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REVIEW ARTICLE

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Making trauma ecological momentary assessment studies FAIR: review of design considerations and data procedures

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ABSTRACT

Background: Ecological momentary assessment (EMA) involves collecting data from people in their everyday lives one or more times per day over the course of days, weeks, or months. EMA has been used in the traumatic stress field to better understand how trauma-relevant symptoms, experiences, and behaviours occur under naturalistic conditions and in relation to one another. The FAIR principles specify that data should be Findable, Accessible, Interoperable, and Reusable to maximise the knowledge gained from individual research studies. However, it is unclear how EMA design decisions and data procedures might affect the implementation of these principles.
Objective: We articulate key design considerations and data procedures when performing trauma EMA research and outline some challenges and recommendations for implementing the FAIR data principles in trauma EMA research.
Method and Results: Using examples from existing trauma EMA studies, we discuss the decisions made when preparing a trauma EMA study; data processing and analytic procedures performed following data collection; and challenges that exist for their implementation, as well as practices that trauma EMA researchers can incorporate into their research to promote FAIR data.
Conclusions: Implementing the FAIR data principles in trauma EMA research is critical to advancing scientific knowledge. Researchers should deposit their data in reputable repositories and include documentation detailing design decisions and the steps taken to clean and prepare data. Many challenges remain for the implementation of these practices including balancing privacy concerns and efforts to make trauma EMA data readily shareable.

Haciendo estudios de evaluación momentánea ecológica en trauma FAIR: revisión de consideraciones de diseño y procedimientos de datos

Antecedentes: La evaluación momentánea ecológica (EMA, por sus siglas en inglés) implica recolectar datos de las personas en su vida cotidiana una o más veces al día durante días, semanas o meses. La EMA se ha utilizado en el campo del estrés traumático para comprender mejor cómo se presentan, en condiciones naturales y en relación entre sí, los síntomas, experiencias y comportamientos relevantes al trauma. Los principios FAIR especifican que los datos deben ser Localizables (Findable), Accesibles (Accessible), Interoperables (Interoperable) y Reutilizables (Reusable) para maximizar el conocimiento obtenido de estudios de investigación individuales. Sin embargo, no está claro cómo las decisiones de diseño y el procesamiento de datos en los estudios EMA podrían afectar la implementación de estos principios.
Objetivo: Articular las principales consideraciones de diseño y procesamiento de datos al realizar investigaciones EMA en trauma, y exponer algunos desafíos y recomendaciones para la implementación de los principios FAIR en la investigación EMA en trauma.
Método y Resultados: Utilizando ejemplos de estudios EMA en trauma existentes, se discuten las decisiones tomadas al preparar un estudio EMA en trauma, el procesamiento de datos y procedimientos analíticos realizados tras la recolección de los datos y los desafíos existentes para su implementación, así como las prácticas que los investigadores de EMA en trauma pueden incorporar en su investigación para promover datos FAIR.
Conclusiones: Implementar los principios FAIR en la investigación EMA en trauma es fundamental para avanzar en el conocimiento científico. Los investigadores deben depositar sus datos en repositorios acreditados e incluir documentación que detalle las decisiones de

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Evaluación momentánea ecológica; principios de datos FAIR; trauma; TEPT; evaluación ambulatoria; diario; muestreo de experiencia

HIGHLIGHTS
- Incorporating the FAIR data principles into trauma EMA research can advance scientific knowledge in the field of traumatic stress and ensure participants' contributions are fully realised.
- Implementation of the FAIR data principles is impacted by design decisions and data processing/analytic procedures.
- Multiple tension points must be navigated by trauma EMA researchers to implement the FAIR data principles.

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diseño y los pasos tomados para limpiar y preparar los datos. Muchos desafíos persisten en la implementación de estas prácticas, incluyendo el equilibrio entre las preocupaciones de privacidad y los esfuerzos para hacer que los datos EMA en trauma sean fácilmente compartibles.

Ecological momentary assessment (EMA) is a research methodology in which data are repeatedly collected in people's natural environments, often multiple times per day, over the course of days, weeks, or months (Shiffman et al., 2008). Research using EMA in the field of traumatic stress has increased in the past decade with the widespread adoption of smartphones, tablets, and mobile devices (Scopus, 2024; Statistica, 2024). Given that peri- and post-traumatic symptoms fluctuate from day-to-day, and even from hour to hour (Greene et al., 2022; Lenferink et al., 2022; Schuler et al., 2021), EMA has been instrumental in predicting and monitoring the development of physical, psychological, and social health problems in the wake of trauma (Brier et al., 2023; Greene et al., 2018; Grinapol et al., 2022; Pacella, Prabhu, et al., 2018; Mitchell et al. 2022). It has also been an effective method for capturing symptom fluctuations in relation to other dynamic psychological or behavioural variables, such as documenting temporal relationships between daytime posttraumatic stress disorder (PTSD) and nighttime sleep (Schenker et al., 2023). Other EMA-based research highlights potential avenues for intervention regarding comorbid PTSD and substance use, yielding insight into how evening PTSD symptoms contribute to nighttime drinking (Possemato et al., 2015). Collectively, these examples demonstrate the valuable contributions that EMA designs have made thus far to the field of traumatic stress.

Although EMA yields rich datasets – and participants often report benefiting from participation – it is also resource-intensive and burdensome to some respondents, creating recruitment challenges (Tate et al., 2024; Waterman et al., 2021). Consequently, EMA studies often have relatively modest sample sizes, which can constrain the generalisations that can be made from them. These challenges demonstrate the advantages of implementing the FAIR data principles to increase the generalizability of findings from trauma EMA research (Kassam-Adams & Olff, 2020). The FAIR principles state that data should be Findable, Accessible, Interoperable, and Reusable. If practiced by trauma EMA researchers, the FAIR data principles can facilitate data harmonisation across studies and make it easier to share and combine datasets. This will maximise the knowledge that can be gained from trauma EMA research and ensure participants' contributions are fully realised.

To better understand how to implement the FAIR data principles in trauma EMA studies, the current review articulates key design considerations that must be made before EMA data are collected, as well as common data procedures performed after data collection. While highlighting these considerations and procedures, we also note some of the challenges that exist for implementing the FAIR data principles in trauma EMA research. Section 1 discusses decisions that are made when preparing a trauma EMA study. Section 2 reviews data processing and analytic procedures that are often completed following data collection (see Table 1 for a summary of recommendations for designing and analysing trauma EMA studies). When relevant, each section notes how the considerations and procedures described impact data sharing. Section 3 expands on these points, describes some key challenges for practicing the FAIR data principles that are especially relevant to trauma EMA researchers, and offers our recommendations for addressing them. Finally, we conclude with thoughts on future directions that should be taken to encourage wider adoption of FAIR data practices.

1. Design decisions for trauma EMA research

1.1. Selecting a sampling design; density and schedule; and modality

The sampling design, density and schedule, and modality of an EMA study outline its basic structure by governing when, how often, and in what format assessments are administered (Trull & Ebner-Priemer, 2020). Sampling design refers to whether EMA measurements are collected contingent upon the passage of time or the occurrence of an event. Time-based assessments can be further categorised as either interval-contingent – occurring after fixed periods of time– or signal-contingent – occurring after random periods of time. Sampling density and schedule are closely related, defining how frequently and over what time periods assessments are collected (e.g. 3 times per day for 7 days). Finally, sampling modality refers to whether assessments are collected electronically or by paper-and-pencil. While variations on these basic dimensions of a trauma EMA study are expected across different research teams, clearly documenting the justifications supporting a selection is critical for sharing and combining data sets.

Table 1. Trauma EMA research design decisions, data processing and analytic procedures, and recommendations.

Design decisions	Recommendations
Sampling Densities and Schedules	• Select a sampling design and schedule that is informed by the expected rate of change on the focal variables. Use prior literature or perform a pilot study to determine the expected rate of change. • Consider administering assessments at least once during the day and once during the evening, on both weekdays and weekends, to increase the chances of getting a representative sample of the symptoms, experiences, or behaviours being assessed.
Sampling Modality	• Electronic assessments are the typical modality for collecting EMA data; however, paper-and-pencil may offer advantages if the study population is unfamiliar with technology.
Preventing Missing Data	• Escalate the amount of compensation offered on later assessments to reduce missing data. However, recognise that this has its limits if the number of assessments is quite high. • Consider using planned missing data designs to reduce protocol length without having to exclude whole measures.
Selecting Measures	• Utilize EMA item resources that offer commonly used measures in EMA research. • Report the observed psychometric properties of the EMA measures used in a trauma EMA research study.
Determining Sample Size	• Perform an a priori power analysis using simulation techniques.
Data Processing and Analytic Procedures	**Recommendations**
Handling Missing Data	• Use an analytical technique that employs maximum likelihood estimation to derive parameter estimates. • Develop a system of codes that conveys the reasons for missing data (e.g. data collection device failure, skipped assessment). • Perform a sensitivity analysis to assess the influence of missing data on study results.
Performing Key Computations	• Use measures of instability when interested in explicitly examining how data are dispersed around a measure of central tendency. • Use measures of stationarity to assess whether there are time variables that must be included in the model(s) to be tested. • When determining which statistical technique to use to analyse trauma EMA data, consider multilevel modelling first given its flexibility. • For research questions focused on differences between people, examine between-person effects; for research questions focused on differences within people, examine within-person effects.

1.1.1. Sampling design

Time-based assessments are an appropriate sampling design when the symptoms, experiences, or behaviours being assessed occur frequently and thus are likely be reported at the time that assessments are completed (Fritz et al., 2024; Himmelstein et al., 2019; Christensen et al., 2003) In contrast, event-based assessments are suitable when the focal variables of interest occur less frequently (Fritz et al., 2024; Himmelstein et al., 2019).

In a recent review examining trauma EMA research with Veterans (Gromatsky et al., 2020), researchers found that 80% of the studies used time-based assessments, while only 7% used event-based assessments. This reliance on time-based assessments could be because the trauma-EMA studies included examined mental health outcomes that often fluctuate across the day (e.g. avoidance symptoms Naragon-Gainey et al., 2012), making this sampling design ideal. Event-based assessments represent an underutilised approach in trauma EMA research, even though there are trauma-relevant experiences (e.g. trauma triggers) and behaviours (e.g. interpersonal conflicts) that can serve as anchoring events

Indeed, those trauma-EMA studies utilising event-based assessments have examined how frequently specific trauma reminders or intrusive symptoms occur (Devignes et al., 2024; Kleim et al., 2013; Rosi-Andersen et al., 2022). To determine which sampling design is most appropriate, trauma EMA researchers should consult past research to determine the expected frequency of their focal variables or perform a pilot study to estimate these parameters (Teresi et al., 2022). In addition, researchers should also consider their study aims and hypotheses (which should also be informed by past research) to determine which sampling design best fits the purpose of their research project.

1.1.2. Sampling densities and schedules

In a recent review considering EMA studies investigating the relationship between sleep and trauma symptomatology, the modal sampling density was found to be 5 observations per day (range: 1–6) with a modal study length of 7 days (range: 7–28) (Slavish et al., 2022). These values are consistent with what is observed in EMA research more broadly (Wrzus & Neubauer, 2023).

Ultimately, decisions concerning sampling density and schedule depend upon the expected frequency, rate of change, and duration of the focal variables (Trull & Ebner-Priemer, 2020; Stone, Schneider, and Smyth, 2023). In general, the time interval between assessments should be shorter than the expected rate of change in the focal variables (Ram et al., 2017). Examining moderating schedule features, such as day of week or time of day, can also cast light on important factors influencing trauma-related symptoms, experiences, and behaviours. For instance, Hruska and colleagues (Hruska et al., 2017) found that PTSD symptom severity is most strongly associated with alcohol craving and negative drinking consequences when these experiences and behaviours were examined during the evening. Human activities and behaviours typically vary systematically between the daytime and evening, as well as on weekdays relative to weekends. Consequently, trauma EMA researchers aiming to obtain a representative sample of their participants' symptoms, experiences, or behaviours should consider sampling densities that include at least 1 assessment during the day and at least 1 assessment during the evening and that take place on both weekdays and weekends.

1.1.3. Sampling modality

While EMA research – including trauma EMA research – initially relied on paper-and-pencil surveys to collect data (Gromatsky et al., 2020), most studies now use electronic assessments. This development began with daily diaries collected via personal digital assistants, followed by mobile assessments triggered by email, phone call, text message, or smart phone/watch applications (Glaser et al., 2006; Pacella, Girard, et al., 2018b; Price et al., 2018), and the eventual development of software programmes specifically designed for EMA data collection (Henry et al., 2024). Indeed, at the time of this writing, over 60 EMA software platforms exist (Henry et al., 2024). The mobile Ecological Momentary Assessment platform (mEMA) created by ilumivu (iluminivu, 2024) is one example that offers compliance with both the US Health Insurance Portability and Accountability Act and EU General Data Protection Regulation data privacy rules. The Smartphone Ecological Momentary Assessment (SEMA (Statistica, 2024)) mobile apps (O'Brien et al., 2024) for iOS and Android are another example, designed by EMA researchers and is free to use.

Electronic assessments offer several advantages over paper-and-pencil assessments. For example, they may provide more security when working with sensitive trauma-related data given that mobile devices and the software collecting the electronic assessments can be locked. Electronic assessments can also reduce response burden by using question branching to ensure that participants only see questions relevant to them. While these benefits help to explain the rise of electronic assessments in contemporary EMA research, paper-and-pencil assessments may still be appropriate in certain circumstances. Some research suggests that potential participants who are less familiar with technology are more likely to decline participation in EMA studies using electronic assessments (Stone et al., 2023). Thus, researchers should consider their target population when making sampling modality decisions.

1.2. Preventing missing data

Trauma EMA completion rates range from ~65% to ~95% (Lane et al., 2019), with a compliance level of 75% reflecting adequate compliance (Stone, Schneider, & Smyth, 2023). Anticipating reasons for missing data may allow researchers to mitigate data loss. For example, researchers might consider monitoring symptom exacerbations among highly symptomatic trauma survivors and providing resources when appropriate (Mitchell et al., 2022); decreasing the number of assessments per day (Vachon et al., 2019); providing participants with proper training at the study's onset and facilitating comfort with the data collection devices (Ram et al., 2017); suspending or delaying prompts when participants are known to be unavailable (Trull & Ebner-Priemer, 2020); or sharing EMA results with participants (Mitchell et al., 2022; Trull & Ebner-Priemer, 2020).

Providing compensation that matches the time- and effort-related demands of the study is another important strategy that can reduce missing data (Stone et al., 2023b). Although research evaluating compensation in trauma EMA research is sparse, a large meta-analysis of psychology-based EMA studies reported that over one-third included monetary incentives for participation (Wrzus & Neubauer, 2023). Compliance was significantly higher in studies providing financial incentives, with payments averaging $96.47 USD/86.57€ (Wrzus & Neubauer, 2023). Recently Smyth and colleagues (Smyth et al., 2021) used vignette methodology to demonstrate that the conditions resulting in the highest likelihood of participation included lower study duration, lower prompt frequency and length, and higher compensation. Thus, financial incentives could result in higher data quality compliance.

Compensation schedules defining how often and how much participants are compensated for their participation vary widely in EMA studies, from flat or fixed schedules, to random, variable schedules based upon behavioural reinforcement principles (Cai et al., 2022). Bonus payments are sometimes offered in combination with these methods to increase compliance and retention (Hruska & Barduhn, 2021; Short et al., 2018). Often trauma EMA researchers combine several compensation tactics. For example, Hruska and Colleagues (Hruska et al., 2017) offered recent injury survivors $40 USD for providing any EMA data as well as raffle tickets for one of three $100 USD gift cards. The number of tickets earned was dependent upon the amount of EMA measurements completed. Overall, participants completed over 70% of the measurements.

Researchers can also reduce missed assessments occurring on later days of data collection by escalating the amount of compensation offered on each subsequent day of participation (Hruska & Barduhn, 2021). However, monetary compensation may only go so far. A recent meta-analysis found that financial compensation contingent on assessment completion did not offer any benefits when the number of assessments was high (≥ 81 (Wrzus & Neubauer, 2023)). Thus, while compensation matched to study demands can increase compliance with EMA prompts, there are limitations, especially when a lengthy protocol is required to adequately capture fluctuation in symptoms, experiences, or behaviours. Planned missing data designs represent an underutilised strategy that could help to overcome this problem. These designs involve methodically omitting assessment items for subsets of respondents determined by randomisation (Graham et al., 2006). While traditionally applied to cross-sectional research, Monte Carlo simulations indicate that this approach can yield sufficiently powered EMA study designs (Losardo et al., 2024; Silvia et al., 2014). Thus, planned missing data designs may assist trauma EMA researchers with striking a balance between offering adequate compensation and maintaining a manageable protocol length that sufficiently assesses their variables of interest.

1.3. Selecting measures

Self-report measures are one of the most common forms of data collected via EMA. Unfortunately, there are few validated EMA self-report measures (Trull & Ebner-Priemer, 2020). Instead, researchers typically select a subset of items from larger measures based on their face validity, use single-item instruments that may not accurately or reliably reflect assessed constructs (Mitchell et al., 2022), or modify the time frame of trait measures (Trull & Ebner-Priemer, 2020; Stone, Schneider, & Smyth, 2023a). This is true with trauma EMA research as well: The majority (83%) of studies included in a review of EMA research related to PTSD and sleep truncated the number of PTSD Checklist-5 items in their protocol (Slavish et al., 2022).

These common practices have negative implications for data sharing and harmonisation within trauma EMA studies. Fortunately, new developments have begun to take place that can assist with these problems. For example, an EMA item repository Kirtley et al., 2018 has been created to make it easier for researchers to locate commonly used items (Kirtley et al., 2018), guidelines to assist researchers with evaluating EMA measure quality have been created (Eisele et al., 2024), and techniques for evaluating the observed psychometric properties of EMA measures are available (Shrout & Lane, 2012).

1.4. Determining sample size

It is important to strategically think about and justify the target sample size in an EMA study (Trull & Ebner-Priemer, 2020). However, it has not historically been a standard practice in trauma EMA research to do so (Slavish et al., 2022; Chun, 2016). This has been changing in recent times, with contemporary trauma EMA studies providing better justifications for proposed sample sizes (Greene et al., 2024; Lorenz et al., 2019). This development has been facilitated by the availability of R software packages such as *simr* (Green & MacLeod, 2016), *simstudy* (Goldfeld & Wujciak-Jens, 2020), and *PowerAnalysisIl* (Lafit et al., 2021) that make power calculations easier to perform. These software packages estimate required sample sizes by performing simulations informed by the inputs provided by researchers and offer more precise – and thus more accurate – sample estimates relative to existing rules of thumb (e.g. > = 80 participants per level 2 unit) (Gabriel et al., 2019).

2. Data processing and analytic procedures

EMA studies produce rich datasets that require complex data processing and analytic procedures. These procedures involve handling missing data and performing key computations examining instability and stationarity in the data, as well as assessing between- and within-person differences on variables of interest.

2.1. Handling missing data

As noted above, there are many steps that trauma EMA researchers can take during the design of the project to reduce missing data. However, despite these efforts, missing data can still be a problem that must be handled post-data collection. Many frequently used analytic approaches for EMA data use maximum likelihood estimation (MLE). MLE provides robust estimates for repeated measures (Enders, 2022). A thorough review of the strengths and weaknesses of MLE is beyond the scope of this manuscript, but readers are encouraged to consult other resources to ensure that the patterns of missingness detected in their dataset are appropriate for MLE (Enders, 2022; Allison, 2009; Little & Rubin, 2019).

When sharing data, it is important to code missing values so that other users can easily identify it. EMA items might be missing for different reasons (e.g. data collection device failure, participant skipped assessment). Including different codes for these missing items can help future users evaluate biases that might be present in the data. A sensitivity analysis is an important technique that can also help to determine the influence of missing data on findings, and it should be performed even when using MLE. This analysis involves comparing results when using different subsets of the dataset that have different missingness levels. Including a sensitivity analysis when sharing data is important because future users might not use MLE, and a sensitivity analysis can alert them to missing data issues that require attention.

2.2. Performing key computations

At times it might not be feasible to share raw trauma EMA data due to privacy or confidentiality concerns. Additionally, researchers may wish to combine data sets with different sampling densities. In both cases, a common approach is to aggregate data to a higher level of analysis (Martorana et al., 2022). For example, researchers might take data that they collected 5 times per day for two weeks and average within each day and across weeks to produce a single daily measurement for each day of the week. When using this strategy, there are several EMA-relevant computations performed after data collection that will deviate from the raw data. These include computations to examine instability and stationarity, as well as within- and between-person differences.

2.2.1. Instability and stationarity

Instability refers to the dispersion of time series data around a measure of central tendency while accounting for temporal order (Ebner-Priemer et al., 2009). Instability may be critically important when examining changes in trauma symptoms in response to intervention (Hruska, 2020). The intraclass correlation coefficient (ICC) captures the dispersion aspect of instability. It refers to the proportion of outcome variance that is due to between-person differences, while its complement – 1-ICC – provides a measure of within-person variability (Hoffman, 2015). The root mean square of successive differences (RMSSD) offers a more direct measure of instability because it accounts for variance in the outcome variable in addition to the autocorrelation of successive responses. Larger RMSSD values indicate larger variation across time (Ebner-Priemer et al., 2009).

Stationarity is the extent to which the descriptive components of a time series – the mean, variance, and covariance with other variables – remain the same across its full range (Jebb et al., 2015). Evidence of non-stationarity indicates the presence of time variables in the dataset that need to be modelled (e.g. seasonality). The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is a well-regarded statistical test of stationarity (Kwiatkowski et al., 1992). Many software packages have dedicated functions for the KPSS test. Non-stationary data can also be detrended, which refers to removing the temporal process responsible for the non-stationarity (Becketti, 2020). For example, EMA researchers can regress their outcome variable onto a time variable modelling the trend (linear, quadratic). The residuals of this model can then serve as the outcome variable in subsequent analyses.

When these statistics are performed on EMA data that will not be shared in their raw form, it can be helpful to include analytic code that describes their computation. By providing this information, future users will better understand the operations that were performed on the raw data and will be able to replicate these actions using the aggregated data that is shared.

2.2.2. Between- and within-person differences

In recent years, advances in software have expanded the number of statistical approaches available to trauma EMA researchers. For example, latent class vector autoregressive models are useful when it is hypothesised that respondents belong to latent subgroups sharing similar fluctuation characteristics on EMA variables of interest (Ernst et al., 2020); multilevel factor analysis provides a method to evaluate the construct validity of EMA measures (Huang, 2017); and multilevel network analysis models offer a multivariate approach for examining how trauma symptoms relate to one another overtime (Greene et al., 2018; Price et al., 2020).

Multilevel modelling (MLM) is one commonly used, well-established approach (Snijders & Bosker, 2012). In trauma EMA research, MLM has been used in a variety of ways. For example, it has been used to compare fluctuations in negative affect across the day among people experiencing PTSD (Dornbach-Bender et al., 2020) and to consider how different daily occupational experiences relate to daily mental health symptoms in emergency medical service workers (Hruska & Barduhn, 2021). MLM is often used by trauma EMA researchers because of its flexibility: It can test moderating and mediating effects at different levels of analysis, permit the representation of non-linear changes across time, and accommodate different error structures that often better fit models consisting of variables that are intensively measured across time (Snijders & Bosker, 2012). MLM is also often used because it is capable of partitioning an outcome into fixed and random effects. A fixed effect is a parameter estimate that reflects the average value that respondents have on the outcome across all EMA measurements. For example, the fixed effect in an EMA study examining PTSD symptoms among recent trauma survivors would represent the average symptom levels reported by all respondents across all EMA occasions. On the other hand, a random effect is a parameter estimate that represents the variability associated with the outcome that exists because respondents have values that differ from the average outcome value. For example, any given trauma survivor might have PTSD symptoms that are higher or lower than the average outcome value observed across all respondents across all EMA measurements. Thus, MLM can represent both mean levels of an outcome as well as the individual differences that exist around those mean levels.

In addition to this feature, MLM can represent between- and within-person relationships that might exist for predictors that are intensively measured as part of an EMA design. For instance, trauma survivors who routinely engage in avoidance coping might have higher PTSD symptoms relative to trauma survivors who less frequently engage in avoidance coping. This is an example of a between-person relationship. On the other hand, for any given trauma survivor, there might be occasions during the day when avoidance coping is used more often than at others (e.g. evening vs. morning). And on those occasions when avoidance is more likely to be used, the trauma survivor might report higher PTSD symptoms. This is an instance of a within-person relationship. These two types of relationships can offer complementary information about the association between variables. In the examples above, the between-person relationship between avoidance coping and PTSD symptoms indicates *who* is most likely to experience higher symptom levels (i.e. trauma survivors who routinely engage in avoidance coping). In contrast, the within-person relationship indicates *when* a trauma survivor is most likely to report elevated symptoms (i.e. on occasions when a trauma survivor uses more avoidance coping) (Stange et al., 2019).

To model within- and between-person relationships in MLM, the variables that are repeatedly collected on the EMA measurements must be centred. Within-person associations are calculated by taking each respondent's personal average and subtracting it from their individual raw scores. On the other hand, between-person relationships are calculated by taking the grand mean and subtracting it from each person's personal average. Because these computations involve various versions of the mean at different levels of analysis, aggregating raw data to protect privacy and confidentiality will profoundly impact the values and meaning of centred variables. Thus, trauma EMA researchers should carefully consider what options exist for safeguarding privacy.

3. Challenges and recommendations associated with implementing the FAIR data principles in trauma EMA research

While trauma researchers are largely positive about data sharing and reuse, there are notable barriers to implementing the FAIR data principles (Prakash et al., 2023). Table 2 presents the FAIR principles and our recommendations concerning how they can be applied in trauma EMA studies. Here we note some of the most significant challenges facing trauma EMA researchers who wish to apply the FAIR data principles and how those challenges might be addressed.

Managing confidentiality is one challenge especially relevant to trauma EMA researchers due to the highly identifiable and sensitive information that is often collected in trauma EMA protocols (e.g. trauma memories/narratives, substance use behaviour). To navigate this challenge, we propose that trauma EMA researchers clearly outline how data will be shared in the consent form presented to study participants. Altruism and advancing scientific knowledge are often cited by participants as motivations for participating in research studies (Soule et al., 2016; Sheridan et al., 2020) and describing how data sharing aligns with these motivations could be a way to encourage participation.

We suggest that researchers document the steps taken to preserve confidentiality. This practice may help to create transparency and foster trust between researchers and participants, while also making it easier for other researchers to understand which data are available and how data might be used. We propose that such documentation – along with other relevant meta-data including a descriptive title, author details, digital object identifier, and descriptions of the data – be included when researchers deposit their data in a reputable repository. Other key documentation includes a description of the research protocol, along with justifications supporting the design decisions and analytic actions taken both pre- and post-data collection. Collectively, we think these practices will promote the findability as well as accessibility of trauma EMA research.

One tension point that might arise as trauma EMA researchers engage in these practices is their potential conflict with interoperability. For example, providing the amount and type of data needed to maximise interoperability – including timestamps in data deposited in a repository with limited data restriction options – may render the available data identifiable. Therefore, we encourage trauma EMA researchers to consider selecting a repository that allows flexible data access restrictions (e.g. the Data Archiving and Networked Services Repository in Europe; the Harvard Dataverse in the United States). Alternatively, researchers may choose to share a version of the data that includes recoded variables to maximise privacy protection (e.g. recoding raw timestamps to a less granular level of analysis – 'morning', 'afternoon', 'evening'). Other ways to promote interoperability that do not conflict with confidentiality concerns include using established EMA measures (Kirtley et al., 2018) and validating EMA measures used in research (Shrout & Lane, 2012).

Navigating ethics concerns is another significant challenge facing trauma EMA researchers. Research

Table 2. The FAIR data principles and recommendations for their implementation in trauma EMA research.

Principle	Description	Recommendations	Resources
Findable	Data should be discoverable to allow both researchers and search engines to locate the data and associated meta-data via unique and persistent identifiers.	Clearly describe the data using multiple details outlined in meta-data (e.g. DOI, title, authors, and characteristics of the data) Use a repository with a preservation plan (e.g. Open Science Framework) Consider whether there are repository-specific limits on who can access stored data (i.e. restricted by institution, country, etc.)	**Considerations for sharing psychological data and materials:** • Campbell, R., Goodman-Williams, R., Javorka, M., Engleton, J., & Gregory, K. (2023). Understanding Sexual Assault Survivors' Perspectives on Archiving Qualitative Data: Implications for Feminist Approaches to Open Science. *Psychology of Women Quarterly*, *47*(1), 51–64. https://doi.org/10.1177/03616843221131546 • Forero, D.A., Curioso, W.H. & Patrinos, G.P. The importance of adherence to international standards for depositing open data in public repositories. *BMC Res Notes* 14, 405 (2021). https://doi.org/10.1186/s13104-021-05817-z • Gilmore R.O., Kennedy J.L., Adolph KE. Practical Solutions for Sharing Data and Materials From Psychological Research. Advances in Methods and Practices in Psychological Science. 2018;1(1):121–130. https://doi.org/10.1177/2515245917746500 • Meyer M.N. Practical Tips for Ethical Data Sharing. *Advances in Methods and Practices in Psychological Science*. 2018;1(1):131–144. https://doi.org/10.1177/2515245917747656 • Morehouse, K.N., Kurdi, B., & Nosek, B.A. (2024). Responsible data sharing: Identifying and remedying possible re-identification of human participants. *American Psychologist*. https://doi.org/10.1037/amp0001346 • Wicherts, J.M., Klein, R.A., Swaans, S.H.F., Maassen, E., Stoevenbelt, A.H., Peeters, V.H.B.T.G., de Jonge, M., & Rüffer, F. (2022). How to protect privacy in open data. *Nature Human Behaviour*, *6*(12), 1603–1605. https://doi.org/10.1038/s41562-022-01481-w
Accessible	Contact information for the research team is clearly identifiable from the meta-data associated with a data set and the study protocol used to collect or analyse the data can be used by researchers not familiar with the study.	At a minimum, contact information for the study PI should be clearly accessible via meta-data The following study materials also should be posted on a repository to maximise accessibility: • Data collection protocol to promote replication (e.g. number of assessments, assessment intervals, compensation, etc.) • Codebooks containing variable names, descriptions, etc. Consider what amount or type of data can be shared to maximise accessibility and what type of authentication procedures should be implemented to protect sensitive data.	**Increasing accessibility of (ecological momentary assessment) study protocols and procedures**: • Kirtley O.J., Lafit G., Achterhof R, Hiekkaranta A.P., Myin-Germeys I. Making the Black Box Transparent: A Template and Tutorial for Registration of Studies Using Experience-Sampling Methods. *Advances in Methods and Practices in Psychological Science*. 2021;4(1). https://doi.org/10.1177/2515245920924686 • Krypotos, A.-M., Klugkist, I., Mertens, G., & Engelhard, I. M. (2019). A step-by-step guide on preregistration and effective data sharing for psychopathology research. *Journal of Abnormal Psychology*, *128*(6), 517–527. https://doi.org/10.1037/abn0000424 • Peterson, Apfelbaum, & McMurray (2022). Adapting open science and pre-registration to longitudinal research. *Infant and Child Development, 33*(1), e2315. https://doi.org/10.1002/icd.2315 • Van den Akker, … , & Bakker (2021). Preregistration of secondary data analysis: A template and tutorial. *Meta-Psychology, 5*. https://doi.org/10.15626/MP.2020.2625 • van Eijk, N. L., Jiao, H., & Peters, G. Y. (2023, March 17). Making Preregistration Accessible: An R Package to Make Machine-Readable Preregistrations and Create New Preregistration Forms. https://doi.org/10.31234/osf.io/qfjy7 • Horstmann, K. T., Arslan, R. C., & Greiff, S. (2020). Generating Codebooks to Ensure the Independent Use of Research Data: Some Guidelines. *European Journal of Psychological Assessment*, *36*(5), 721–729. https://doi.org/10.1027/1015-5759/a000620

(*Continued*)

Table 2. Continued.

Principle	Description	Recommendations	Resources
Interoperable	Data and related study materials should be able to be integrated with other data sources so that a researcher who is not familiar with the data can use a common or easily understandable vocabulary to make use of the study data, materials, and meta-data.	Ensure that data from multiple data sources or dataset types are able to be easily linked Consider including analytic code for cleaning and integrating data from multiple sources. Use established measures that are common in the field	Kirtley, O., Gudrun, E., Kunkels, Y.K., Hiekkaranta, A.P., Van Heck, L., Pihlajamaki, M., Kunc, B., Schoefs, S., Vermaelen, N., & Myin-Germeys, I. (2018).
Reusable	Meta-data should be clearly labelled with instructions for how to use or reference materials and data in future research.	Provide clear instructions to outline any restrictions or considerations for future use of the data, including: • The type of licensing that best corresponds to the level of use desired • Preferences for authorship on projects that make use of the data • Whether a data use agreement is needed to access the data (and consider providing a templated data use agreement if so) Consider the level of meta-data detail and format for dataset or data structures that will maximise replicability Provide sufficient details to inform future researchers on what steps were taken to clean or prepare the data to maximise replicability	**Increasing reusability by documenting data cleaning/pre-processing:** • Revol, J., Carlier, C., Lafit, G., Verhees, M. W. F. T., Sels, L., & Ceulemans, E. (2023, October 26). Preprocessing ESM data: a step-by-step framework, tutorial website, R package, and reporting templates. https://doi.org/10.31234/osf.io/hnu2t

ethics requirements vary widely across international settings (Goodyear-Smith et al., 2002) and the data that are permissible to share – as well as the process needed to obtain permission – may differ depending upon geographic location. In addition, conflict could occur between stakeholders who wish to maximise reusability (e.g. National Institute of Mental Health Data Archives) and Institutional review boards who oversee protection of human subjects data or community advisory boards consisting of participants with lived experience who are likely to be concerned with strategies that maximise findability. Balancing the needs of multiple stakeholders regarding data sharing represents a significant challenge, and we encourage researchers to use resources that can facilitate FAIR data collection (e.g. the Global Collaboration on Traumatic Stress maintains a FAIR toolkit Global Collaboration on Traumatic Stress, 2024).

Time constraints are one final challenge to FAIR principle implementation that are especially pertinent to trauma EMA research. Collecting data in a FAIR manner is time-intensive and could disincentivize trauma EMA researchers from engaging in practices that support these principles given that EMA already requires a significant investment of resources to ensure retention and to minimise missing data. To address this challenge, we propose that the trauma field recognise trauma EMA researchers when they engage in FAIR practices. Trauma-relevant academic journals and professional societies could elevate the visibility of research using repository data by featuring it in their publications, websites, and social media, as well as promoting repository usage by recognising research utilising these sources in annual programming.

4. Conclusion

We believe that implementing the FAIR data principles in trauma EMA research is critical given the continued uptake of open science practices and increase towards data sharing mandates from funding agencies. Furthermore, we anticipate that the field of traumatic stress is just beginning to leverage the potential for consortium-wide collaborations to advance knowledge on the etiology, maintenance, and treatment of trauma-related disorders (see Hien et al., 2023; McLean et al., 2020 for examples). While such efforts represent a vital avenue to increase data reusability, their success requires considerable skills in data management and data stewardship.

To ensure that trauma EMA researchers are knowledgeable on these subjects, it is important for training programmes to facilitate greater exposure to data management skills. Furthermore, interdisciplinary research collaborations should be broadened to routinely include subject matter experts in knowledge preservation and data sharing (e.g. library scientists).

Collectively, these efforts will assist with navigating the challenges of integrating the FAIR data principles into trauma EMA research, ensuring that the knowledge and public health implications generated from this research is fully realised.

Data availability statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Allison, P. D. (2009). Missing data. In *The SAGE handbook of quantitative methods in psychology* (pp. 72–90). SAGE Publications Ltd. https://doi.org/10.4135/9780857020994.n4.

Becketti, S. (2020). *Introduction to time series using stata* (Revised ed.). Stata Press.

Brier, Z. M. F., Hidalgo, J. E., Espeleta, H. C., Davidson, T., Ruggiero, K. J., & Price, M. (2023). Assessment of traumatic stress symptoms during the acute posttrauma period. *Focus*, *21*(3), 239–246. https://doi.org/10.1176/appi.focus.20230001

Cai, L., Barnes, L. E., & Boukhechba, M. (2022). A framework for adaptive mobile ecological momentary assessments using reinforcement learning. In K. Arai (Ed.), *Intelligent systems and applications* (pp. 31–50). Vol 294. Lecture Notes in Networks and Systems. Springer International Publishing. https://doi.org/10.1007/978-3-030-82193-7_3

Christensen, T. C., Barrett, L. F., Bliss-Moreau, E., Lebo, K., & Christensen, T. C. (2003). A practical guide to experience-sampling procedures. *Journal of Happiness Studies*, *4*(1), 53–78. https://doi.org/10.1023/A:1023609306024

Chun, C. A. (2016). The expression of posttraumatic stress symptoms in daily life: A review of experience sampling methodology and daily diary studies. *Journal of Psychopathology and Behavioral Assessment*, *38*(3), 406–420. https://doi.org/10.1007/s10862-016-9540-3

Devignes, Q., Ren, B., Clancy, K. J., Howell, K., Pollmann, Y., Martinez-Sanchez, L., Beard, C., Kumar, P., & Rosso, I. M. (2024). Trauma-related intrusive memories and anterior hippocampus structural covariance: An ecological momentary assessment study in posttraumatic stress disorder. *Translational Psychiatry*, *14*(1), 74. https://doi.org/10.1038/s41398-024-02795-1

Dornbach-Bender, A., Ruggero, C. J., Schuler, K., Contractor, A. A., Waszczuk, M., Kleva, C. S., Bromet, E., Luft, B., & Kotov, R. (2020). Positive and negative affect in the daily life of world trade center responders with PTSD: An ecological momentary assessment study. *Psychological Trauma: Theory, Research, Practice, and Policy*, *12*(1), 75–83. https://doi.org/10.1037/tra0000429

Ebner-Priemer, U. W., Eid, M., Kleindienst, N., Stabenow, S., & Trull, T. J. (2009). Analytic strategies for understanding affective (in)stability and other dynamic processes in psychopathology. *Journal of Abnormal Psychology*, *118*(1), 195–202. https://doi.org/10.1037/a0014868

Eisele, G., Hiekkaranta, A. P., Kunkels, Y. K., aan het Rot, M., van Ballegooijen, W., Bartels, S. L., Bastiaansen, J. A., Beymer, P. N., Bylsma, L., Carpenter, R. W., Ellison, W. D., Fisher, A. J., Forkmann, T., Frumkin, M., Fulford, D., Naragon-Gainey, K., Greene, T., Heininga, V. E., Jones, A., … Kirtley, O. J. (2024). ESM-Q: A consensus-based quality assessment tool for experience sampling method items. https://doi.org/10.31234/osf.io/sjynv

Enders, C. K. (2022). *Applied missing data analysis* (2nd ed.). The Guilford Press.

Ernst, A. F., Albers, C. J., Jeronimus, B. F., & Timmerman, M. E. (2020). Inter-individual differences in multivariate time-series: Latent class vector-autoregressive modeling. *European Journal of Psychological Assessment*, *36*(3), 482–491. https://doi.org/10.1027/1015-5759/a000578

Fritz, J., Piccirillo, M. L., Cohen, Z. D., Frumkin, M., Kirtley, O., Moeller, J., Neubauer, A. B., Norris, L. A., Schuurman, N. K., Snippe, E., & Bringmann, L. F. (2024). So you want to Do ESM? 10 essential topics for implementing the experience-sampling method. *Advances in Methods and Practices in Psychological Science*, *7*(3), 25152459241267912. https://doi.org/10.1177/25152459241267912

Gabriel, A. S., Podsakoff, N. P., Beal, D. J., Scott, B. A., Sonnentag, S., Trougakos, J. P., & Butts, M. M. (2019). Experience sampling methods: A discussion of critical trends and considerations for scholarly advancement. *Organizational Research Methods*, *22*(4), 969–1006. https://doi.org/10.1177/1094428118802626

Glaser, J. P., Van Os, J., Portegijs, P. J. M., & Myin-Germeys, I. (2006). Childhood trauma and emotional reactivity to daily life stress in adult frequent attenders of general practitioners. *Journal of Psychosomatic Research*, *61*(2), 229–236. https://doi.org/10.1016/j.jpsychores.2006.04.014

Global Collaboration on Traumatic Stress. (2024). *FAIR tools. Global collaboration on traumatic stress: FAIR tools*. Retrieved October 4, 2024, from https://www.global-psychotrauma.net/fair-tools

Goldfeld, K., & Wujciak-Jens, J. (2020). Simstudy: Illuminating research methods through data generation. *Journal of Open Source Software*, *5*(54), 2763. https://doi.org/10.21105/joss.02763

Goodyear-Smith, F., Lobb, B., Davies, G., Nachson, I., & Seelau, S. M. (2002). International variation in ethics committee requirements: Comparisons across five Westernised nations. *BMC Medical Ethics*, *3*(1), 2. https://doi.org/10.1186/1472-6939-3-2

Graham, J. W., Taylor, B. J., Olchowski, A. E., & Cumsille, P. E. (2006). Planned missing data designs in psychological research. *Psychological Methods*, *11*(4), 323–343. https://doi.org/10.1037/1082-989X.11.4.323

Green, P., & MacLeod, C. J. (2016). SIMR: An R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution*, *7*(4), 493–498. https://doi.org/10.1111/2041-210X.12504

Greene, T., Contractor, A. A., Dicker-Oren, S. D., Fentem, A., & Sznitman, S. R. (2024). The effects of the processing of positive memories technique on posttrauma affect and cognitions among survivors of trauma: Protocol for a daily diary study. *JMIR Research Protocols*, *13*, e51838. https://doi.org/10.2196/51838

Greene, T., Gelkopf, M., Epskamp, S., & Fried, E. (2018). Dynamic networks of PTSD symptoms during conflict. *Psychological Medicine*, *48*(14), 2409–2417. https://doi.org/10.1017/S0033291718000351

Greene, T., Sznitman, S., Contractor, A. A., Prakash, K., Fried, E. I., & Gelkopf, M. (2022). The memory-experience gap for PTSD symptoms: The correspondence between experience sampling and past month retrospective reports of traumatic stress symptoms. *Psychiatry Research*, *307*, 114315. https://doi.org/10.1016/j.psychres.2021.114315.

Grinapol, S., Gelkopf, M., Pagorek-Eshel, S., & Greene, T. (2022). The role of sensory processing sensitivity in the early traumatic stress reaction: Predicting posttraumatic stress symptoms following motor vehicle accidents. *Personality and Individual Differences*, *185*, 111278. https://doi.org/10.1016/j.paid.2021.111278

Gromatsky, M., Sullivan, S. R., Spears, A. P., Mitchell, E., Walsh, S., Kimbrel, N. A., & Goodman, M. (2020). Ecological momentary assessment (EMA) of mental health outcomes in veterans and servicemembers: A scoping review. *Psychiatry Research*, *292*, 113359. https://doi.org/10.1016/j.psychres.2020.113359

Henry, L. M., Hansen, E., Chimoff, J., Pokstis, K., Kiderman, M., Naim, R., Kossowsky, J., Byrne, M. E., Lopez-Guzman, S., Kircanski, K., Pine, D. S., & Brotman, M. A. (2024). Selecting an ecological momentary assessment platform: Tutorial for researchers. *Journal of Medical Internet Research*, *26*, e51125. https://doi.org/10.2196/51125

Hien, D. A., Morgan-López, A. A., Saavedra, L. M., Ruglass, L. M., Ye, A., López-Castro, T., Fitzpatrick, S., Killeen, T. K., Norman, S. B., Ebrahimi, C. T., & Back, S. E. (2023). Project harmony: A meta-analysis with individual patient data on behavioral and pharmacologic trials for comorbid posttraumatic stress and alcohol or other drug use disorders. *American Journal of Psychiatry*, *180*(2), 155–166. https://doi.org/10.1176/appi.ajp.22010071

Himmelstein, P. H., Woods, W. C., & Wright, A. G. C. (2019). A comparison of signal- and event-contingent ambulatory assessment of interpersonal behavior and affect in social situations. *Psychological Assessment*, *31*(7), 952–960. https://doi.org/10.1037/pas0000718

Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change*. Retrieved March 23, 2021, from http://public.ebookcentral.proquest.com/choice/publicfullrecord.aspx?p=1968925

Hruska, B. (2020). Incorporating symptom fluctuation metrics from the field of ambulatory assessment into traumatic stress research. In B. Hruska (Chair), *Current research utilizing ambulatory assessment to investigate PTSD and associated correlates and impairments. Presented at: Symposium conducted at the 36th annual meeting of the international society for traumatic stress studies*. Virtual.

Hruska, B., & Barduhn, M. S. (2021). Dynamic psychosocial risk and protective factors associated with mental health in emergency medical service (EMS) personnel. *Journal of Affective Disorders*, *282*, 9–17. https://doi.org/10.1016/j.jad.2020.12.130

Hruska, B., Pacella, M. L., George, R. L., & Delahanty, D. L. (2017). The association between daily PTSD symptom severity and alcohol-related outcomes in recent traumatic injury victims. *Psychology of Addictive Behaviors*, *31*(3), 326–335. https://doi.org/10.1037/adb0000262

Huang, F. L. (2017). *Conducting multilevel confirmatory factor analysis using R* (Unpublished manuscript). http://faculty missouri edu/huangf/data/mcfa/MCFA% 20in% 20R% 20HUANG pdf

iluminivu. (2024). mEMA App. *ilumivu*. Retrieved December 19, 2024, from https://ilumivu.com/solutions/ecological-momentary-assessment-app/

Jebb, A. T., Tay, L., Wang, W., & Huang, Q. (2015). Time series analysis for psychological research: Examining and forecasting change. *Frontiers in Psychology*, 6. https://doi.org/10.3389/fpsyg.2015.00727

Kassam-Adams, N., & Olff, M. (2020). Embracing data preservation, sharing, and re-use in traumatic stress research. *European Journal of Psychotraumatology*, *11*(1), 1739885. https://doi.org/10.1080/20008198.2020.1739885

Kirtley, O., Gudrun, E., Kunkels, Y.K., Hiekkaranta, A.P., Van Heck, L., Pihlajamaki, M., Kunc, B., Schoefs, S., Vermaelen, N., & Myin-Germeys, I. (2018). *The experience sampling method (ESM) item repository*. https://doi.org/10.17605/OSF.IO/KG376

Kleim, B., Graham, B., Bryant, R. A., & Ehlers, A. (2013). Capturing intrusive re-experiencing in trauma survivors' daily lives using ecological momentary assessment. *Journal of Abnormal Psychology*, *122*(4), 998–1009. https://doi.org/10.1037/a0034957

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root : How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1-3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Lafit, G., Adolf, J. K., Dejonckheere, E., Myin-Germeys, I., Viechtbauer, W., & Ceulemans, E. (2021). Selection of the number of participants in intensive longitudinal studies: A user-friendly Shiny App and tutorial for performing power analysis in multilevel regression models that account for temporal dependencies. *Advances in Methods and Practices in Psychological Science*, *4*(1), 251524592097873. https://doi.org/10.1177/2515245920978738

Lane, A. R., Waters, A. J., & Black, A. C. (2019). Ecological momentary assessment studies of comorbid PTSD and alcohol use: A narrative review. *Addictive Behaviors Reports*, *10*, 100205. https://doi.org/10.1016/j.abrep.2019.100205

Lenferink, L. I. M., Van Eersel, J. H. W., & Franzen, M. (2022). Is it acceptable and feasible to measure prolonged grief disorder symptoms in daily life using experience sampling methodology? *Comprehensive Psychiatry*, *119*, 152351. https://doi.org/10.1016/j.comppsych.2022.152351

Little, R., & Rubin, D. (2019). *Statistical analysis with missing data, third edition* (1st ed.). Wiley. https://doi.org/10.1002/9781119482260.

Lorenz, P., Schindler, L., Steudte-Schmiedgen, S., Weidner, K., Kirschbaum, C., & Schellong, J. (2019). Ecological momentary assessment in posttraumatic stress disorder and coping. An eHealth study protocol. *European Journal of Psychotraumatology*, *10*(1), 1654064. https://doi.org/10.1080/20008198.2019.1654064

Losardo, D., Chow, S. M., Panter, A. T., Burkley, M., & Burkley, E. (2024). Ecological momentary assessment (EMA) designs with planned missingness. In M. Stemmler, W. Wiedermann, & F. L. Huang (Eds.), *Dependent data in social sciences research* (pp. 657–698). Springer International Publishing. https://doi.org/10.1007/978-3-031-56318-8_26

Martorana, M., Kuhn, T., Siebes, R., & Van Ossenbruggen, J. (2022). Aligning restricted access data with FAIR: A systematic review. *PeerJ Computer Science*, *8*, e1038. https://doi.org/10.7717/peerj-cs.1038

McLean, S. A., Ressler, K., Koenen, K. C., Neylan, T., Germine, L., Jovanovic, T., Clifford, G. D., Zeng, D., An, X., Linnstaedt, S., Beaudoin, F., House, S., Bollen, K. A., Musey, P., Hendry, P., Jones, C. W., Lewandowski, C., Swor, R., Datner, E., … Kessler, R. (2020). The AURORA Study: A longitudinal, multimodal library of brain biology and function after traumatic stress exposure. *Molecular Psychiatry*, *25*(2), 283–296. https://doi.org/10.1038/s41380-019-0581-3

Mitchell, R. J., Goggins, R., & Lystad, R. P. (2022). Synthesis of evidence on the use of ecological momentary assessments to monitor health outcomes after traumatic injury: Rapid systematic review. *BMC Medical Research Methodology*, *22*(1), 119. https://doi.org/10.1186/s12874-022-01586-w

Naragon-Gainey, K., Simpson, T. L., Moore, S. A., Varra, A. A., & Kaysen, D. L. (2012). The correspondence of daily and retrospective PTSD reports among female victims of sexual assault. *Psychological Assessment*, *24*(4), 1041–1047. https://doi.org/10.1037/a0028518

O'Brien, S. T., Dozo, N., Hinton, J. D. X., Moeck, E. K., Susanto, R., Jayaputera, G. T., Sinnott, R. O., Vu, D., Alvarez-Jimenez, M., Gleeson, J., & Koval, P. (2024, June 24). SEMA3: a free smartphone platform for daily life surveys. *Behavior Research Methods*, *56*(7), 7691–7706. https://doi.org/10.3758/s13428-024-02445-w

Pacella, M. L., Girard, J. M., Wright, A. G. C., Suffoletto, B., & Callaway, C. W. (2018). The association between daily posttraumatic stress symptoms and pain over the first 14 days after injury: An experience sampling study. *Academic Emergency Medicine*, *25*(8), 844–855. https://doi.org/10.1111/acem.13406

Pacella, M., Prabhu, A., Morley, J., Huang, S., & Suffoletto, B. (2018). Postconcussive symptoms over the first 14 days after mild traumatic brain injury: An experience sampling study. *Journal of Head Trauma Rehabilitation*, *33*(3), E31–E39. https://doi.org/10.1097/HTR.0000000000000335

Possemato, K., Maisto, S. A., Wade, M., Barrie, K., McKenzie, S., Lantinga, L. J., & Ouimette, P. (2015). Ecological momentary assessment of PTSD symptoms and alcohol use in combat veterans. *Psychology of Addictive Behaviors*, *29*(4), 894–905. https://doi.org/10.1037/adb0000129

Prakash, K., Kassam-Adams, N., Lenferink, L. I. M., & Greene, T. (2023). Data sharing and re-use in the traumatic stress field: An international survey of trauma researchers. *European Journal of Psychotraumatology*, *14*(2), 2254118. https://doi.org/10.1080/20008066.2023.2254118

Price, M., Legrand, A. C., Brier, Z. M. F., Gratton, J., & Skalka, C. (2020). The short-term dynamics of posttraumatic stress disorder symptoms during the acute posttrauma period. *Depression and Anxiety*, *37*(4), 313–320. https://doi.org/10.1002/da.22976

Price, M., Van Stolk-Cooke, K., Legrand, A. C., Brier, Z. M. F., Ward, H. L., Connor, J. P., Gratton, J., Freeman, K., & Skalka, C. (2018). Implementing assessments via mobile during the acute posttrauma period: Feasibility, acceptability and strategies to improve response rates. *European Journal of Psychotraumatology*, *9*(sup1), 1500822. https://doi.org/10.1080/20008198.2018.1500822

Ram, N., Brinberg, M., Pincus, A. L., & Conroy, D. E. (2017). The questionable ecological validity of ecological momentary assessment: Considerations for design and analysis. *Research in Human Development*, *14*(3), 253–270. https://doi.org/10.1080/15427609.2017.1340052

Rosi-Andersen, A., Meister, L., Graham, B., Brown, S., Bryant, R., Ehlers, A., & Kleim, B. (2022). Circadian influence on intrusive re-experiencing in trauma survivors' daily lives. *European Journal of Psychotraumatology*, *13*(1), 1899617. https://doi.org/10.1080/20008198.2021.1899617

Schenker, M. T., Theoswin, P. M., Qian, H., Jordan, A. S., Nicholas, C. L., & Felmingham, K. L. (2023). Sleep and day-to-day PTSD symptom variability: An ecological momentary assessment and actigraphy monitored study in trauma-exposed young adults. *European Journal of Psychotraumatology*, *14*(2), 2202058. https://doi.org/10.1080/20008066.2023.2202058

Schuler, K., Ruggero, C. J., Mahaffey, B., Gonzalez, A., L. Callahan, J., Boals, A., Waszczuk, M. A., Luft, B. J., & Kotov, R. (2021). When hindsight is not 20/20: Ecological momentary assessment of PTSD symptoms versus retrospective report. *Assessment*, *28*(1), 238–247. https://doi.org/10.1177/1073191119869826

Scopus. (2024). *Ecological momentary assessment and (Posttraumatic Stress Disorder or PTSD)* [Internet]. Retrieved September 10, 2024, from https://www.scopus.com/results/results.uri?sort=plf-f&src=s&st1=%22ecological+momentary+assessment%22+and+%28%22posttraumatic+stress+disorder%22+or+%22PTSD%22%29&sid=a8dcef1130e97dfb6921610eb244c082&sot=b&sdt=cl&sl=86&s=ALL%28%22ecological+momentary+assessment%22+and+%28%22posttraumatic+stress+disorder%22+or+%22PTSD%22%29%29&origin=resultslist&editSaveSearch=&yearFrom=Before+1960&yearTo=Present&sessionSearchId=a8dcef1130e97dfb6921610eb244c082&limit=10&cluster=scosubtype%2C%22ar%22%2Ct

Sheridan, R., Martin-Kerry, J., Hudson, J., Parker, A., Bower, P., & Knapp, P. (2020). Why do patients take part in research? An overview of systematic reviews of psychosocial barriers and facilitators. *Trials*, *21*(1), 259. https://doi.org/10.1186/s13063-020-4197-3

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Short, N. A., Boffa, J. W., Clancy, K., & Schmidt, N. B. (2018). Effects of emotion regulation strategy use in response to stressors on PTSD symptoms: An ecological momentary assessment study. *Journal of Affective Disorders*, *230*, 77–83. https://doi.org/10.1016/j.jad.2017.12.063

Shrout, P., & Lane, S. P. (2012). Psychometrics. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 302–320). Guilford Press.

Silvia, P. J., Kwapil, T. R., Walsh, M. A., & Myin-Germeys, I. (2014). Planned missing-data designs in experience-sampling research: Monte carlo simulations of efficient designs for assessing within-person constructs. *Behavior Research Methods*, *46*(1), 41–54. https://doi.org/10.3758/s13428-013-0353-y

Slavish, D. C., Briggs, M., Fentem, A., Messman, B. A., & Contractor, A. A. (2022). Bidirectional associations between daily PTSD symptoms and sleep disturbances: A systematic review. *Sleep Medicine Reviews*, *63*, 101623. https://doi.org/10.1016/j.smrv.2022.101623

Smyth, J. M., Jones, D. R., Wen, C. K. F., Materia, F. T., Schneider, S., & Stone, A. (2021). Influence of ecological momentary assessment study design features on reported willingness to participate and perceptions of potential research studies: An experimental study. *BMJ Open*, *11*(7), e049154. https://doi.org/10.1136/bmjopen-2021-049154

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Sage.

Soule, M. C., Beale, E. E., Suarez, L., Beach, S. R., Mastromauro, C. A., Celano, C. M., Moore, S. V., & Huffman, J. C. (2016). Understanding motivations to participate in an observational research study: Why do patients enroll? *Social Work in Health Care*, *55*(3), 231–246. https://doi.org/10.1080/00981389.2015.1114064

Stange, J. P., Kleiman, E. M., Mermelstein, R. J., & Trull, T. J. (2019). Using ambulatory assessment to measure dynamic risk processes in affective disorders. *Journal of Affective Disorders*, *259*, 325–336. https://doi.org/10.1016/j.jad.2019.08.060

Statistica. (2024). Mobile phone users worldwide 2015-2020. *Statista*. Retrieved July 16, 2024, from https://www.statista.com/statistics/274774/forecast-of-mobile-phone-users-worldwide/

Stone, A. A., Schneider, S., & Smyth, J. M. (2023). Evaluation of pressing issues in ecological momentary assessment. *Annual Review of Clinical Psychology*, *19*(1), 107–131. https://doi.org/10.1146/annurev-clinpsy-080921-083128

Stone, A. A., Schneider, S., Smyth, J. M., Junghaenel, D. U., Wen, C., Couper, M. P., & Goldstein, S. (2023). Shedding light on participant selection bias in Ecological Momentary Assessment (EMA) studies: Findings from an internet panel study. *PLoS One*, *18*(3), e0282591. https://doi.org/10.1371/journal.pone.0282591

Tate, A. D., Fertig, A. R., de Brito, J. N., Ellis, É. M., Carr, C. P., Trofholz, A., & Berge, J. M. (2024). Momentary factors and study characteristics associated with participant burden and protocol adherence: Ecological momentary assessment. *JMIR Formative Research*, *8*, e49512. https://doi.org/10.2196/49512

Teresi, J. A., Yu, X., Stewart, A. L., & Hays, R. D. (2022). Guidelines for designing and evaluating feasibility pilot studies. *Medical Care*, *60*(1), 95–103. https://doi.org/10.1097/MLR.0000000000001664

Trull, T. J., & Ebner-Priemer, U. W. (2020). Ambulatory assessment in psychopathology research: A review of recommended reporting guidelines and current practices. *Journal of Abnormal Psychology*, *129*(1), 56–63. https://doi.org/10.1037/abn0000473

Vachon, H., Viechtbauer, W., Rintala, A., & Myin-Germeys, I. (2019). Compliance and retention with the experience sampling method over the continuum of severe mental disorders: Meta-analysis and recommendations. *Journal of Medical Internet Research*, *21*(12), e14475. https://doi.org/10.2196/14475

Waterman, E. A., Edwards, K. M., Dardis, C. M., Kelley, E. L., & Sessarego, S. (2021). Assessing intimate partner violence via daily diary surveys: Feasibility, reporting, and acceptability. *Journal of Interpersonal Violence*, *36*(19-20), 9121–9142. https://doi.org/10.1177/0886260519865964

Wrzus, C., & Neubauer, A. B. (2023). Ecological momentary assessment: A meta-analysis on designs, samples, and compliance across research fields. *Assessment*, *30*(3), 825–846. https://doi.org/10.1177/10731911211067538