions, there is an increasing interest in studying their effects not only in the lab or in the clinical center, but also how interventions eventually impact

people's functioning in daily life. For these reasons, ESM is being used to also study different forms of non-natural variation in the context of people's lives.

A first step in this type of research is when researchers decide to observe people using ESM during specific periods or surrounding particular significant events. There are several interesting examples in the literature where ESM was used to study people's feelings, thoughts and behavior around well-specified type of events. For instance, Kalokerinos et al. (2019) studied students' emotions from several days before to a week after receiving their exam grades in first year of higher education, a milestone in the context of Belgium education. In a similar vein, Belisario et al. (2017) studied the course of pregnant women's mood and mood disorder symptoms over the course of pregnancy. A famous n=1 example of where researchers examined changes in the wake of an important event is the study by Wichers et al. (2016) where they examined symptom fluctuations before and after decreasing anti-depressant medication in a single patient. These kinds of designs are very meaningful to study anticipatory and regulatory processes in the context of important life events. An important requirement however is that the event is predictable so a study can be set up around it. And, as we all know, not all that happens to us in life is predictable.

Therefore, researchers have tried to introduce a manipulation in people's lives to study its effects. Rather than using predictable events, here researchers create the events themselves. For example, Koval & Kuppens (2012) sampled participants' emotions in daily before and after they were subjected to a classic stress manipulation (having to give a public speech). While the manipulation itself is classic in laboratory research, the interesting element is that here in this type of research, researchers can examine the effects beyond the lab, and see how the effect of such type of manipulation is anticipated and lives on in daily life.

Finally, researchers may want to test the effect of interventions meant to benefit people's everyday feelings, thoughts, and behaviors. In a way, whether or not people's real lives are eventually affected by certain type of intervention or treatment should be the ultimate criterion to

evaluate them on [link to intervention chapter]. Increasingly researchers are therefore incorporating ESM in outcome assessment of new or existing treatments. For instance, Van der Gucht et al. (2019) examined the effect of a mindfulness-based intervention on the ability to differentiate negative emotions in the context of daily life. A special example of intervention is when the ESM data itself is being used as an element of the intervention, for instance when the idiographic data is used to provide feedback and lifestyle advice (see, e.g., Kramer, et al., 2014). Finally, the use of smartphones in contemporary ESM research carries in it the possibility to deliver interventions using the same smartphone and evaluating them at the same time. This is the domain of so-called ecological momentary interventions (EMI), which lies at the base of the current spread of mobile health and mental health applications (for reviews, see Heron & Smyth, 2010; Myin-Germeys, et al., 2016; see also chapter X [link to chapter interventions]).

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