Technology based Ecological Momentary Assessment in clinical psychology

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**Abstract**

Over the last years, Ecological Momentary Assessment (EMA) emerged as an alternative data collection strategy to repeatedly assess people in real-life, thus improving the ecological validity and reliability of data. As a matter of fact, the increasing field of Information and Communication Technologies (ICT) and the growing availability of smartphones in people’s lives allowed to further foster the potentiality of this approach, leading to the development of technology based EMA. So far, a huge amount of studies has shown the feasibility, acceptability and effectiveness of this procedure in many clinical fields. Nevertheless, EMA approach is still far from being applied to routine care. Beyond describing the advantages and potentialities of this approach starting from the available evidence-based literature, this chapter will focus on the issues that still need to be addressed in order to transfer the scientific knowledge from the research field to the clinical practice.

**Keywords:** Biosensors, clinical assessment, clinical psychology, ecological momentary assessment, experience sampling method, information and communication technologies, mobile devices, passive sensing, routine outcome monitoring, self-reports, sensors, smartphones, wearable devices

**1.0**  **Introduction**

According to recent estimates, one in four people worldwide suffers from mental disorders, which are expected to be the largest contributor to disease burden by 2030 (World Health Organization, 2008). This prevalence increase is the consequence of many critical issues that the clinical field is currently facing, such as failures in psychopathological understanding (Krueger et al., 2018), difficulties in the dissemination of existing treatments (McHugh and Barlow, 2010), and the presence of many untreated patients due to social stigma or difficult access to the health care system (Alonso et al., 2018; Kazdin & Blase, 2011). As a matter of fact, new solutions are needed to overcome these barriers. In that sense, the emerging field of Information and Communication Technologies (ICT) offered promising and innovative tools, that are fostering the understanding, assessment and treatment of mental disorders.

Ecological Momentary Assessment (EMA) emerged as an alternative approach to traditional clinical assessments to repeatedly assess people in real-life, thus increasing the reliability, validity and ecological validity of data. In this chapter, we will try to provide an overview of the current state of the art of EMA in the clinical field starting from existing systematic reviews and cutting-edge investigations. After providing an historical overview of EMA’s roots and a definition of this method, we will discuss different types of assessments (active versus passive) that can be performed by means of technology based EMA, and we will briefly introduce some of the available technological solutions. Barriers and challenges of the implementation of EMA will also be deeply discussed, as well as the advantages of this methodology for the clinical field and how to statistically analyze EMA data. Finally, EMA’s fields of applications will be mentioned, including prevention, assessment, monitoring and intervention, and concrete examples coming from evidence-based research will be provided.

**2.0 What is Ecological Momentary Assessment?**

Traditionally, clinical assessments are performed through periodic face-to-face meetings with a therapist. During these sessions, patients are assessed by means of structured / semi-structured interviews and/or self-report questionnaires, that are intended to provide clinicians with a detailed overview of one’s psychological condition. The objective of a psychological assessment is to formulate an appropriate diagnosis and deliver a proper treatment, if needed. Nevertheless, clinical assessments are also essential throughout the whole therapeutic process (i.e., to investigate whether there is a clinical improvement and the treatment is adequate) as well as at the end of the treatment (i.e., to explore whether the intervention worked and symptoms decreased). Consequently, clinical assessments play a fundamental role at different steps of a clinical intervention.

Even though face-to-face assessments still represent the gold standard in routine care, there is increasing evidence showing the limits of this approach, including: (1) The impossibility of grasping the dynamic nature of affects, emotions and symptoms, as well as the multiplicity and complexity of aspects that may influence the appearance and maintenance of a psychopathological condition, and (2) the growing evidence of what is called “recall bias”, that is, the inaccuracy in recalling past experiences.

Regarding the first issue, the previous literature evidenced that people show large mood fluctuations over time: They can feel really happy in a specific moment of the day and experience a great feeling of sadness after a few hours. These dynamics can be even larger in some clinical conditions: Depressed patients, for instance, are characterized by emotional lability, and their mood shifts are faster and stronger than in healthy people (Peeters, Berkhof, Delespaul, Rottenberg, & Nicolson, 2006a). Similarly, also psychopathological symptoms have been shown to largely oscillate over time or even within one day (McConville & Cooper, 1996). As a matter of fact, affect and symptoms dynamics can’t be captured by traditional assessment procedures, thus leading to many critical consequences, including (1) a limited understanding of psychopathology, and (2) a partial and incomplete assessment of one’s clinical condition.

Beyond this issue, increasing studies have shown that people are not able to recall past affective experiences without altering their content, and this bias is even greater in subclinical and clinical populations (Ben-Zeev, Young, & Madsen, 2009; Desiree Colombo et al., 2019). Furthermore, patients have been shown to be biased in estimating their clinical condition and, for example, clinically depressed individuals tend to exaggerate symptoms severity (Möller & von Zerssen, 1995). Still, traditional clinical assessments are retrospective (i.e. patients are asked to summarize how they felt in the last period), thus underestimating the potential role played by the recall bias and providing potentially biased assessments, which in turn may undermine the quality of the treatment provided to a patient.

Ecological Momentary Assessment (EMA), also called Experience Sampling Method (ESM) or ambulatory monitoring, emerged in the late 80s as an alternative strategy to overcome the limitations of traditional clinical tools and, more specifically, to better capture people’s affective and behavioral dynamics (Desirée Colombo et al., 2020; Csikszentmihalyi & Larson, 1987; A A Stone & Shiffman, 1994). On the one hand, the term “*ecological*” refers to the environment in which data are collected: Patients are asked to annotate behaviors, thoughts and feelings in the real-world context and during the flow of daily experiences. On the other hand, the term “*momentary*” refers to the focus of the assessment on the current state of the individual: Patients are asked to report their affective state in precise moments of the day, and not to retrospectively recall it. In that sense, EMA permits to obtain repeated measures of a single individual, increasing the reliability, generalizability and ecological validity of data.

The first studies in this direction adopted paper-and-pencil diaries. Patients were traditionally asked to complete daily diaries at the end of the day or in response to an automatic prompt produced by a watch. However, the intrusiveness, discomfort and commitment made these paper-and-pencil tools barely feasible and not adequate to patients. Past research evidenced, indeed, that paper diaries imposed several barriers for EMA procedures, such as difficulties in obtaining a reliable measure of timely compliance because of social desirability. Moreover, researchers had low control on adherence (i.e. the percentage of answered self-reports out of the total reports) and time response (i.e. the temporal delay in completing the diary after the prompt), thus obtaining biased assessments (Arthur A Stone, Shiffman, Atienza, & Nebeling, 2007).

The past decades have seen a surge in studies using technology based EMA as a result of the emerging field of ICT, which offered innovative solutions to conduct ecological assessments by means of hand-held technologies (Desirée Colombo, Fernandez Alvarez, Garcia-Palacios, et al., 2019). The increasing availability of smartphones and the explosion of mobile applications, which have been successfully used both for subjective (Suso-Ribera, Castilla, et al., 2018) and objective data collection (Mohr, Zhang, & Schueller, 2017), allowed to overcome the shortcomings of paper-diaries by eliminating the need for manual data entry, increasing compliance and enhancing control over data (García-Palacios et al., 2014). Moreover, the adoption of technologies such as smartphones to deliver EMA allowed to integrate all the needed processes into one device. Accordingly, patients are automatically prompted to fill in self-reports by a device such as a smartphone, that stores and safely sends data to clinicians and/or researchers.

So far, many research fields adopted EMA procedures to investigate several psychological conditions, including stress-related diseases (Yoshiuchi, Yamamoto, & Akabayashi, 2008), alcohol abuse (Morgenstern, Kuerbis, & Muench, 2014), anxiety disorders (Walz, Nauta, & aan het Rot, 2014), eating disorders (Engel et al., 2016), borderline personality disorder (Santangelo, Bohus, & Ebner-Priemer, 2014), and depression (Desirée Colombo, Fernandez Alvarez, Palacios, et al., 2019). Recent studies also confirmed the feasibility, adherence and interest of people in using mental health (mHealth) technologies, thus highlighting the great potential of these tools for the clinical assessments (Desirée Colombo et al., 2018; Donker et al., 2013).

**3.0 Active and passive data collection**

As briefly mentioned in the previous paragraph, the use of EMA by means of ICT solutions such as smartphones or personal digital assistants (PDA) gave the opportunity to ecologically assess people during the flow of daily experiences. Beyond self-reports, which represent the greatest portion of the current literature, the potential of technology-based EMA also relies on the possibility of collecting data gathered from smartphones’ embedded sensors and/or wearable biosensors: While sensors make it possible to indirectly collect data about patients’ behaviors and habits, such as social media use, physical activity, or social interactions (Mohr et al., 2017; van de Ven et al., 2017), wearable biosensors allow to continuously monitor physiological parameters throughout the day with high precision (Marzano et al., 2015). In this paragraph, we will therefore distinguish between two types of assessments that may be performed by means of EMA procedures: Active assessments (i.e. self-reports), which require an “active” role from the user in self-reporting his/her state; and passive assessments, which refer to the information that can be collected without the direct involvement of the user (i.e., data coming from sensors).

**3.1 Active assessment**

According to Csikszentmihalyi, EMA is “[…] *an attempt to provide a valid instrument to describe variations in self reports of mental processes*” (Csikszentmihalyi & Larson, 1987). This definition represents what we call “active assessment”. Subjective experiences are indeed the core aspect of the definition of what an emotion is (LeDoux & Hofmann, 2018); accordingly, a proper clinical assessment should always take into account the one’s subjective perception about the experienced emotional states and symptoms.

EMA consists of repeated assessments over time about one’s feelings, symptoms or behaviors, that can be scheduled according to different sampling schemas. On the one hand, signal-contingent sampling relies on a prompt (i.e. a notification) provided to the user, which can be sent at prefixed, randomized or semi-randomized time-points during the day. Differently, event-based sampling requires participants to personally fill in the assessment after the occurrence of a specific behavior or event during the day. Whereas signal-contingent schemas are useful to collect repeated measures of a variable in order to explore its dynamics and obtain a representative mean value (e.g., positive and negative affect throughout the day), event-contingent schemas are used when the main focus is on a specific behavior that occurs randomly or less frequently during the day (e.g., smoking a cigarette).

The number of daily assessments as well as the duration of the EMA can hugely vary between studies. From clinicians’ and researchers’ perspective, the definition of sampling details usually depends upon the main aim of data collection. However, this aspect also plays a fundamental role from users’ perspective: The higher the efforts required (many daily assessments, long protocols), the higher the invasiveness and discomfort perceived by the user. It is therefore important to build balanced protocols in order to ensure users’ adherence to the assessments (Van Genugten et al., 2020). However, this aspect will be further deepened and discussed in the next sections.

To date, one of the biggest issues of EMA self-reports is the lack of validated and ad hoc items to be used in these protocols, thus raising important concerns about the psychometric validity of this approach. As mentioned before, it is important to decrease as much as possible the number of items of each assessment in order to reduce patients’ burden and increase adherence to the procedure. Reduced versions of standardized clinical screening tools have been already developed, such as the two-item version of the Patient and Health Questionnaire (PHQ-9) for the assessment of depressive symptoms or the two-item adaptation of the Generalized Anxiety Disorder (GAD-7) for the detection of anxiety (Staples et al., 2019). These standardized, reduced scales represent adequate candidates to be integrated into EMA procedures. However, further ad-hoc scales are needed in order to increase the reliability and validity of this method for clinical assessments.

So far, there are two main technological solutions to perform active assessments. On the one hand, ecological assessments can be administered by means of mobile applications, which automatically send notifications to the user’s smartphone. From a technological point of view, this solution is the most expensive: The development of a customized mobile application requires, indeed, sophisticated programming skills, that usually lie far from clinical psychologists’ expertise. However, some online platforms are currently available, that allow non-experts to build simple Android and IOS mobile applications (Conner, 2014). These platforms, which can be either free or paid services, allow to create surveys through easy web interfaces. Two examples are represented by Movisens (<https://www.movisens.com/en/products/movisensxs/>) and the recently developed mobileQ (Meers, Dejonckheere, Kalokerinos, Rummens, & Kuppens, 2020). Beyond mobile applications, there is a second solution that lies on the use of web-based surveys services. Differently to mobile applications that rely on the use of notifications, web-based surveys allow to automatically send emails with a web-link containing the momentary assessment. An example is Qualtrics ([www.qualtrics.com](http://www.qualtrics.com)), a platform designed to administer surveys and analyze data. Thanks to its easy web interface, this tool allows clinical psychologists to autonomously create an EMA, which can be repeatedly administered to patients by means of automatic emails.

**3.2 Passive assessment**

Wearable devices are best known for their potential to acquire data without the need of the individual to consciously be aware of it. The low participant burden associated with passive techniques enables more intensively repeated and sustained collection of data, and thus these techniques can provide a larger amount of information compared to active assessments.

Under the big umbrella of wearable technologies, all kind of sensors and biosensors that permit to track physiological processes, people’s locations, behavioral activity, social media activity, among other features, can be mentioned. This wealth of automated data can enhance the understanding of the vulnerable, triggering and maintaining factors associated with different clinical conditions. Indeed, the possibility of identifying contextual determinants that explain not only nomothetic but also ideographic triggers of a mental disorder constitutes a fundamental aspect to meet scientific and clinical needs (Piccirillo & Rodebaugh, 2019).

Among the existing literature into this topic, the review conducted by Mohr, Zhang and Schueller (Mohr et al., 2017) provides a comprehensive critical overview of sensing research in mental health, including smartphones and all types of wearable, social medias and computers. In particular, a hierarchical sensemaking framework is outlined, in which four different layers are structured: From sensors (including location, movement, phone screen, phone apps, ambient light, microphone and in-phone communication) through low-level features (like activity type, bedtime / wake time, paralinguistic information, etcetera) and high-level behavioral markers (like depressed mood, stress or social avoidance, among many others) to finally predict the clinical state (e.g. depression, anxiety, and all other clinical constructs). Overall, this model represents the vastness of the field of personal sensing in mental health. The myriad of possibilities that arise from exploring the combinations of these layers has started to be translated into research programs seeking to better understand and predict clinical states. In particular, the integration of passive assessment and EMAs is starting to emerge as a result of the improvement of sensors and biosensors. Broadly speaking, while sensors permit to assess behaviors, biosensors are made for the psychophysiological tracking.

Despite the fact that the integration is only in its infancy, some examples are worth mentioning. In terms of behavioral markers, sleep patterns have been shown to be key in the appearance and maintenance of many mental disorders, and this relation is suggested to be mediated by an impairment in emotion regulation (O’Leary, Small, Panaite, Bylsma, & Rottenberg, 2017). Thus, by means of built-in sensors, a range of smartphone-based sensing systems enables to monitor sleep periods in a passive way. Ōura Ring is an example, that permits to combine sleep patterns, heart rate variability measures and self-reports (de Zambotti, Rosas, Colrain, & Baker, 2019). Besides, wearable instruments based on accelerometers were created to track a range of processes like physical activity (T. Choudhury et al., 2008). Indeed, higher levels of accelerometer-based physical activity has been found to be associated with lower rates of depression (Vallance et al., 2011). Other key domains are social context and social support, which can be traceable by mean of Global Position System (GPS).

In terms of physiological activity, the whole body constitutes a relevant source of information. In that sense, when acquiring data from biosensors, both the central and peripheral systems provide potentially useful data. However, the autonomic system has been more studied in ecological contexts given the fact that is easier to acquire, for example, blood pressure or skin conductance activity data rather than neuronal activity.Growing evidence is starting to complement these procedures with active assessments. One of the first attempts has been Psychlog, a mobile based platform designed to integrate physiological and self-reported data (Gaggioli et al., 2013). Over the last years, there has been a spark of interest in this integration, which has allowed for the proliferation of more complex platforms and for the publication of an increasing body of studies with promising results in the understanding, assessment and intervention of a vast array of mental disorders (Bertz, Epstein, & Preston, 2018; Conrad, Wilhelm, Roth, Spiegel, & Taylor, 2008; Ottaviani et al., 2015; W. Adams et al., 2017).

The field of passive sensing is expanding, and an undoubted growing interest is emerging. Indeed, many sensors are already commercially available (for a comprehensive review of existing options see Peake, Kerr, & Sullivan, 2018). However, both at a research and commercial level, there are still many pitfalls, such as the precision of data acquirement, the quality of existing research and its reproducibility, usability privacy and ethical issues, among others.

**4.0 Implementation: Advantages and challenges**

As a matter of fact, it is widely known that a large number of university-based controlled studies and new clinical procedures often never make it to routine care, and those who achieve it often require more than 15 years to be implemented (McGlynn et al., 2003; Proctor & Landsverk, 2009). In this scenario, implementation research (that is, the scientific research field that supports the transfer of evidence-based treatments from clinical knowledge and experimental environments to routine use) is gaining ground (Rubenstein & Pugh, 2006).

The main goal of this section is to summarize the main conclusions from existing literature which might help the reader have an overview of the most frequent implementation barriers and challenges with EMA in clinical psychology, as well as to observe the strong points of this methodology. A brief description of the most frequent outcomes of interest in the implementation literature will be provided. Most importantly, we will present the existing evidence on EMA implementation in real-life settings. As noted earlier, this kind of studies is crucial if we want to learn whether our newly developed procedures can be effectively used in routine practice in the contexts where they were planned to be used. In this sense and consistent with the existing standards (NICE, 2007; Thorpe et al., 2009), we will include the perceptions of all involved stakeholders, from managers, administrators, and policy makers to professionals (i.e., clinicians or practitioners) and, most importantly, end users. Due to the relatively recent nature of implementation research, however, some implementation outcomes have been largely unexplored in EMA studies into clinical psychology and not all relevant stakeholders have been systematically included in the literature. This will be discussed in detail at the end of the present chapter and future lines of research will be presented.

**4.1 Key concepts**

Implementation research has grown considerably in the past decades and, as a result of this, we now have a relatively well-accepted set of important outcomes that should be part of studies aimed at exploring the implementation potential of a given procedure. These key implementation elements are: Acceptability, adoption, appropriateness, feasibility, fidelity, implementation cost, coverage (also known as penetration), and sustainability. Acceptability refers to the stakeholders’ perception that a procedure is comfortable, agreeable, credible, and advantageous. Adoption is understood as the uptake and covers from the initial intention to try the new procedure to the effective decision to use it. Appropriateness is defined as the perceived relevance, compatibility, suitability, or fit of the procedure with the context or the needs of the stakeholders. Feasibility refers to the degree to which a procedure can be effectively and practically used in a given context. Fidelity is related to extent to which the procedure is implemented as intended. Implementation cost refers to any cost associated with the procedure, from its development and maintenance to its versioning. Coverage or penetration is understood as the extent to which the eligible population actually benefits from the new procedure, that is, what is the level of institutionalization, coverage, and spread of the procedure. Finally, sustainability taps into maintenance, durability, incorporation, and continuation of the procedure during ongoing, stable functioning of a service (Hermes, Lyon, Schueller, & Glass, 2019; Enola Proctor et al., 2011).

It is important to note that some of these concepts are at times used erroneously (e.g., used as synonyms or interchanged). Again, this might be due to the relatively recent proliferation of implementation studies and definition of key outcomes, but also because some of these constructs are interrelated. In this sense and to adjust to the most recent conceptualizations from implementation science, we will adapt the original terminology from studies when needed.

**4.2 Users’ perspective**

As EMA is not the usual practice in clinical psychology, implementation research is necessary to investigate whether we have concrete examples to support the use of this new assessment procedure in our field of interest. Not surprisingly, terms like compliance rates, usability, acceptability, and feasibility have now become frequent in research into EMA in clinical psychology, which has been reflected in reviews in this field (see for example Santangelo, Bohus and Ebner-Priemer, 2014; Wen *et al.*, 2017; Dubad *et al.*, 2018).

Several general conclusions can be extracted from the literature into EMA in clinical psychology, despite the field is very broad and some differences might be attributable to the specific population targeted (e.g., different age populations or populations with different diagnoses). The conclusions presented in the following lines are derived from different age populations (e.g., children, adolescents, adults, and elderly), as well as different clinical populations (e.g., mood and anxiety problems, psychotic disorders, eating disorders, substance use disorders, and personality disorders, among others).

Overall, EMA appears to be well accepted, frequently adopted, felt as appropriate and feasible for most end users’ (i.e., patients), as well as a credible, agreeable, and useful tool, which suggests that this is generally a feasible methodology for clinical psychology. Importantly, the user’s perception about EMA has been usually explored once the study has started or at its conclusion (i.e., acceptability), and the results suggest that patients with psychological problems tend to be content and feel comfortable and confident when conducting technology-supported EMA (Bell, Lim, Rossell, & Thomas, 2017; Wenze & Miller, 2010). There are fewer examples of exploring the end users’ experience of the appropriateness, practicability, and perceived fit of technology-supported EMA, but the literature suggests that including this patients’ perspective is crucial to adjust the EMA methodology to the users’ needs and requirements (Burke et al., 2017).

Compliance rates are usually satisfactory, and reactivity (e.g., increased stress or changes in behavior due to EMA) tends to be very low (Aan het Rot, Hogenelst, & Schoevers, 2012; Husky et al., 2010; Santangelo et al., 2014). Specifically, compliance with prompted EMA generally represents between 70% and 90% of prompted assessments and these results are consistent across clinical populations (Bell et al., 2017; Goldschmidt et al., 2014; Husky et al., 2010; Jones et al., 2019; Serre et al., 2012). Similar compliance rates have also been reported in older psychiatric samples (i.e., over 65 years of age) (Cain, Depp, & Jeste, 2009) and when comparing psychiatric and non-psychiatric populations of different ages, including children, adolescents, and the elderly (Cain et al., 2009; Wen et al., 2017; Wenze & Miller, 2010). There are indeed some factors in the individual that are known to influence compliance, such as being engaged in a competing activity or forgetting to respond, but factors associated with EMA design, as we will explain in the next lines, or problems with the technology, such as device malfunctioning, appear to be more important contributors to EMA compliance (Burke et al., 2017; Gaudiano, Moitra, Ellenberg, & Armey, 2015; Wen et al., 2017). Therefore, what these findings suggest is that young and old age, as well as the presence of mental health problems should not be drawbacks for the use of EMA in clinical psychology.

Similarly, compliance with non-prompted assessments (i.e., measurements associated with the occurrence of a real-life event, such as smoking) has also been generally satisfactory, which in this case suggests that monitoring of daily events as they occur is also likely to be feasible (Shiffman et al., 2008). The study of compliance with non-prompted assessments, however, is more problematic: It is indeed difficult to ascertain whether all events experienced by an individual are effectively and timely registered, so the trustworthiness of reported non-prompted events is more difficult to verify (Armey, Crowther, & Miller, 2011).

Beyond population characteristics, there are factors associated with EMA design that do influence compliance (Desirée Colombo et al., 2018). For example, compliance rates appear to decrease as daily sampling frequency increases (Rodríguez-Blanco, Carballo, & Baca-García, 2018). In this sense, in a recent review of EMA in children and adolescents, compliance rates over 73% were revealed when 2-3 daily assessments were imposed, while higher frequencies of 4-5 times daily resulted in lower compliance rates (< 67%) (Wen et al., 2017). In relation to the assessment frequency, there is evidence to suggest that intensive daily monitoring (e.g., over 5 times daily) can also be feasible. However, in these cases the duration of the overall EMA process should be very short (e.g., three days) (Husky et al., 2010; Wen et al., 2017). In general, 5 prompts per day has been recommended to be superior limit for daily EMA (Burke et al., 2017), but 4 times a day has also been preferred by other samples (Spook, Paulussen, Kok, & Van Empelen, 2013). Thus, it is not surprising that 2-3 daily prompts are the most frequent practice in the literature into EMA in clinical psychology (Walz et al., 2014).

In addition to the frequency of daily assessments, studies have also frequently reported that compliance decreases with time (e.g., from week one to week two) (Spook et al., 2013; Wen et al., 2017). This is consistent with the fact that EMA duration so far has been short (frequently of one or two weeks). In this sense, it is not surprising that most EMA observational studies tend to have short durations (i.e., one week or less) and those that monitor treatment evolution are used for brief interventions (i.e., less than one month) (Miklowitz et al., 2012; Rofey et al., 2010; Ruscio, Muench, Brede, & Waters, 2016). Therefore, most of the current evidence on compliance comes from short-term studies, which additionally tend to include relatively small samples. Subjective acceptability reports, however, tend to be encouraging (Czyz, King, & Nahum-Shani, 2018), but the fact that compliance rates decrease dramatically with time indicate that early acceptability reports are not likely to be indicative or sufficient to ensure future compliance. Notably, there is also an example of a successful long-term EMA study (i.e., 12 months) in obesity (Burke et al., 2017), but it is important to note that monthly monetary incentives were given to participants for EMA completion, modern smartphones were purchased for those having an incompatible phone, and a support person was needed to assist participants with EMA and technology.

As a final remark on EMA duration, it is important to note that no specific cut-off has been proposed for effective EMA in clinical psychology settings and the findings suggest that many factors, such as the perceived EMA utility, satisfaction with the tool used, and the duration of each assessment, among others, are likely to interact with the duration of the whole EMA procedure in the prediction of compliance. In this sense, reminders (e.g., SMS messages or, preferably, the use of push systems in smartphones) have been shown to be important for compliance and should be a frequent practice (Rofey et al., 2010). In sum, EMA compliance rates appear to be acceptable, especially in the short term, but their utilization during prolonged periods (i.e., during routine care) for clinical samples is uncertain. This refers to both feasibility and sustainability.

While acknowledging some promising implementation results in the literature, it is also true that most of the findings come from controlled investigations that do not shed light into the real-life feasibility and sustainability possibilities of EMA. Therefore, the implementation possibilities of this methodology during routine care in clinical psychology are very difficult to anticipate. Note that, to date, the vast majority of studies have required a research assistant for some or all aspects of EMA (e.g., recruitment, explanation and demonstration of the EMA procedure, administration of alarms, and technical problems with technology, to name some examples) (Gaudiano et al., 2015; Suso-Ribera, Mesas, et al., 2018). It is unknown to which extent EMA continues to be feasible without such additional support or whether institutions are sensitive to incorporating this figure into their services (i.e., institutionalization). Related to this, the extent to which EMA procedures are delivered as intended when no researcher is involved (i.e., fidelity) is unknown. Additionally, most investigations implementing EMA in clinical populations have included a monetary incentive for participants to complete EMA (Gaudiano et al., 2015; Goldschmidt et al., 2014; Spook et al., 2013; Wen et al., 2017). Again, this is problematic because compensating patients for EMA in routine care is not likely to be feasible in the short-term, nor sustainable in the long-term. Because compliance rates have been shown to decrease when no monetary compensation is given (Rodríguez-Blanco et al., 2018), the fact that a significant amount of evidence on EMA feasibility is based on studies that include economic compensations for participants makes it difficult to anticipate how effectively EMA can be applied in clinical psychology routine care. In this scenario, other investigations have used alternative procedures to encourage EMA compliance, such as gamification (e.g., leveling patients up in the assessment app) (Stinson et al., 2013). However, this is still an infrequent practice in clinical psychology research and the impact of this strategy in the long-term in real-life contexts is uncertain.

In terms of coverage or penetration, it has been argued that EMA has limited spread in patients present a more severe symptomatology (e.g., sedated, confused, or cognitively-impaired, or those experiencing higher distress and negative affect) (Aan het Rot et al., 2012; Gaudiano et al., 2015; Moitra, Gaudiano, Davis, & Ben-Zeev, 2017; Sokolovsky, Mermelstein, & Hedeker, 2014). Patient status is also likely to impact negatively on traditional assessment methods, but EMA is certainly likely to be more demanding and patient-dependent than onsite, episodic, face-to-face evaluation. Encouragingly, though, EMA has been satisfactorily implemented in patients with severe conditions too, such as major depressive disorders, bipolar disorders, borderline personality, substance abuse disorders, and psychotic disorders. However, it has also been suggested that very severe patients are frequently excluded during the recruitment process, which might affect the coverage of EMA (Wenze & Miller, 2010). Overall, what these findings suggest is that, while expectations about compliance should be adjusted and efforts to simplify the EMA process might be required for some populations, EMA should not be absolutely discarded in patients with severe psychiatric disorders and further investigations with these severe patients should be conducted. There are, however, some very severe patients (e.g., catatonic or highly unorganized manic states) for whom EMA will not be possible and alternative measurement options (e.g., observation by others) will be needed.

In relation to the use of technologies other than PDAs and smartphones, the former are more rarely used in clinical psychology and, therefore, implementation outcomes are scarce. So far, the most consistent finding appears to be that adding a wearable in addition to the phone imposes an additional burden on participants, which suggests that passive information should be obtained, when possible, with one device only (i.e., using the phone’s sensors).

**4.3 Clinicians’ and organizations’ perspective**

In the previous paragraphs, EMA implementation outcomes have been explored from the end users’ perspective and have included active, subjective data monitoring technologies (e.g., PDAs or smartphones). A general finding in the literature is that implementation outcomes in technology supported EMA are almost uniquely investigated from the end user’s perspective. There is a very little evidence on the psychologist’s perspective (Lemey et al., 2019) and a lack of research exploring the manager’s and administrator’s perspective about EMA implementation in clinical psychology. This is important because, even though EMA has been repeatedly argued to be the gold standard measure for assessment in clinical settings by researchers (Shiffman, Stone, & Hufford, 2008), ultimately the implication of policy makers, administrators, and managers, as well as the clinician’s willingness will be required if this new methodology is to be implemented in routine practice in clinical psychology settings. It is also important to note that technologies that facilitate EMA have been traditionally expensive. Therefore, in the reviewed literature some investigators have had to assume the cost of technologies such as PDAs or even smartphones in the past (Santangelo et al., 2014; Wen et al., 2017). The increasing availability of smartphones in the population is likely to reduce the economic barriers of using EMA and, particularly, mEMA in the future (Suso-Ribera, Mesas, et al., 2018).

EMA is likely to reduce the clinicians’ burden associated with traditional monitoring by eliminating the need for face-to-face evaluations and data transference from paper into electronic datasets, which are expensive and potentially error-prone procedures (Santangelo et al., 2014). The clinicians’ perspective about technology supported EMA, though, has been rarely investigated in the field of clinical psychology. What the literature suggests, however, is that the main concerns of clinicians are related to patient data protection and storage, as well as perceived benefits and burden of this new approach (Lemey et al., 2019). Additionally, responding to the alarms generated by EMA appears to be challenging for clinicians, as less than half of alarms are likely to be responded to (Bell et al., 2017). Therefore, efforts should be made to ensure that both patient safety and clinician comfort and perceived EMA utility are maximized (e.g., safely and anonymously storing patient data and simplifying and minimizing clinician reports).

A final implementation outcome, which is mostly observed from the organization’s perspective, is cost-effectiveness. EMA has been argued to be a key tool to reduce the costs of treatment for the institutions by facilitating the implementation of more cost-effective interventions (e.g., by rapidly detecting shifts in mood or behavior and allocating the necessary resources for that specific person in that specific scenario) (Kim, Marcusson-Clavertz, Yoshiuchi, & Smyth, 2019; Teachman et al., 2019). However, this has not been systematically explored and thoughtfully conducted cost-effectiveness studies are required to support the institutionalization of this new monitoring procedure in clinical psychology settings.

**4.4 Going beyond unidirectional implementation**

Despite the advancements in implementation science, the majority of its developments have the underlying idea that knowledge is created in laboratories and later applied into clinical contexts. However, a complementary manner of implementing science is doing what it is called Practice Research Networks, which means to focus on the elaboration of infrastructures that can create active and solid collaborations between researchers and clinicians in naturalistic settings (Youn et al., 2019).

EMAs have the enormous potential of helping to bridge science and practice by means of being incorporated in Practice Research Network infrastructures. EMAs are indeed ideal to acquire large amount of individual data and therefore to create personalized networks that may be helpful to inform treatment strategies, to predict trajectories of change in treatments. Given the unobtrusive nature of mobile phones, these assessments appear as ideal assets to integrate science and practice.

The implementation of ROM in clinical practices has been a matter of research itself (Harmon & Lambert, 2012) and despite the difficulties that any kind of implementation entails, there are solid reasons to think that ROM will play an instrumental role in “plugging the holes of the practice-based evidence colander” (Boswell, 2019). Indeed, a vast array of studies, including solid randomized control trials, have demonstrated the contributions of feedback to treatment outcome (Lambert, 2017). However, more research is needed, and there are still concerns if this approach can be generalized to all mental disorders. For example, in the field of personality disorders ROM has shown to be detrimental (Lambert, 2017).

**5.0 Statistical analysis**

Earlier in the present chapter, it has been discussed that a paradigm change towards real-time, frequent data collection is required in clinical psychology. This, however, poses new challenges into practitioners and researchers which refers to how EMA data is analyzed. As noted during the present episode, EMA has been traditionally rare compared to episodic or laboratory measurements. Thus, the interest in developing analytic strategies to effectively deal with the data resulting from EMA has been increasing in the past decades as EMA has gained popularity.

Data analysis in EMA frequently differs significantly from analytic strategies from cross-sectional or traditional trials with a reduced amount of measurements for a number of reasons. First, EMA often results in large amounts of data which cannot be analyzed using traditional analytic strategies. Next, EMA allows for the implementation of study designs that require repeated measurement (e.g., single case designs) and, therefore, particular analytic strategies. Related to this, clinicians and researchers interested in EMA implementation are likely to be interested in research questions that are intrinsic to EMA (e.g., how a particular variable changes in real-life settings and in real-time when measured repeatedly during a certain period of time or how two or more variables mutually influence each other when repeatedly measured using an EMA approach).

Note, for example, how research questions could differ when implementing a randomized controlled trial (RCT) with traditional episodic, onsite measurement or EMA for a given population (e.g., sixty patients with social anxiety) and comparing two active treatments (cognitive-behavioral therapy and acceptance and commitment therapy). Traditionally, an RCT would include a reduced number of measurements (e.g., pre-treatment, post-treatment, and a number of follow-ups, generally no more than three). Then, average-group scores tend to be compared across time to explore whether one of the two conditions resulted in greater improvement at the group level at end of the intervention or time later. Additionally, researchers might be interested in exploring whether the change in outcomes (e.g., social anxiety and number of social interactions in the past week) was partially or totally explained by changes in a psychological mechanism tapped into treatment (e.g., irrational beliefs and acceptance), also known as treatment mediations. To do this, complex analyses using a structural equation modelling approach could be implemented. However, in traditional RCTs the study of treatment mediators is usually conducted using simpler analyses that include change scores between two measurement points only.

The previously described scenario can be largely different in a trial using EMA. First, a series of single-case designs focusing on patient change as opposed to group-average scores could be implemented and both treatment conditions could be tested for every individual (i.e., alternating treatments single case design) as opposed to splitting the sample into two. Consequently, treatment effectiveness would be explored at the individual level, so, different to the previous example, the question here would be whether one of the two conditions resulted in greater improvement at the individual level. Importantly, because assessment would be performed repeatedly during the whole study, treatment effectiveness and change trajectories could be investigated at all treatment and post-treatment stages. By doing this, for example, one could study whether recovery occurred early or late after treatment onset or whether more significant changes were observed after a given treatment component. Even if a single case perspective was not adopted, research questions could differ using EMA and more complex relationships between variables could be investigated (whether different mediators emerged at different treatment stages or whether reciprocal changes in two or more variables occurred so that variations in one variable resulted in same- or next-day changes in the other and vice-versa).

Another challenge in EMA refers to the amount of data available and the relatively unstructured nature of such data. Thus, different to traditional, episodic assessment, defining the research question and selecting which temporal frame is relevant for the study become a crucial conceptual work which directly affects the analytic plan (Shiffman, 2014). For example, going back to the social anxiety example, researchers and clinicians might not be more interested in effective social interactions when social anxiety is high (e.g., in the presence of feared situations such as interactions with new people or in large groups), which only represents a portion of the data. Therefore, data framing according to the research question becomes a key goal for investigators using EMA.

Because clinicians and researchers are more familiar with analytic methods that require independent observations, data analysis of datasets that include a large number of observations for a single individual might be intimidating. However, an increasing number of strategies have now been developed and included in most statistical packages. Even though an in-depth description of how each of these analyses can be conducted in each statistical package is out of the scope of the present chapter, a general overview of the most popular analytic options for EMA data will be provided and recommendations for further information will be given.

Multilevel or hierarchical regression models are amongst the most popular methods for EMA data analysis (Santangelo et al., 2014; Shiffman, 2014). However, as noted earlier, the nature of the specific analysis to be conducted is not necessarily straightforward in EMA and different analyses are possible due to the frequently large number of data obtained with this methodology. Therefore, a crucial aspect will be to determine the question of interest, which will serve guide the selection of the portion of data to be used for analyses and will also help structure the data (i.e., convert it to long form, that is, an observation in each row, when conducting multilevel analysis) and determine the specific analytic strategy to be selected. Different research questions include between-subject differences with no reference to time (e.g., whether more impulsive individuals experience more craving during abstinence), within-person associations between events (e.g., whether gambling is more likely to occur after an argument with the spouse), variations in behavior over time (e.g., how anxiety levels change during a certain period of time), or changes in effects over time (e.g., whether the relationship between self-esteem and alcohol use changes over time), to name some examples (Shiffman, 2014). Thus, depending on the question of interest, analyses might change from simple bivariate associations to more complex multilevel modelling strategies, such as generalized estimating equations or hierarchical linear modelling, and time-varying effect modelling (Beal & Weiss, 2003; Lanza, Vasilenko, & Russell, 2016; Terhorst et al., 2017).

Hierarchical linear modelling allows to explore within-individual processes that would be missed by collapsing and averaging individual data. This analytic strategy has been argued to be a particularly useful analytic approach for EMA and is becoming increasingly popular because they are sensitive to the repeated nature of measurements in EMA (e.g., dependencies) and because they deal well with missing data, which is frequent in EMA (Collins, 2006; Terhorst et al., 2017). Recent examples of hierarchical modelling use for EMA can be found in the literature (Kleiman et al., 2017; Maher, Rebar, & Dunton, 2018).

Different to hierarchical linear modelling, time-varying effect modelling does not assume any trajectory over time (e.g., linear, quadratic, or cubic). Regression coefficients are estimated as continuous functions of time, which enables the exploration of effects that vary with time (e.g., how mood has changed over the course of psychological treatment). Moderation effects are also possible, so it can be examined whether changes in a given variable (e.g., mood) differ as a function of another variable (e.g., type of treatment) (Lanza et al., 2016). Examples of time-varying effect modelling use for EMA analysis also exist (Shiyko, Naab, Shiffman, & Li, 2014; Shiyko, Lanza, Tan, Li, & Shiffman, 2012).

Multilevel models are now accessible in the most popular statistical packages, such as SAS, MPlus, SPSS, and R. Time-varying effect modelling is also accessible in SAS and Mplus.

**6.0 Future Research Directions**

Several milestones have already been achieved in the research field of EMA, and the promising results discussed in this chapter suggest the important role that this approach could have in facilitating a more comprehensive understanding of mental disorders, a more ecological assessment and monitoring of patients’ symptoms, and a more customized and real-time delivery of psychological support. Moreover, the findings from the implementation literature into technology based EMA suggests that EMA is generally accepted, experienced as appropriate, and frequently adopted by a large number of individuals with different clinical problems and ages. However, this approach is still far from being adopted in routine care. There are indeed some issues that still need to be addressed, and that could facilitate a translation of this huge body of knowledge from the research field to the clinical practice.

To the state of the art, the use of EMA as a tool for clinical assessments show a critical limitation: That is, the lack of standardized and ad-hoc items to be included in these protocols, which makes comparison of results across studies difficult and raises many concerns about the validity of such assessments. Specific scales to be integrated in EMA protocols should be developed by future studies, and their psychometric properties should be tested in order to ensure their validity and reliability as assessment methods. Beyond self-reports, the advantage of integrating active data with passive assessments also show a limitation. To the state of art, indeed, the information obtained with smartphone embedded sensors is still limited and it cannot provide a complete overview of daily behaviors. Similarly, the accuracy of physiological data collected “into the wild” with wearable biosensors is not as accurate as data collected in laboratory settings. Although these technological barriers are likely to be addressed in the coming years, replication of findings will be crucial in order to ensure their reliability and generalizability.

As seen in this chapter, compliance has represented a fundamental aspect of EMA research, and many studies tried to explore factors that could reduce patients’ dropout and increase their adherence to the procedure. The available literature indicates that EMA frequency (i.e., the number of daily assessments) and duration (i.e., duration of each EMA and duration of the overall study) should be kept to the minimum to maximize compliance. Generally, more compliance as well as cost-effectiveness, fidelity, and sustainability studies are needed in the form of formal implementation investigations. Moreover, consistent recommendations to develop EMA for clinical aims are still missing and future research should consider working on the development of specific guidelines, thus guiding clinicians in the development and implementation of this method in their clinical practice.

Another critical issue regards the gap between the research field and the clinical practice. EMA and, more generally, mHealth represent an increasingly growing field of research. However, the translation of this body of knowledge is still very difficult, and concrete applications of EMA in routine health care system are still really scant. Importantly, communication between researchers, practitioners and stakeholders should be fostered, as well as the multidisciplinary of research, which should cover all the fundamental aspects of EMA: (1) Coding and engineering knowledge for the technological development, (2) clinical expertise for the definition of the content, (3) human computer interaction experts for the improvement of usability and other technological issues, (4) research experience for the validation of these tools, and, of course (4) end-users, in order to listen to their needs and preferences, and increase their satisfaction and engagement.

Smart-home devices also entail an enormous source of possibilities in order to impel the continuous and unobtrusive acquisition of relevant multimodal data. Not only, they permit to acquire longitudinal data in objective, third-person observable ways, but most importantly in a very ecological context like a home. Important aspects could be determined by means of smart-home devices, such as emotion dynamics, risk of suicide, interpersonal relationships, sleep patterns, among others The integration of smart-home devices and other passive sensing with existing EMA self-report will foster a multimodal assessment, which will allow for a combination of both first-person subjective experience and third-person observation of that experience and behaviors (Nelson & Allen, 2018).

It is important to underline that it is out of the scope of this chapter to claim that EMA should substitute traditional clinical procedures and assessment tools. However, there is evidence showing the potentialities and advantages of this approach, and more research is needed in order to identify which specific fields and clinical populations could actually benefit from it. This could lead to a balanced integration between different methods, traditional and technological, which in turn could help to increase the quality of the clinical health system.

**7.0 Clinical Applications and Recommendations**

**7.1 Prevention and screening**

Among the many advantages of EMAs, the possibility of predicting future mental states and behaviors constitutes a central characteristic. The science of prevention has numerous difficulties and EMAs is fostering its investigation, as it permits to identify risk factors and anticipate dynamics of change. Although this is potentially implemented in all areas of clinical psychology, suicide ideation and behavior, mood dynamics or schizophrenia are some of the most researched topics.

For instance, the continuous monitoring of variation in suicidal ideation allows to prompt certain actions that may prevent people from escalating to more riskier situations or behaviors. This field is rapidly growing, and there is already a large body of evidence available. Unlike many other areas using EMAs, there has been developed a psychometrically sound item set in order to assess suicide ideation through daily assessments (Forkmann et al., 2018).

As previously mentioned, sensing has the capacity to not only detect behaviors that are already identified as markers of a specific clinical condition, but also to uncover new data that shed light into unknown processes related to pathological states. This has for example been used in the field of schizophrenia, as onset and relapse episodes have been identified with previous patterns of multimodal data obtained both from active and passive assessments (Barnett et al., 2018).

A final example, among many other areas that could also be described, is the field of emotional disorders, including not only depression and bipolar disorder, but also borderline personality disorder or eating disorders, which can also be defined by a distortion in the generation, expression and regulation of emotions (Bullis, Boettcher, Sauer-Zavala, & Barlow, 2019). In this sense, EMAs can be of particular relevance to explore affect dynamics and behavioral activation and, accordingly, monitor relevant variables that predict the onset or exacerbation of certain symptoms. For example, Vansteelandt et al. (2019) have investigated how self-criticism and dependency predict affective variability in borderline personality disorder (Vansteelandt et al., 2019). Additionally, depressive symptoms have been shown to be predicted by different features like social media activity, voice pitch or level activation. For example, GPS features have shown to enable the prediction of depression many weeks before the onset (Saeb, Lattie, Schueller, Kording, & Mohr, 2016).

A final remark regards the indisputable growing of social media use over the past years. Social media platforms constitute a huge source of information in order to assess online behavior, which in turn could be paramount to detect people in risk or experiencing possible clinical disorders. In particular, an increasing number of studies have been developed in the field of depression, for example for its detection (M. De Choudhury, Gamon, Counts, & Horvitz, 2013). Social media datasets, including e-mail records, very often comprise significant personal datastores that span multiple years. These datasets offer considerable potential for retrospective analyses that explore linguistic content and temporal factors in order to characterize mental health. However, as stated by a recent review (Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017), the findings in this field are still inconclusive.

**7.2 Monitoring**

One of the most powerful applications of EMA is symptoms’ monitoring. As abovementioned, clinical assessments are essential not only to formulate a diagnosis when the patient is seeking help, but also to monitor patients throughout the therapeutic process. Indeed, clinical monitoring allows clinicians to explore the course of a patient, which in turn allows to adjust the intervention. In traditional health-care system, patients are usually monitored by therapists through face-to-face sessions, which can also happen once a month. Nevertheless, this procedure does not allow to determine what is happening in-between: Whether the patient is improving, whether symptoms are worsening, or whether the treatment and/or the medication need to be changed because of side-effects or low efficacy. Moreover, the aforementioned recall bias also undermines the quality of a patient’s report, which could be biased and not representative of his/her clinical course.

As a matter of fact, EMA offers the opportunity to continuously monitor patients outside the traditional face-to-face setting with higher precision. Rather than just improving the quality of traditional monitoring in routine care, there are two main clinical implications of adopting EMA in this field.

First of all, professionals have the possibility to check for the efficacy of a treatment over time, thus identifying medication and/or treatment side-effects , specific needs to be addressed through the therapeutic process and prevent patients deterioration (Boswell, Kraus, Miller, & Lambert, 2015). *PsyLOG,* for instance, is an Android mobile application that monitors patients receiving psychotropic medications and assesses potential side-effects by means of specific daily assessments (Kuzman et al., 2017). Similarly, the mobile application *iHope* has been created for the continuous monitoring of symptoms in clinically depressed patients during daily life (Husky et al., 2010). Another interesting example is represented by *Medlink*, a mobile application developed by Mohr and colleagues to support and monitor patients receiving antidepressant medication (Mohr et al., 2015). Rather than assessing patients’ symptoms and medication intake through daily self-reports as the apps mentioned before, *Medlink* also provides users with weekly psychoeducational material and tailored suggestions about medication and symptoms management. Preliminary results on a sample with clinical depression already showed promising results: Patients using this app reported taking 84% of their medication, which is significantly higher than medication adherence rates reported in the literature.

Second, EMA monitoring allows clinicians to identify significant mood changes in real-time (Mikus et al., 2017), thus detecting emergency situations in an early stage (Nuij et al., 2018). The *Mood Tracking and Alert* (MTA) mobile application, for instance, was developed to monitor depressive and anxiety symptoms in vulnerable pregnant women (Hantsoo et al., 2018). Beyond the continuous symptoms monitoring by means of self-reports, MTA transfers data to clinicians in real-time and automatically generates alerts when a potential emergency situation is detected.

In the therapeutic context, EMA monitoring may also help to elucidate how the treatment is working not only in terms of symptoms change, but also considering a broader array of variables such as therapeutic alliance, interpersonal relationships, quality of life, overall functioning or any relevant dimension that is being targeted in a clinical context. In the field of psychotherapy this has been labelled Routine Outcome Monitoring (ROM) and has principally enabled to build algorithms to detect on-track patients and off-track patients (Lambert & Shimokawa, 2011). For example, the Outcome Questionnaire 45 is the most used instrument to track patients, and it entails one subscale of symptomatology, one of overall functioning and one of interpersonal relationships (Lambert, 2017). This research line has recently experienced an upsurge of interest, particularly due to the incorporation of patient’s feedback.

The examples mentioned in this chapter provide concrete illustrations of the value and potentialities of technology based EMA for the clinical monitoring of patients. Taken together, the advantages of this approach to the clinical field mainly rely on (1) the possibility of monitoring the clinical course of patients, thus increasing treatment customization based on specific personal needs, and (2) the possibility of creating a continuous communication between the patient and the clinician outside traditional face-to-face meetings, which includes the automatic detection of emergency situations and the early intervention of a professional. Nevertheless, there is still a very huge gap between the clinical practice and the research field, and EMA- based monitoring in real clinical settings is still very scant.

Besides, one innovative use of EMAs has been the monitoring of the baseline before starting a psychological treatment. The most ambitious approach has recently been implemented by Fisher et al. (Fisher et al., 2019), who monitored patients for 30 days before the first session and, based on a previously developed algorithm, a personalized treatment was offered. That is, this approach can be of paramount importance to improve treatment selection strategies in line with the previously mentioned pursuit of increasing ideographic approaches. If combined with a continuous monitoring of treatments as will be described later, this would permit to apply complex statistical models that can go linear mediation and thus to shed light on the complex dynamic mechanisms of change in clinical change (Hofmann, Curtiss, & Hayes, 2020).

**7.3 Intervention**

Beyond its value as a data collection strategy in the fields of prevention, screening and monitoring, EMA has shown promising results also in terms of intervention. In this section, two different applications of EMA to the treatment of patients will be discussed: The use of EMA and EMA-derived feedbacks as an adjunctive therapeutic tool, and the development of mobile applications that deliver just-in-time interventions based on users’ needs.

It is important to say that, beyond these two solutions, so far most of the available mobile health (mHealth) interventions are represented by mobile applications (Weisel et al., 2019). These apps are usually developed to address the needs of patients suffering from a generic mental disorder, e.g. anxiety or depression, and they can be easily downloaded from Apple or Google’s marketplaces. Despite the availability of an incredible number of apps, most of them often lack of scientific evidence (Shen et al., 2015), highlighting the need for clear regulations regarding the use and recommendation of these tools. Furthermore, these apps are neither ecological nor momentary, in the sense that they are not tailored on the needs of the individual patient and they are not able to provide psychological support in real-time. In other words, they are not just-in-time interventions. Accordingly, this category of technological interventions will not be discussed in this section.

First of all, providing patients with a feedback about EMA patterns has been shown to be useful to increase patients’ awareness about affect and symptoms fluctuations: In other words, showing the data collected by means of daily assessments to patients would increase their insight about their clinical condition. *Psymate*, for instance, is an EMA that allows patients to monitor depressive symptoms and daily affect ( Snippe *et al.*, 2016; Widdershoven *et al.*, 2019). *Psymate* was tested in a three-arm randomized controlled trial, where the sole use of the app was compared to the additional value of providing patients with weekly EMA-based feedback sessions. Results showed that the use of the EMA (regardless to the feedbacks) was associated with increased levels of perceived empowerment and positive affect, as well as improved negative and positive emotions differentiation, i.e. the ability to make nuanced distinctions and differentiate between emotions. Furthermore, a significant reduction in depressive symptoms was observed, which was only maintained over time by patients receiving weekly EMA-derived feedbacks sessions with a trained clinician. Similar results were observed by Delgadillo and colleagues, who showed that providing outcome-monitoring graphs about depressive and anxiety symptoms in addition to cognitive-behavioral psychotherapy was likely to improve clinical outcomes in patients at risk of poor response to treatment (Delgadillo et al., 2018). Despite these encouraging results, EMA-derived feedbacks were provided to patients through face-to-face meetings with a clinician in both examples, thus raising the question whether similar results would be obtained by incorporating this feedback component within the EMA device.

Beyond graphical feedbacks, the “ecological” and “momentary” concepts that characterize EMAs have been implemented to develop *Ecological Momentary Interventions* (EMIs) (Heron & Smyth, 2010), that extend the delivery of a treatment from the traditional clinical setting to daily life. EMI are interventions that are provided to patients by means of hand-held technologies at specific time points during the day, i.e. when the patient is more likely to be in need. These interventions always involve an active and/or passive data component, that serves as an input to detect when to provide psychological support to the user. *Mobylize*, for instance, is an ecological intervention that includes a mobile application, a website, and a system for email/telephone support (Burns et al., 2011). Thanks to a machine learning algorithm that analyze both self-reports and data gathered by smartphone embedded sensors, the application can predict the state of the patient and send tailored feedbacks and suggestions when low mood is detected. *Mobylize* was tested on a sample of depressed patients through a pilot study. Despite the accuracy of the predictive models was low, promising results were observed, showing an association between the use of the app and a significant reduction of depressive symptoms and anxiety symptoms. A more complex example of EMI is represented by *Calm Mom*, a mobile application that integrates daily self-reports with electrodermal activity measures collected by means of a wearable biosensor (Leonard et al., 2018). Thanks to the continuous active and passive monitoring, the application automatically creates alerts when a high level of stress is detected, providing users with customized psychological support about how to regulate emotions.

**8.0 Conclusion**

As outlined in this chapter, in the last decades the field of EMA has experienced a great expansion, consistently with the increasing availability of mobile devices in people’s lives. There is a growing body of evidence coming from the research field that shows the potentialities of EMA for the clinical practice under different points of view, such as patients’ assessment and monitoring in daily life, or patients’ support by means of tailored interventions.

First, EMA procedures allow to capture affective or symptoms dynamics by asking throughout the day a person’s feelings or behaviors (i.e., active assessments). Differently to retrospective questionnaires, the use of this approach results in the collection of repeated measurements, thus making data more ecological, reliable and generalizable. On the one hand, clinicians have the possibility to obtain a more comprehensive overview of one’s psychological condition, that also takes into account environmental associations (for instance, the presence of contextual triggers) and symptoms/affect fluctuations over time. On the other hand, the use of momentary assessments reduces the risk associated with the recall bias and the consequences of memory distortions associated with the presence of a psychopathological condition (for instance, the tendency to overestimate negative affect or to exaggerate symptoms severity observed in clinically depressed patients). Besides, technology based EMA procedures further extend the potentiality of traditional clinical assessments by integrating self-reports with passive data collected by means of embedded sensors and/or wearable biosensors. While the former allows to obtain indirect data about one’s behaviors (for instance, social media use, sleep patterns or physical activity), the latter enables professionals to monitor physiological parameters in ecological environments. In both cases, the advantage of passive assessment is to acquire data without the need of the individual to consciously be aware of it, thus reducing users’ burden. Notably, the increasing availability of smartphones and of inexpensive wearable sensors in people’s lives is making EMA procedures easier than in the past decades, when paper-and-pencil diaries were the gold standard. Moreover, the increasing interest of researchers and clinicians in adopting this approach resulted in the development of several technological solutions that allow to implement EMA designs without the need of programming skills. As mentioned in this chapter, there is indeed the possibility to create mobile applications to administer EMA through easy web interfaces (e.g., Movisens or MobileQ), or web platforms that allow to automatically send surveys through emails (e.g., Qualtrics).

Second, a growing body of literature explored the implementation of EMA into the clinical field, that is, the field that explores the transfer of evidence-based outcomes from research environments to routine use. Generally, the EMA procedures have been shown to be well accepted, regardless of age, psychopathological condition and type of sampling (prompted versus not prompted). Compliance rates are usually good (between 70% and 90%), and patients’ satisfaction and interest in using technology based EMA is high. The previous literature also recommends 4 or 5 prompts to be the superior limit for daily EMA assessments, and short designs are preferred to long ones. However, no specific guidelines have been so far developed to guide researchers and clinicians through the creation and implementation of EMA designs, and more research is needed in order to clarify the adequate characteristics to make EMA procedures even more successful. Besides, implementation literature mainly focused on end users’ perspective. The clinicians’ and organization’s perspectives remain so far understudied, which are instead essential to finally implement EMA procedure in routine practice.

Finally, there is evidencing supporting the advantages of EMA in different clinical fields: (1) Prevention and screening, to identify risk factors and anticipate dynamics of change in real-life; (2) monitoring, to detect symptoms change and treatment efficacy while administrating a treatment to a patient, as well as to create a continuous communication outside traditional face-to-face settings between clinicians and patients; and (3) intervention, to increase patients’ awareness about their clinical condition and clinical progresses through graphical representations of symptoms and affect fluctuations, but also by means of EMI, which allow to provide just-in-time interventions when detecting a specific need in a patient.

While these results are promising, the path is intricate and there are still many obstacles to overcome before integrating EMAs into the clinical practice. More research is indeed needed in order to translate the growing body of knowledge produced by the research field into the routine health care. As mentioned above, future research should indeed focus on the development of specific guidelines based on the previous evidenced-based literature that clarify the “best” characteristics to be owned by an EMA design, including sampling scheme, number of daily prompts, duration, and items. Regarding the latter, no specific scales and/or questionnaires to be included into EMA procedures have been so far developed. Reduced scales of traditional questionnaires, such as the PHQ-2, should be created, as well as state rather than trait measures, which would represent the perfect candidates to be included in such momentary assessments. Finally, a multidisciplinary approach should be ideally pursued to fully cover and further improve all the aspects that are implied in technology based EMA, i.e. informatic engineers, human-computer interaction experts, clinical psychologists and, of course, end users.

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