**Better together: A systematic review of studies combining Magnetic Resonance Imaging
with Ecological Momentary Assessment**

**Reuma Gadassi Polack¹, Gabriela Paganini¹, Julia Winschel¹, Hadas Benisty¹, Jutta
Joormann¹, Hedy Kober¹, & Gal Mishne²**

¹Yale University

²University of California, San Diego

Abstract

Magnetic resonance imaging (MRI) and Ecological Momentary Assessment (EMA) are two powerful methods to study psychological processes that have become increasingly popular in the last two decades. Though each method is valuable in its own right, their complementary strengths have the potential to further advance our understanding of typical and atypical human behavior. Despite the increase in the number of studies that combine these methods over the last decade, there are no existing recommendations for best practices or norms for conducting and reporting the findings from these types of studies. To address the absence of such standards in the field, we conducted a systematic review of papers that combine these methods. A systematic search of peer-reviewed papers using Google Scholar resulted in a pool of 11,558 articles. Inclusion criteria were 1) data-based study in which 2) participants completed (a) Structural or functional MRI and (b) an EMA protocol that included self-report. Seventy-one papers met inclusion criteria. The following review compares these studies based on several key parameters (e.g., population age and type, type of MRI scans and EMA assessments, sample size) with the aim of determining feasibility and current standards for design and reporting in the field. The

review concludes with recommendations for future research guidelines. A special focus is given to the ways in which the two methods are combined on an analytical level and suggestions for novel computational methods that could further advance the field.

Keywords: Magnetic Resonance Imaging, Experience Sampling Methods, Ecological Momentary Assessment, Daily-Diaries, Ambulatory Assessment

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Understanding the human experience and behavior is a challenging task. Self-report questionnaires can be used to probe subjective experience or behavioral intentions. However, such data may be incomplete, as mental processes may be inaccessible to conscious awareness or biased. Even when information is accessible, it is not always shared accurately (e.g., due to social desirability). To circumvent these challenges, researchers have often turned to other – objective – measures, such as physiological assessments (e.g., heart-rate variability), hormonal assessments (e.g., cortisol), and neuroimaging (e.g., functional magnetic resonance imaging [fMRI]). However, translating the results from such objective into meaningful conclusions about subjective experience is not straightforward. Conducting a multimethod (or multimodal) study is one obvious solution for addressing this translational challenge. The current review focuses on studies that combine two powerful methods for measurement of subjective behavior and objective assessment of mental processes: Ecological Momentary Assessment (EMA) and structural and functional Magnetic Resonance Imaging (for brevity sake, we use MRI for both).

MRI: Tapping into mental processes at the source. Using MRI, we can learn whether different tasks engage common or distinct mental processes, we can pinpoint specialized mechanisms that underlie particular mental processes, and we can learn how different stimuli are represented in the mind (e.g., Bassett et al., 2020; Brooks et al., 2017; Matejko & Ansari, 2018; Mather et al., 2013; Schurz et al., 2021; Zilverstand et al., 2017). Of course, MRI has several limitations (e.g., Elliott et al., 2020; Hall et al., 2016; Logothetis, 2008; Mather et al., 2013; Poldrack, 2011; Shamay-Tsoory & Mendehlsion, 2019). Of relevance to the current review, a major limitation of MRI is ecological validity. The measurement of neural activation when

individuals are mostly passive, practically immobile, and socially deprived is highly problematic (Shamay-Tsoory & Mendehelson, 2019). A related limitation is the fact that MRI scans are conducted typically once in a highly-controlled environments, which is at odds with our knowledge that human behavior is highly situation-dependent (Mischel & Shoda, 1995). These challenges limit the external validity and clinical utility of data collected with MRI.

EMA: Capturing dynamic processes in everyday life. EMA involves repeated assessments of what naturally occurs in participants' everyday lives, typically by having them complete brief self-report assessments between one to several times a day over several days or weeks. As such, EMA is highly ecologically valid (Bolger & Laurenceau, 2013). EMA is highly feasible in diverse populations and has unique scientific contribution (e.g., Russell & Gajos, 2020; Strange et al., 2019). While discussing every advantage and disadvantage of EMA is beyond the scope of this review, we will note a few strengths that make it such a good counterpart to MRI. First, EMA allows us to study state and trait characteristics— i.e. we can simultaneously examine between-individual and within-individual processes, thus learning not only *who* experiences certain behaviors, but also *when* behaviors are experienced. Teasing apart state and trait and examining their interactions is crucial to psychological research in general (Mischel & Shoda, 1995), and of particular importance in the context of clinical populations as this method can help us understand not only who is at risk but also when risk is more acute (Strange et al., 2019).

Second, although based on self-report, EMA can be utilized to assess psychological processes in an indirect way. For example, instead of asking individuals under which circumstances they do or feel certain things (e.g., harm themselves), EMA can infer the antecedence and consequence of behaviors by assessing what happened before and after the

target behavior (e.g., Snir et al., 2015). Third, EMA can capture the dynamic aspects of variables – the pattern of change over time (e.g., emotional instability; Strange et al., 2019).

Along with its advantages, EMA has some limitations. First, it is essentially observational; therefore, the results from EMA cannot be used to infer causality. However, statistical methods can help to determine directionality and reduce third-variable explanations (Bolger & Laurenceau, 2013). Second, EMA is based on self-report, though the frequent assessments reduce memory biases, and repeated measurements reduce noise (Russ & Gajos, 2020). Finally, its high ecological validity comes hand-in-hand with noise. Individuals are not exposed to the same events, thus many alternative explanations are possible. Statistical methods such as mean-centering help to alleviate some of these noise issues, but they do not correct them completely (Strange et al., 2019).

Better together: How MRI and EMA complement one another. MRI and EMA are a good combination as they address each other's limitations (Berkman et al., 2013; Wilson et al., 2014). MRI (brain structure or the BOLD signal) are objective measures, thus balancing the fact that EMA is reliant on subjective self-report. fMRI (similar to any task-based method) typically relies on standardized stimuli which increases internal reliability – thus complementing the unstandardized, idiosyncratic occurrences captured by EMA. Supplementing EMA to MRI can help examine brain-behavior links and translate MRI findings to everyday life. The two methods also complement each-other's time scale: fMRI captures online-real time processes that occur over seconds or minutes – EMA captures processes that occur over hours and days.

The present study

The goal of the current systematic review is twofold. First, we aim to describe the current state of research combining MRI and EMA. We do so by examining the logistics of the studies

(e.g., design, number of measurements etc.), as well as a description of more essential topics (e.g., which constructs are assessed via each method). Second, we make several recommendations in an attempt to provide future research teams with explicit guidelines and questions to consider when planning this type of study.

Method

We carried out a systematic review following the recommendations of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Liberatti et al., 2009).

Study selection criteria. Studies were eligible for inclusion if they met the following criteria: Participants' data included (1) structural or functional MRI scan and (2) EMA. Our definition of EMA included repeated assessments at least once a day for at least three consecutive days. Studies in which EMA and MRI were completed by different sets of participants were excluded; (3) EMA protocol had to include a self-report component. Studies including only passive sensing (e.g., GPS) were excluded, as we were interested in the measurement of subjective experience (see Camacho et al., [2021] for a review of studies combining MRI with passive sensing); (4) Participants were neurologically intact; studies on populations with neurological conditions (e.g., stroke) were excluded; (5) papers were written in English; and were (6) published in peer-reviewed journals.

Search strategy, study selection and data extraction. We searched scholar.google.com using the following search string: (EMA OR ESM OR "ecological momentary assessment" OR "experience sampling method") AND (fMRI OR neuroimag* OR "functional MRI" OR "functional magnetic resonance imaging"). Since Google Scholar presents a maximum of 1,000 results per search, we searched by year for the years 1996-2020 (including). Search results from

each year were downloaded into CSV files and inspected manually. The search was completed by May 2019 and updated (including forward and backward searches) in June 2021. Figure 1 presents the PRISMA flow diagram for study selection and exclusion process. Table S1 includes full-text articles excluded with reasons. Articles were coded according to joint characteristics (e.g., sample size, number of MRI scans) by two coders (one of them was the first author), and discrepancies were resolved by discussion. Table S2 in supplementary materials includes the full list of papers and characteristics that were coded.

Results

Seventy-one published papers were included in this systematic review, summarized in Table 1. As can be seen in Figure 2, the majority of papers (40 papers; 56%) were published in the last four years, indicating a trend of increased use of this specific multimethod design.

1. Practical issues

1.1. Participants

Sample size varied between studies, with an average number of 50.94 participants ($SD=37.02$, $Median=45$, $range=16-294$). Retention rate could be computed for studies that provided the initial number of participants (47 studies, 66.20%). Retention rates were high ($M=0.75$, $SD=0.17$, $Median=0.83$, $range=0.33-0.94$). Sample size justification was not provided for most of the studies ($N=60$; 84.5%). Of those that justified sample size, six papers justified sample size by what is within standards from previous literature. Five studies (7%) conducted a power analysis. None of the papers reported the amount of time it took to recruit the samples.

One thing that may influence retention is participant compensation. Of the 71 papers included in this review, half ($N=36$, 51.70%) provided information regarding participant compensation. Of those, 25 (35.21%) only stated that participants were compensated without

reporting the amount. Eleven papers (15.49%) reported the maximum total payment that participants could receive for their participation. For these papers, the average maximum amount of payment was \$140.69 (range= \$46 - \$400). In seven papers the maximum payment available was contingent upon compliance to the EMA protocol. Finally, three papers offered participants alternative means of compensation in addition to monetary reward: experimental hours for study plans (Martin-Soelch et al. 2020), referral information for local psychological services (Kaiser et al. 2019), or course credit (Chester & DeWall 2014).

1.2. Measurement

1.2.1. MRI. Participants typically completed one MRI scanning session (N=66 papers; 93%). Five papers (7%) asked participants to be scanned twice. Most of the papers included a task-based fMRI (N=60; 85%), seven papers (10%) had participants complete resting-state fMRI, three papers (4%) used structural MRI or diffusion tensor imaging, and one paper (1%) used structural, resting state, and task-based fMRI scans.

1.2.2. EMA. On average, participants completed a 13.24 days-long EMA protocol ($SD=12.78$, $Median=14$, $range$ 4-105) with a mean of 4.62 daily assessments ($SD=4.18$, $Median=3$, $range$ 1-25), generating an average total of 46.82 separate assessments per paper ($SD=42.95$, $Median=28$, $range$ 5-250)¹.

1.3. Publication Impact

To assess the quality of publications based on MRI-EMA we retrieved journal impact factors for the year 2020 from Journal Citation Reports for each publication outlet. The average impact factor of the journals was high ($Mean=6.09$, $SD=4.46$, $Median=4.88$, $range$: 2.08-24.88).

¹ Numbers reported here are the maximum number of assessments required from the participants, unless that was not provided (e.g., in event-contingent design), and the average number of assessments completed by participants was reported.

Another metric when considering the impact of a publication is examining how well-cited it is. To assess that, we extracted from scholar.google.com the number of times each paper was cited. Since the number of years that have passed since publication greatly influences number of citations ($r[71]=.748, p<.0001$), we computed the number of citations per year. Across the 71 papers included in the review, the average number of citations per year was 9.40 ($SD=9.46$, $Median=6.25$, $range\ 0-45.4$).

1.4. Number of authors & research groups

Combining methods requires a research team with expertise in both methods. The average number of authors of the papers in this review was 6.23 ($SD=2.94$, $Median=6$, $range\ 2-14$). Not all studies reported if they originated from the same datasets; however, by extracting the location of the study from the university who gave the IRB approval, we were able to assess, as can be seen in Figure 3, that the 71 papers included in the review originated from 30 universities and medical centers. Many studies originated at the University of Pittsburgh ($N=12$, 16.90%) and UCLA ($N=11$, 15.49%). Based on this information, we can say with some certainty that 21 papers (30%) were the single publication from their datasets.

2. Thematic issues

2.1. Population

As can be seen in Table 1, the populations studied using the MRI-EMA combination are diverse: the age range of participants spanned from 8 years to 69 years, with 27 papers (38.0%) including participants younger than 18 years. Thirty-three papers (46.48%) focused on populations that was either diagnosed with current or at risk for a psychiatric disorder, or with a psychopathology-related traits (e.g., chronic dieters). In other words, most of the studies included

in the review (N=51, 72%) focused on clinical and/or developmental populations or romantic couples, and only 28% of papers focused on populations considered as easily recruited.

2.2. Psychological constructs

EMA constructs. Using EMA, the most frequently assessed construct was daily affect/stress (N=51, 71.8%), followed by social interactions (N=26; 36.6%). Two additional frequent themes were self-regulation/craving/consumption of substances (including alcohol, cigarettes, and food; N=14; 19.7%), and psychopathology symptoms (N=11; 16%). Additional constructs were sleep quality (N=5; 7%), reward processing (N=4; 6%), and self-esteem (N=3; 4%). Most EMA protocols assessed more than one construct.

MRI constructs. Using task-based fMRI, the constructs most commonly assessed were social (N=21, 30%) and emotional (N=16, 22%), followed by inhibition/self-regulation in response to stimuli (either non-emotional or of appetizing stimuli such as alcohol; N=14, 20%), reward processing² (N=13, 18%), and risk taking (N=3, 4%).

3. Combining MRI and EMA

When conducting a multimethod study, the research team must make decisions regarding three topics: (1) the order that participants will complete measurements, (2) will the different methods assess the same constructs, and (3) analytical techniques used to analyze the data from two different sources.

3.1. Design considerations: Order of measurement

We identified four research designs: (a) *MRI first, followed by EMA*. This order was used by 33 of the papers (46%), with one of the papers reporting a subtype in which this order was repeated twice – once prior to and once following an intervention (Chen et al., 2018). (b) *EMA*

² Social reward task counted under social as well as under reward processing

first, followed by MRI. This sequence was used by 24 of the papers (34%). (c) *MRI scans during EMA period.* In four studies (6%) participants completed a baseline period of EMA to assess mean stress levels and were invited for two MRI scans within the EMA period – one scan on a day when they experienced lower than their baseline level of stress, and a second scan on a day when they experienced higher than their typical level of stress (e.g., Uy & Galván, 2017a). The four papers originated from the same research group and may have resulted from the same dataset. (d) In five papers (7%) participants completed the two methods in varying orders. One of them (Grosse Rueschkamp et al., 2019) counterbalanced the order of the MRI and EMA so that about half of the participants completed the EMA first, and the other half completed the MRI first. Finally, five papers (7%) did not report any information regarding the order in which participants completed the methods.

In addition to deciding the order that participants will complete EMA and MRI, research teams must also establish the time gap between the two methods. Most studies reported no time gap i.e., (EMA was started the day of the scan) or minimal times lag (e.g., EMA was completed within days or weeks of the scan). A large minority of the papers (N=24; 34%) did not provide any information on the time gap between methods.

3.2. Similarities in measured constructs

Another issue that when planning a multimethod study is whether the same construct was measured using the two methods. Constructs were similar in both methods in 86% of the papers that used fMRI to assess inhibition/craving, 87.5% of the papers that used fMRI to assess emotion processing/regulation, 71.4% of the studies that used fMRI to assess social constructs, 31% of the studies that used fMRI to assess reward processing, and none of the studies that used fMRI to assess risk-taking.

3.3. Increasing the ecological validity of fMRI tasks

Several research teams made explicit efforts to bring “real life” into the scanner. This trend of increasing the ecological validity of the fMRI has become increasingly popular in recent years (e.g., in our review, since 2018).

3.3.1. Using individualized stimuli. One option for bringing “real life” into the scanner is using familiar people as stimuli, thus allowing researchers to assess participants’ neural responses to meaningful, personalized stimuli in addition to the EMA. Five papers adopted this strategy (Alcaron et al., 2020; Dodell-Feder et al., 2016; Hooker et al., 2010; Vekaria et al., 2020; Woods et al., 2020). For example, Hooker et al., (2010) focused on committed couples and examined how each partner reacted to the other’s emotional facial expressions.

3.3.2. Bringing the social context into the lab. Another option for bringing “real life” into the scanner is scanning participants’ close others. Four papers included in the current review (6%) adopted this strategy. Two of these papers focused on committed couples (Dodell-Feder et al., 2016; Hooker et al., 2010), and two (Lee et al., 2017a, 2017b) focused on parent-child dyads. All four studies had dyad members complete the EMA simultaneously, allowing the researchers to track interpersonal effects of neural responses.

3.4. Analytic methods

In this section we characterize how papers combined the two methods analytically. It should be noted that the vast majority (N=68, 95.77%) of the papers included in the review reported statistically significant associations between the two methods, suggesting the value of combining the methods for gaining understanding of certain behavioral processes.

3.4.1. Brain-EMA correlations: Averaging over time. The simplest way of combining EMA data with MRI data was averaging across the EMA period and computing a correlation

between the EMA variable and activation in a Region of Interest (ROI). For example, Forbes et al. (2009) examined the associations between mean positive affect across the EMA period and activation in striatal clusters in response to reward. For 16 of the papers in this review (22%), this was the only strategy used to analytically combine methods. Eight papers used it as a secondary strategy.

3.4.1.1. Brain activity as a mediator. A subtype of the studies that compute averages from across the diary period used brain activation as a mediator (i.e., a variable that accounts for the association between two other variables; Hayes, 2017). Specifically, these papers examined neural activation as a mediator between the averaged EMA variable and an additional variable. For example, Price et al. (2016) examined if amygdala-dlPFC connectivity mediated the relationship between attentional vigilance during a task and distraction during the EMA. Four papers in the review (6%) used this analytic strategy.

3.4.2. Dynamic average. Whereas a simple average is an aggregate of mean levels, EMA can be used to capture changes over time, or the dynamic aspects of processes which are difficult to capture otherwise (Strange et al., 2019). Twenty-one papers (30%) combined MRI and EMA by extracting these types of variables from the EMA. The largest fraction of these papers used EMA to assess constructs related to emotional dynamics (e.g., affective instability; Servaas et al 2017 & Provenzano et al 2018). Other variables computed using this strategy were changes in sleep quality from weekdays to weekend (Hasler et al., 2012), the chronicity of peer conflict (Telzer et al., 2015), the proportion of food desire enactment (Lopez et al., 2017), and the proportion of helping familiar vs. unfamiliar people (Vekaria et al., 2020). Another analytic options we include in this category is instances in which researchers extracted the correlations

between two variables, such as social distress and social disconnection (Eisenberger, Gable et al., 2007), and then examined if these associations were related to averaged neural activation.

3.4.3. Brain as a moderator of momentary processes. The most common method for analytically combining the methods was examining if neural activation moderates the associations between momentary variables, thus examining Person (or brain region) by Situation interaction. A moderating variable is a variable that influences the strength of the association between two other variables (Hayes, 2017). For example, Hooker et al. (2010) examined if neural activation while watching a romantic partner's negative (vs. positive) emotional expressions moderated the associations between daily interpersonal conflict and mood. Of the papers included in this review, 22 (31%) used this analytic strategy.

3.4.4. EMA moderates neural processes. Five papers (7%) analyzed EMA as a moderator of neural responses. One study (Bourne et al., 2013) had participants watch clips of potentially traumatic videos during fMRI, and then complete an EMA entry every time they experienced a flashback from a video they watched during the fMRI. The fMRI contrast compared videos that were classified as flashback-provoking were contrasted with videos that were not. The other four papers in this category had participants complete MRI scans on days when participants experienced stress levels that were higher or lower than their individually calculated averages as determined by the EMA (Rahdar & Galván, 2014; Uy & Galván, 2017a,b, 2020).

3.4.5. Dimension reduction across methods. One study (Giuliani et al., 2015) combined assessments from both methodologies using a factor analysis, thus proposing a type of multi-modal "dimension reduction". This study examined reactivity and regulation of food craving, and measured these constructs using self-report, EMA, and fMRI. Assessments from

each method were extracted and entered into a principal component analysis. Then, results from the factor analysis were entered into a regression analysis to predict food consumption.

Discussion

The current systematic review provides an organized account of common research practices and reporting standards for papers combining MRI and EMA. Below we describe what such studies typically include, limitations and recommendations for future research, and a special section about future analytical directions.

1. Current practices: What do MRI-EMA studies typically look like?

1.1. Who are the participants? The current review demonstrates that the combination of MRI and EMA is feasible and worthwhile even for populations that are difficult to recruit (developmental and psychiatric populations).

1.2. What are the main constructs? The constructs assessed most frequently were emotions and social interactions. Surprisingly, there was not always an overlap in constructs assessed using the two methods. Assessing the same construct in both methods allows for replication and can contribute to construct and convergent validity. Moreover, from a multimodal perspective, using different methods to capture similar processes allows us, assuming that the process is shared, to find meaningful shared variance across modalities. A related point is that while MRI typically assessed a single psychological construct, the EMA typically examined multiple constructs. The relative ease of assessing additional constructs via EMA can be leveraged in future studies to determine the convergent and divergent validity of MRI by examining which constructs can be predicted by neural activation and which ones cannot.

1.3. Methodological choices. Across studies, there was variation in the order in which the methods were used, with a slight preference to conducting the MRI first. Although temporal

precedence is not sufficient to deduce causality, it provides evidence of directionality from brain activation to behavior and predictive validity for neural structure or activation. Only one study counter-balanced the order of method - this variation is important as it helps rule out (or mitigate) order effects of the methods.

1.4. Analytical choices. Many of the studies used neural activation as a moderator of daily processes, thus adopting a Person by Situation examination of processes. In contrast, several studies extracted variables from the EMA that capture the dynamic nature of psychological processes (e.g., emotion instability). Still, many other studies extracted an average across the EMA period and correlated it with averaged neural activation. Interestingly, two studies used processes assessed by EMA to determine the timing of MRI scans (Rahdar & Galván, 2014; Uy & Galván, 2017a) or to determine how MRI contrasts were computed (Bourne et al., 2013). Only one paper attempted to converge data across methods (Giuliani et al., 2015) using a multivariate approach. Almost all of the papers reported at least one significant finding. Significant associations between levels of analysis are not trivial, considering that the method of assessment often impacts results (e.g., Avinun & Knafo, 2014) and that coherence across levels can be weak (e.g., Mauss & Robinson, 2009).

2. Reporting limitations & recommendations. Multimethod studies are incredibly complex; understandably, not all the details are always reported. However, in many of the papers, specific information regarding study design was missing (e.g., time required to recruit sample, number of publications from the same dataset). This information could be helpful for researchers planning to conduct similar studies. Additionally, some of the details that are commonly unreported may impact interpretation of the results; for example, not all studies report

the time gap between the methods. A possible solution for this issue could be inclusion of a detailed study protocol in an online platform (e.g., OSF).

A second common limitation across the papers we reviewed is that sample sizes were rarely justified, and the use of a-priori power analyses was even rarer. The inclusion of power analyses is necessary for the field to advance. Relatedly, pre-registration of research hypotheses was not reported in any of the included studies. This is a notable issue because both MRI and EMA produce rich datasets, especially when combined. This issue, together with the typically-limited sample sizes in studies of this kind, raises questions regarding the robustness and reproducibility of the effects found in these studies.

3. **Analytic future directions.** From a data-analysis perspective EMA and MRI consist of hundreds of features, i.e., they are high-dimensional data sets. The richness of the dataset may also raise concerns about the robustness of the findings. Therefore, we believe that in addition to pre-registered, hypotheses-driven analysis, researchers should consider multimodal, data-driven methods. Data driven approaches include (but are not limited to) multimodal modeling and analyses, pattern recognition and machine learning. We present here several recommendations for analysis approaches that can combine EMA and MRI and help uncover patterns that emerge from the integration of these two modalities. Computational data-driven methods can be divided into two categories: a) *Supervised methods* aiming to train parametric models based on a-priori knowledge and/or external labels values. b) *Unsupervised methods* which are data-driven approaches for extracting alternative parsimonious representations for the data, thus simplifying further analysis and enabling meaningful visualization.

Supervised methods can be extremely efficient and easy to implement for establishing a statistical relation between EMA and MRI data and other external features such as clinical diagnosis, age, gender, etc. When training a supervised model (for example prediction, classification or regression; James et al., 2013) one modality can take the part of the input variable (i.e., independent variable) used to predict a feature taken from the other modality taking the part of the outcome variable. For example, EMA features can be used to predict whether a specific brain region is activated or not, or if two brain regions are highly connected or not. This can be done, for example, in a diagnosed group vs. a healthy control group to demonstrate statistical relations between EMA and brain activity in different populations.

The large number of features in EMA and MRI studies presents a great challenge – deciding which features are important. Feature selection, which is part of the supervised methods, provides a way of making that decision (Park & Casella, 2008; Kohavi & John, 1997; Zou & Hastie, 2005; Yamada et al, 2020). These methods are based on training an optimization model (for example classification or regression) while restricting the number of features used. Feature selection methods provide two major advantages: i) *Model interpretability*: a consistent quantification of the importance of each input feature with respect to the trained task. ii) *Regularization*: in many cases the number of features is large relatively to the sample size, which may cause overfitting (i.e., the trained model is unable to generalize and describe unseen data). Feature selection would help reduce overfitting.

Unsupervised methods are also used to extract a low dimensional representation capturing the major trends and patterns of each modality can be useful as a pre-processing stage, but without an external variable guiding the dimension-reduction. The most straightforward approach is to use dimensionality reduction methods such as Principal Component Analysis

(PCA) or kernel-based methods (Belkin & Niyogi, 2003, Coifman & Lafon, 2006). The extracted representations can facilitate easier visualization of the data sets, as well as training and implementation of pattern recognition and clustering algorithms such as k-means or Gaussian Mixture Models (GMM) used for establishing a statistical relation between the detected patterns across participants between the two modalities.

A more advanced approach is to use multiview (also called multimodal) analysis such as Canonical Component Analysis (CCA) (Hardoon et al., 2004). The multiview paradigm requires a joint dimension, such as participants, that are “observed” through different “views” (or modalities), e.g., EMA and MRI. Each view yields different features and multiview analysis reveals information that is shared by the two views. As a specific example, the aim of CCA is to calculate a linear transformation of the features from each modality to a low-dimensional joint space such that the correlation, across participants, between the new (low dimensional) representations is maximized. CCA also provides an interpretable transformation indicating which features of each modality are most correlated with the joint space (i.e. with the global pattern detected by the CCA). Non-linear variates of CCA such as kernel CCA (Schölkopf et al., 1998; Michaeli et al., 2016; Lindenbaum et al., 2020), may provide better modeling when linear approaches fail to capture the intrinsic relations between the two modalities; however, they are not able to provide the same interpretability capabilities provided by linear approaches. Both linear and non-linear unsupervised methods for dimensionality reduction allow us to visualize the data and measure statistics such as clustering or prediction or regression of an external variable, such as age or clinical group membership.

Summary. The current review describes common research practices, advantages, and limitations of studies that combine MRI and EMA. We demonstrate how the distinct strengths

and weaknesses of each method uniquely complement one another and help to generate particularly impactful, clinically relevant research. Specifically, this combination increases the clinical utility and ecological and predictive validities (and potentially the convergent and divergent validities) of MRI studies. Though the combination of these methods is demanding, both for research teams and study participants, this review demonstrates the practicality of conducting such studies on diverse developmental and clinical populations.

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Table 1

Summary of 71 Studies that Combine MRI/fMRI and EMA, 2007-2020, in chronological order by year of publication.

Study ^a	Authors ^b	Citations per Year ^c	IF ^d	Study population ^e	Sample Size ^f	Compensation ^g	EMA assessments (Prompts/Days) ^h	EMA constructs	MRI constructs	Method order
Eisenberger et al. (2007)	3	11.93	4.329	Non-clinical; adults, age=20.7 ⁱ	30	-	80/10	Social interactions, affect	Social	EMA before MRI
Eisenberger et al. (2007)	5	36.64	6.556	Non-clinical; adults, age=18-36	30	60	80/10	Social interactions, affect	Social	EMA before MRI
Forbes et al. (2009)	11	45.42	18.112	Clinical depression; adolescents, age=8-17	43	75	12/4	Social interactions, affect	Reward processing	EMA before MRI
Holm et al. (2009)	6	12.42	5.012	Non-clinical; adolescents, age=11-13	58	-	NA/4 ^m	Sleep	Reward processing	Varied
Forbes et al. (2010)	9	28.09	8.829	Non-clinical; adolescents, age=11-13	77	-	12/4	Social interactions, affect	Reward processing	Varied
Hooker et al. (2010)	5	5.55	13.382	Non-clinical; adults in committed relationships; age=21 ⁱ	27	-	21/21	Social interactions, affect, substance use	Social	-
Berkman et al. (2011)	3	20.30	7.029	Heavy cigarette smokers; adults, age=28-69	27	248	168/21	Affect, substance use, craving	Regulation/inhibition	MRI before EMA
Forbes et al. (2011)	4	12.30	2.253	Non-clinical; adolescents, age=11-13	76	-	12/4	Affect	Emotion processing	Varied
Habets et al. (2012)	11	5.33	7.723	Psychotic disorders; adolescents and adults, age=16-55	89	-	60/6	Social interactions, affect	Structural/DTI	EMA before MRI
Hasler et al. (2012)	8	12.56	13.382	Non-clinical; adolescents, age=11-13	56	-	12/4	Affect	Reward processing	Varied
Masten et al. (2012)	5	20.56	3.436	Non-clinical; adolescents, mean age=17.77	21	N.A.	14/14	Social interactions	Social	EMA before MRI
Rameson et al. (2012)	3	31.56	3.225	Non-clinical; adults, age=19 ⁱ	32	-	14/14	Social interactions	Social	EMA before MRI
Bourne et al. (2013)	3	14.88	7.723	Non-clinical; adults, age=22 ⁱ	22	-	6.82/7	Psychopathology symptoms	Emotion processing	MRI before EMA

Collip et al. (2013)	8	6.25	7.723	Psychotic disorders; adolescents and adults, age=16-55	89	-	60/6	Social interactions, affect	Structural/DTI	EMA before MRI
Winkleman et al. (2013)	9	13.13	5.849	Primary insomnia; adults, age=18-60	76	N.A.	14/14	Sleep	Structural/DTI	EMA before MRI
Chester & DeWall (2014)	2	5.00	6.556	Non-clinical; adults; mean age=18.92 ⁱ	37	N.A., course credit	7/7	Social interactions, affect, substance use, self-regulation	Social, regulation/inhibition	EMA before MRI
Dodell-Feder et al. (2014)	3	4.86	3.436	At-risk for schizophrenia; adolescents and adults, age=15-32	32	N.A.	28/28	Social interactions, affect	Social	MRI before EMA
Hooker et al. (2014)	6	7.14	6.673	Non-clinical; adults, age=19-52	30	-	21/21	Affect, psychopathology symptoms	Social	MRI before EMA
Kashdan et al. (2014)	8	6.57	3.240	Non-clinical; adults, age=20.9 ⁱ	25	-	21/21	Social interactions, affect, self-esteem	Social	EMA before MRI
Lopez et al. (2014)	5	22.29	7.029	Non-clinical; adults, age=18-28	28	-	49/7	Craving	Regulation/inhibition	MRI before EMA
Morelli et al. (2014)	3	40.86	3.436	Non-clinical; adults, age=19.9 ⁱ	32	-	14/14	Social interactions	Social	MRI before EMA
Olino et al. (2014)	10	16.14	6.464	At-risk for depression; children and adolescents, age=8-17	26	-	12/4	Affect	Reward processing	-
Rahdar & Galvan (2014)	2	9.00	6.556	Non-clinical; adolescents and adults, age=15-30	45	-	42/14	Affect	Regulation/inhibition	MRIs during EMA period
Tully et al. (2014)	3	5.29	4.881	Schizophrenia; adults, age=18-65	47	N.A.	21/21	Affect, psychopathology symptoms	Emotion processing	MRI before EMA
Giuliani et al. (2015)	4	1.17	4.312	Non-clinical (food restriction intervention) ^j ; adults, age=18-30	46	50	56/14	Craving	Regulation/inhibition	MRI before EMA
Heller et al. (2015)	6	7.83	6.167	Non-clinical; adults, age=18-24	40	N.A.	250/10	Affect, reward processing	Reward processing	EMA before MRI

Telzer et al. (2015)	5	21.83	3.436	Non-clinical; adolescents, age=14-17	46	N.A.	28/28	Social interactions	Risk-taking	EMA before MRI
Dodell-Feder et al. (2016)	4	2.80	3.436	Non-clinical; adults in committed relationships, age=18-35	22	N.A.	21/21	Social interactions, affect, self-esteem	Social	MRI before EMA
Lopez et al. (2016)	4	7.80	3.868	Non-clinical (chronic dieters) ^j ; adults, age=18-23	69	-	49/7	Craving	Regulation/inhibition	MRI before EMA
Powers et al. (2016)	3	6.20	3.436	Non-clinical; adults, age=18-21	33	N.A.	49/7	Social interactions	Social, emotion processing	MRI before EMA
Price et al. (2016)	8	7.60	6.464	Clinical anxiety; children and adolescents, age=9-14	78	-	14/5	Affect, psychopathology symptoms	Emotion processing	MRI before EMA
Fischer et al. (2017)	9	8.50	4.791	Bulimia nervosa and EDNOS; adults, age=18-40	16	N.A.	98/14	Affect, craving, psychopathology symptoms	Regulation/inhibition	MRI before EMA
Lee et al. (2017)	3	1.00	6.464	Non-clinical; adolescents and caregivers, age=13-57	53	-	14/14	Sleep	Resting state	-
Lee et al. (2017)	3	10.25	6.556	Non-clinical; adolescents and caregivers, age=13-57	53	-	14/14	Affect	Resting state	MRI before EMA
Lopez et al. (2017)	6	8.75	3.436	Non-clinical (chronic dieters) ^j ; adults, age=18-23	69	-	49/7	Craving	Regulation/inhibition	MRI before EMA
Pace-Schott et al. (2017)	6	7.00	2.376	Primary insomnia; adults, age=mid-30s ⁱ	26	-	14/14	Sleep	Resting state	EMA before MRI
Servaas et al. (2017)	14	5.00	7.853	Remitted clinical depression; adults, age=mid-50s ⁱ	69	-	60/6	Social interactions, affect, self-esteem	Resting state	EMA before MRI
Uy & Galvan (2017)	2	5.50	6.556	Non-clinical; adolescents and adults, age=15-30	45	N.A.	42/14	Affect	Risk-taking	MRIs during EMA period
Uy & Galvan (2017)	2	5.50	3.139	Non-clinical; adolescents and adults, age=15-30	44	N.A.	42/14	Affect	Risk-taking	MRIs during EMA period
Waugh et al. (2017)	6	4.00	3.436	Non-clinical; adults, age=21-65	29	60	7/7	Affect	Social	MRI before EMA
Wonderlich et al. (2017)	6	5.50	3.868	Bulimia nervosa; adults, age=18-40	16	350	98/14	Affect, craving, psychopathology symptoms	Regulation/inhibition	MRI before EMA

Bastiaansen et al. (2018)	6	1.00	3.240	Non-clinical ^k ; adults, age=18-25	69	N.A.	70/14	Affect	Emotion processing	EMA before MRI
Chen et al. (2018)	4	2.00	2.083	Non-clinical (chronic dieters) ^j ; adults, age=19 ⁱ	36	-	98/14 ⁿ	Craving	Regulation/inhibition	MRI before EMA ⁿ
Flores et al. (2018)	7	3.33	3.282	Non-clinical; adolescents, age=14-18	33	-	28/10	Social interactions, affect	Reward processing, social reward	EMA before MRI
Ismaylova et al. (2018)	7	3.67	3.169	Non-clinical; adults, age=32-36	42	-	5/5	Affect	Emotion processing, structural/DTI, resting state	MRI before EMA
Kluge et al. (2018)	8	11.00	4.939	Schizophrenia; adults, age=32 ¹	18	N.A.	40/4	Social interactions, affect	Reward processing	EMA before MRI
Kronke et al. (2018)	7	6.33	3.282	Non-clinical; adults, age=20-26	118	47	56/7	Social interactions, substance use, self-regulation, craving	Regulation/inhibition	MRI before EMA
Nook et al. (2018)	6	2.33	4.881	At-risk for schizophrenia; adolescents and adults, age=15-32	36	-	28/28	Social interactions, affect, psychopathology symptoms	Social	MRI before EMA
Provenzano et al. (2018)	6	0.67	3.169	Non-clinical ^k ; adults, age=18-25	65	-	70/14	Affect	Social	EMA before MRI
Seidel et al. (2018)	14	10.33	6.222	Anorexia nervosa; adolescents and adults, age=12-29	70	-	84/14	Affect, psychopathology symptoms	Emotion processing	MRI before EMA
Wonderlich et al. (2018)	6	5.33	4.791	Bulimia nervosa; adults, age=18-40	16	N.A.	98/14	Affect, psychopathology symptoms	Regulation/inhibition, emotion processing	MRI before EMA
Bakker et al. (2019)	14	9.50	7.723	Clinical depression; adolescents and adults, age=16-25	87	-	150/15	Social interactions, affect, reward processing	Reward processing	MRI before EMA
Butterfield et al. (2019) ⁽⁵⁾	9	2.50	5.131	Clinical anxiety; children and adolescents, age=9-14	120	-	14/5	Affect	Emotion processing	EMA before MRI
Grosse-Rueschkamp et al. (2019)	4	1.50	3.436	Non-clinical; adults, age=18-25	63	106	60/10	Affect	Emotion processing	Varied
Kaiser et al. (2019)	10	2.00	6.204	Clinical depression; adolescents, age=13-19	28	N.A., referrals to local psychological services	14/14	Affect	Emotion processing	MRI before EMA

Moran et al. (2019)	4	6.50	6.673	Schizophrenia; adults, age=mid-30s ⁱ	58	N.A.	28/7	Affect, reward processing	Reward processing	EMA before MRI
Rattel et al. (2019)	8	4.00	6.204	Non-clinical; adults, age=22.9 ⁱ	53	-	NA/4 ^m	Affect, psychopathology symptoms	Emotion processing	MRI before EMA
Scholz et al. (2019)	4	1.50	4.267	Non-clinical ^l ; adults, age=19-33	52	105	90/30	Social interactions, affect, substance use	Regulation/inhibition	MRI before EMA
Schwartz et al. (2019)	7	8.50	4.839	Clinical depression; adults, age=18-35	64	N.A.	105/21	Social interactions, affect, psychopathology symptoms	Resting state	MRI before EMA
Tost et al. (2019)	11	22.00	24.884	Non-clinical; adults, age=18-28	52	-	87/7	Affect	Emotion processing	EMA before MRI
Alarcon et al. (2020)	6	1.00	6.464	Non-clinical; adolescents, age=14-18	45	-	28/10	Social interactions, affect	Social reward	MRI before EMA
Blaine et al. (2020)	7	5.00	18.112	Alcohol use disorder; adults, age=21-60	69	-	14/14	Substance use	Regulation/inhibition	MRI before EMA
Culbreth et al. (2020)	5	2.00	7.169	Schizophrenia; adults, age=37 ⁱ	28	N.A.	28/7	Reward processing	Reward processing	-
Heller et al. (2020)	7	15.00	24.884	Non-clinical; adults, age=18-31	58	N.A.	22-78/3-4	Affect, sleep	Resting state	EMA before MRI
Hua et al. (2020)	6	5.00	2.376	Mood disorders; adults, age=25 ^l	26	400	100/11-16	Affect	Emotion processing	MRI before EMA
Kronke et al. (2020)	7	4.00	3.139	Non-clinical; adults, age=19-27	294	47	56/7	Self-regulation	Resting state	-
Martin-Soelch et al. (2020)	11	0.00	4.157	At-risk for depression; adults, age=18-40	32	N.A., experimental hours for study plans	28/7	Affect	Reward processing, emotion processing	MRI before EMA
Oppenheimer et al. (2020)	7	15.00	2.350	Clinical anxiety; adolescents, age=11-16	36	N.A.	28/10	Affect	Social	EMA before MRI
Uy & Galvan (2020)	2	1.00	6.464	Non-clinical; adolescents and adults, age=15-30	38	N.A.	42/14	Affect	Social	MRIs during EMA period

Vekaria et al. (2020)	9	5.00	4.027	Non-clinical; adults, age=21-55	48	N.A.	14/14	Social interactions	Social	MRI before EMA
Woods et al. (2020)	7	0.00	2.083	Non-clinical; adolescents, age=14-18	48	N.A.	28/10	Affect	Social	EMA before MRI

Note. Information that was not reported as part of the publications is marked with a single dash. For example, the presence of a dashed line under “Compensation” only indicates that information regarding participant compensation was not reported in the publication; it is not representative of authors explicitly stating that participants were not compensated.

^aIncludes the first author and the year of publication

^bThe number of authors listed for the publication

^cThe number of citations per year for each publication as of July 2021

^dIncludes the 2020 impact factor for the journal in which each study is published, extracted from Journal Citation Reports.

^eDescribes the population of interest and the age range of participants in years. For clinical populations, the diagnostic group of interest is listed.

^fSize of the sample that completed both EMA and fMRI, and were included in analyses for each paper

^gInformation regarding participant compensation. If studies reported that participants did receive monetary compensation, but the total amount of payment was unreported, this is listed as “N.A.”. If non-monetary forms of compensation were offered to participants, these are described. For studies that reported the maximum amount of payment participants could receive, all sums are listed in USD

^hNumber of overall number of prompts that participants received over (/) total number of EMA days. “NA” denotes that overall number of prompts is unspecified. Some studies reported average or range of prompts completed instead of overall number of prompts; in those cases the average or range are reported the right side of the dash (/).

ⁱSome papers reported the mean age of participants whose data was included in analyses (in years) rather than the age range of participants

^jNon-clinical study populations with specific criteria are described in parentheses, such as chronic dieters (Lopez et al. 2016; Lopez et al. 2017; Chen et al. 2018) and non-clinical participants that were assigned to a food restriction intervention as part of the study (Giuliani et al. 2015)

^kStudies by Bastiaansen et al. (2018) and Provenzano et al. (2018) used non-clinical study populations, though they selected participants such that they would have a normal distribution of neuroticism within their samples

^lScholz et al. (2019) selected young adult participants who reported drinking a standard drink containing alcohol at least 2-3 times per month or more for the last 12 months

^mStudies by Holm et al. (2009) and Rattel et al. (2019) did not specify the overall number of prompts sent to participants throughout the EMA period. The study by Rattel et al. (2019) used an event-based design and the number of overall EMA prompts differed between participants

ⁿIn Chen et al. (2018), participants completed two fMRI scans and two sets of EMA. They completed one fMRI scan, followed by a 14-day EMA. This sequence was then repeated. The overall number of EMA prompts reported represents one 14-day EMA period

Figure 1. PRISMA 2009 Flow Diagram

Figure 2. *Number of Identified Papers Published Each Year, 2007-2020*

Figure 3. *Place of Publication for Studies Combining EMA and MRI/fMRI, 2007-2020*

Figure 4. Four Study Designs Used to Combine EMA with MRI/fMRI.