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Ecological Momentary Assessment: Enriching Knowledge of Occupation Using App-based Research Methodology

Niki Kiepek
Dalhousie University, niki.kiepek@dal.ca

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Niki C. Kiepek, PhD, MSc(OT), OT Reg. (N.S.), Assistant Professor

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Ecological Momentary Assessment: Enriching Knowledge of Occupation Using App-based Research Methodology

Abstract

This paper introduces occupational therapists to ecological momentary assessment (EMA) and outlines factors that guide the process of designing a project. EMA methodology is a research methodology that uses electronic devices and specially designed software, or Apps, to collect real-time data. This methodology may enhance the ecological validity of research by collecting data about daily occupations in situated contexts. EMA data collection provides access to highly detailed and specific data and has the potential to reveal longitudinal patterns of change over a short period of time. It is valued as a means to examine events, precursors, and consequences. EMA methodology presents an innovative approach to explore occupation, thus maximizing existing technology and software. It can also be a useful method for evaluative assessment, given its responsiveness to detecting change over time.

Keywords

Ecological momentary assessment; ecological validity; mHealth; outcome measurement; occupation; research methodology

Cover Page Footnote

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This paper introduces occupational therapists to ecological momentary assessment (EMA) as a research methodology and outlines factors that guide the process of designing a project. EMA uses electronic devices and specially designed software, or Apps, to collect real-time data in situated contexts. While this approach is more prevalent in other disciplines, it is relatively novel in occupational therapy research. There is a potential for EMA methodology to deepen and enrich our understanding of activity and occupation, person and client factors, performance patterns, participation, engagement, quality of life, transitions, occupational identity, and context and environment factors.

EMA is classified under mHealth, or mobile health, which is defined as “the use of mobile and wireless technologies to support the achievement of health objectives” (World Health Organization [WHO], 2011, p. 9). mHealth practices are proliferating internationally in tandem with widespread access to communications infrastructure and increased public reliance on mobile communication devices, such as mobile phones, PDAs (palmtop computers), smartphones, monitoring devices, e-book readers, and iPods. At least 75% of the WHO member states reported at least one national mHealth initiative (WHO, 2011). mHealth is particularly important in underserviced and rural settings, where it can offer the same benefits afforded to health providers in developing countries.

Advantages of EMA Methodology

EMA enhances the ecological validity of research by collecting data in situated contexts, daily activity, and in relation to personal experiences. EMA offers several advantages compared to time-use diaries, which is one method traditionally used in occupation-related research to collect real-time data. EMA is less susceptible to retrospective self-report biases related to personal and subtle external influences and is less prone to errors resulting from memory deficits and cognitive judgement biases (Voogt et al., 2013). EMA can be particularly advantageous when the activities of interest are intermittent and infrequent, since these types of activities are more prone to inaccurate recall. Studies also have shown that participants are receptive to EMA as a research methodology. Participants often preferred electronic reporting over paper-diary reporting, and this preference was independent of the participants’ age, gender, and familiarity with technology (Hufford, Shields, Shiffman, Paty, & Balabanis, 2002).

Geographically explicit ecological momentary assessment (GEMA) integrates EMA data collection and geographic information systems (GIS) data (Kirchner & Shiffman, 2016). This provides a means to collect integrated sources of data, thereby enhancing analysis of occupation in context. An example of the data that could be collected using GEMA would involve simultaneous passive tracking of a person’s movement through a community, a photograph of a barrier encountered, and a self-administered survey completed each time the person encounters a barrier (e.g., collecting data about the feature of the barrier, personal response to encountering the barrier, and/or strategies to overcome the barrier and engage in the occupation). Findings could inform community accessibility initiatives, provide information about emotional responses to occupational injustices, and support strength-based strategies to enhance engagement in meaningful occupation.

EMA methodology offers opportunities to investigate a broad range of factors, and the potential scope of EMA in occupation-related research is still emerging. EMA data collection can be highly detailed and reveal longitudinal patterns of change over time. It is valued as a means to examine events, precursors, and consequences. EMA provides an exciting method to deepen understanding about occupational engagement, occupational performance, meaning, well-being, inclusion, and a myriad of other interests. Occupational contexts expound the situated nature of occupation, including the physical, social, cultural, institutional, political, economic, and virtual environments, and EMA presents the opportunity to systematically integrate analysis of context and occupation.

Potential Use of EMA in Occupational Therapy Research

Studies using EMA to explore occupation have been reported by occupational therapists in Australia. In the occupational therapy literature, the type of EMA being used is referred to as experience sampling methods (EMS), which examine complex relationships between subjective experiences and everyday contexts (Shiffman, Stone, & Hufford, 2008). These researchers have investigated the well-being and participation among university students (Liddle et al., 2017), the everyday experiences of typically developing children (Vilaysack, Cordier, Doma, & Chen, 2016), the occupational patterns of a single person (Erlandsson & Eklund, 2001), and the social participation of children with autism (Chen, Bundy, Cordier, Chien, & Einfeld, 2016). Reported advantages of EMA in the occupational therapy literature include appropriateness for children as young as 5 years of age (Vilaysack et al., 2016), insight into participants' thoughts that were not captured using time-use diaries or observation methods (Erlandsson & Eklund, 2001), fewer cognitive demands (Chen et al., 2016), and access to subjective experience (Liddle et al., 2017). Limitations to EMA noted in the occupational therapy literature include response rates by children due to factors such as low awareness of or attention to the mobile device (Vilaysack et al., 2016) and a need to design the instrument, or App, to collect a manageable dataset and maximize opportunities to collect data unique to this methodology.

While EMA has not been prominent in occupational therapy or occupational science research, the methodology has been used more extensively in other disciplines to explore topics related to occupation, which indicates promise for using EMA to examine occupation specifically. Examples of topics investigated include the influence of social factors, physical context, and emotions on participation in physical activity (Dunton, Liao, Intille, Huh, & Leventhal, 2015); social functioning among participants with schizophrenia (Granholm, Ben-Zeev, Fulford, & Swendsen, 2013); daily functioning among children with arthritis (Bromberg, Connelly, Anthony, Gil, & Schanberg, 2016); participation in rural contexts (Seekins, Ipsen, & Arnold, 2007); sleep in relation to health indicators (Iacob, Donaldson, Neikrug, Nakamura, & Okifuji, 2016); daily activity and depression in relation to stroke (Jean, Swendsen, Sibon, Fehér, & Husky, 2013); community functioning among older adults (Rullier et al., 2014); and coping strategies among participants with osteoarthritis (Murphy, Kratz, Williams, & Geisser, 2012).

Given its responsiveness to detecting change over time, EMA has proven to be an effective approach to enhance evaluative assessment in other disciplines (Voogt et al., 2013). EMA has been used in occupational therapy research to explore momentary subjective experience, well-being, and participation. However, opportunities to use EMA for outcome measurement and evaluation of intervention effectiveness remain untapped and may prove a useful method to enhance evidence-based practice in the profession.

It has long been recognized that occupational therapy requires a strong discipline-specific evidence base to inform best practice; it is therefore imperative that researchers maximize advantages offered through technological advancements to enrich the empirical and professional knowledge base. Integrating novel and progressive methodologies provides opportunity to envision possibilities for more informed understandings about occupation and occupational therapy. Occupational therapy practices are continually advancing in response to profession-specific research. One of the challenges of evidence-informed practice is the time lapse between collecting and disseminating data. Real-time data analysis provides a unique opportunity to expedite dissemination of findings and influence practice.

Considerations for EMA Research Design

Decisions about optimal selection of technology and software are largely influenced by cost, data security, and versatility requirements. EMA requires participants to have access to mobile devices. These devices may be provided by the researcher, or study eligibility may be limited to participants who have their own mobile devices. If participants have access to their own mobile devices, this reduces research costs and expands the geographical location of the study, such that participants are not required to be in sufficient proximity to a research center to obtain a device. Use of personal devices for data collection may also reduce the potential for the equipment to be lost or ignored. One disadvantage is that the study is limited to participants who choose to use a mobile device and can financially afford the required device and data plan. This may limit some populations from participating, including those individuals with fewer economic resources who cannot afford the device or data plan or segments of the population who are less familiar with the technology.

With the emergence of EMA as a valuable method for data collection, there is increased availability of existing software. Factors about ownership of data and security of data must be considered when using third-party software. The researcher needs to ensure that they have ownership of the data and that data management complies with national legislation. The responsiveness of the company to questions and support troubleshooting is a key factor in selecting software. The design and development of software specific to a research project requires access to technological specialists, so the intensive time and financial costs can be prohibitive. Using existing software can pose some limitations with respect to individualizing the data collection instrument; however, the findings can contribute to the knowledge base and support future funding proposals that would allow for project-specific software design.

EMA software is increasingly available across countries. One example is Metricwire software, a cloud-based data collection solution. This software offers versatility for data collection, such as survey data, audio recording, photos, and GPS tracking. Other considerations when using third-party software include reasonable costs, ease of access for researchers and participants, compliance with national privacy legislation, ownership of data being restricted to the researcher, and the level of technological support available. The importance of these factors will be influenced by local ethics requirements, access to resources, and the type of research questions being investigated.

Method

Participants

EMA studies are limited to participants who have the physical and cognitive capacity to use the devices and software, unless data is inputted by a third party. For instance, parents may report the activities of their children or provide information about their children's physical environment (Dunton, Intille, Wolch, & Pentz, 2012).

Recruitment and Screening

Methods of recruitment will vary according to the study population. As with any study, eligibility screening is designed according to inclusion and exclusion criteria. Options for eligibility screening may include self-reported criteria, standardized measures use, or biomarkers evaluation. Whereas EMA software can support self-reported criteria and some standardized assessments, screening that requires participant in-person attendance will not? necessarily limit the geographical range for recruitment.

Training and Follow Up

It is advised that participants receive adequate and ongoing training about the research protocol and how to use the EMA software. Training can occur in individual or group settings, depending on factors such as privacy and time constraints. Training may occur face-to-face or through distance technology (e.g., phone, Internet). Some studies involve one or more follow-up sessions to review protocols and/or conduct periodic assessments. It is recommended that instructions (e.g., written, pictures, or videos) are readily available for participants to access throughout their enrollment in the study. These instructions may be provided directly on the App, on a project website, in print, and/or by email.

Data Collection

EMA data collection frequently involves a self-administered survey-style assessment delivered on an App. Timing of data collection may be signal contingent, interval contingent, and/or event contingent. *Signal contingent* assessments require participants to enter data in response to a prompt that appears on the device. Researchers may program prompts to occur at set times or at random intervals during a set period of time. *Interval contingent* assessments may prompt for data at set times of the day, such as mealtime or bedtime. *Event contingent* assessments occur in relation to stimuli. For example, assessments may be required whenever a certain occupation occurs (e.g., meal preparation, community mobility), when a person is in a location of interest (e.g., playground, drop-in center), or when a target experience occurs (e.g., pain, social exclusion). Signal contingent and interval contingent assessments are typically only available for completion for an established time (e.g., 15 min), which may impact reports (Thrul, Bühler, & Ferguson, 2015). However, event contingent responses rely on participants remembering to input data at the time of the occurrence (Thrul et al., 2015).

Standard EMA software date stamps all entries, though researchers have the option to include features of manual reporting of date and time, geolocation, photographs, and/or videos. More advanced options include the integration of technology to collect physiological and environmental data, such as accelerometers, heart rate monitors, pedometers, decibel measures, pollution measures, and metabolic measures of calorie expenditure. Researchers may develop multiple surveys and make them available at different times throughout the project. For instance, a demographics survey may be provided on a one-time basis or a feedback survey may be posted intermittently to gather information about instrument use.

Factors affecting the quality of data collection include participant burden, rate of prompting, repetitiveness of questions, attentiveness to the process, a tendency toward primacy (choosing the first response option for every item), and potential for another person to complete one or more of the tasks. Factors associated with missed prompts include failure to hear or see a signaled prompt (e.g., loud environment; device muted, switched off, or out of battery), being engaged in specific occupations that cannot be interrupted (e.g., taking a school test, working, driving a car), lack of access to data services, or prompts sent at times when the client is asleep.

Overall, there is limited evidence of reactivity, or reactance, in EMA studies that analyzed this factor. *Reactivity* refers to the potential for repetitive exposure to a particular factor to alter a person's relationship to that factor. However, in one study, approximately 30% of the people who responded to EMA assessment reported increased self-awareness about thoughts, feelings, and actions, which

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influenced their subsequent decisions (Freedman, Lester, McNamara, Milby, & Schumacher, 2006). An awareness of the potential for reactivity is advisable in studies using EMA.

Data collection may integrate in-person assessment, such as standardized assessments, focus groups, and physiological measures, with EMA assessment. Interviews may be integrated into the methodology, with options for conducting in-person interviews or the use of distance technology.

Analysis

Once the participant enters data, the data is automatically transmitted to a server for storage. This provides the researcher with immediate and ongoing access to data, permits real-time quality checking of data, and prevents the loss of data if the device lost. When prompts are integrated into the process, response rates are automatically recorded. EMA data are tagged with a time and date, which can provide a means to monitor and evaluate compliance. EMA methodology increases the ease of instituting changes in the study procedures (Thrul et al., 2015). EMA software design can also integrate analytical features into the dashboard, which enables real-time data analysis.

EMA data analysis is particularly amenable to within-day and across-day analyses. EMA data is suitable for multilevel linear modeling, examining between-subject and within-subject variables, descriptive statistics, and bivariate analysis. In rehabilitation research, EMA is recommended for hierarchical linear modeling analyses (Terhorst et al., 2017). The data is amenable to correlational analysis with limited options for experimental control or casual analysis (Piasecki, Wood, Shiffman, Sher, & Heath, 2012), and comparison groups may also be included in the design.

EMA increases the precision of analysis, since it is a method that is sensitive to change. Type I and type II errors can be reduced through aggregating the data collected over multiple time points and determining an overall intervention effect. Analysis can inform whether intervention effects are robust or whether they vary over time (Voogt et al., 2013). High sensitivity to change may result in options for smaller sample size, thereby alleviating recruitment challenges and reducing research costs (Voogt et al., 2013). Novel research has integrated a modified Stroop evaluation of salience using response time to evaluate implicit influences (Basen-Engquist et al., 2011).

When piloting and evaluating an EMA data collection instrument, it can be helpful to consider the quality of the data collected, the process of data collection, and participant feedback regarding use of the instrument. Criteria can include the researcher and/or participant's perspective regarding clarity of data, the ability to make comparisons between participants, gaps in data, ease of use, perceived accuracy of data provided, and recommendations for modifications to the instrument.

Compliance, Incentives, and Remuneration

Compliance is a multifaceted consideration. The quality of data collected is contingent on the precision of the EMA instrument and the participants' comprehension of the requirements. In EMA, compliance is generally defined by a set proportion of missed responses to signaled (or prompted) events or responses to prompts in a certain time frame. Compliance rates have been reported to range from 50% (Thrul et al., 2015) to 94%. Strategies to increase adherence to protocol include establishing personal contact between the researchers and the participants, tailored feedback regarding participant engagement in EMA assessment (e.g., mean response time, portion of assessments completed), incentives, and remuneration. Compliance with EMA protocol was not impacted by elevated engagement in activity (Dunton, Whalen, Jamner, Henker, & Floro, 2005). This is an important consideration for occupation-related research, as engagement in occupation may be a central factor of interest.

Incentives and remuneration are typically used to enhance compliance with protocol and reduce attrition rates, since EMA typically involves multiple daily reports over several weeks. Remuneration generally occurs for the completion of various stages of the project, such as baseline assessments and follow-up appointments. Remuneration may be contingent on length of involvement (e.g., weekly) or the participant meeting a certain level of compliance (e.g., 80% response rate to prompts). Some existing EMA software has the option for incentives built directly into the software, such as in the form of electronic gift cards. When the researcher loans mobile devices to participants, incentives to return the device in good condition may reduce the likelihood of devices being lost, damaged, or sold. As an alternative, some researchers allow participants to keep the device at the end of the study or return undamaged devices for a monetary incentive.

A significant factor that impacts the quality and quantity of data collection is participant burden. Overall, carrying a mobile device, responding to messages, and inputting data has been integrated into many people's daily lives. Therefore, participants may not view EMA as a burden or disruption in their lives, and they may require only minimal training. If participants already own a suitable device, research costs are reduced.

Limitations

mHealth initiatives require access to technology and a data plan for transmitting information. Cell phone use is widespread internationally, but it is not universal. It is therefore essential to consider the implications of a digital divide when developing projects and to recognize the impact of access in rural communities, among people in lower socioeconomic populations, and with respect to familiarity with newer technology. Prior to commencing an mHealth project, mobile phone penetration should be evaluated for the target population.

Other potential limitations of EMA include cost, eligibility, extent of analysis, compliance, and reactivity. EMA can be costly depending on the need to purchase devices, design and develop research-specific software, and pilot the project. Participation eligibility may be limited to those with access to the resources and with the cognitive capacity to adhere to the procedure, which may introduce a sampling bias. With respect to the extent of analysis, EMA data is not susceptible to establishing causal relationships. The data is amenable to correlational analysis with limited options for experimental control or casual analysis.

Conclusion

EMA methodology presents an innovative approach to explore occupation and occupation-related concepts, such as activity and occupation, person and client factors, performance patterns, participation, engagement, transitions, occupational identity, and context and environment factors, by maximizing the use of existing technology and software. Given the increasing prominence of EMA methodology to investigate topics related to occupation, there is evidence that this approach is feasible and has the potential to provide access to a rich source of data. Increased discussion is required about what aspects of occupation are most amenable to EMA research and what type of data is more suitable for collection using this methodology.

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