Received: 8 March 2024 | Revised: 23 May 2024 | Accepted: 17 August 2024

DOI: 10.1002/mpr.70001

ORIGINAL ARTICLE

WILEY

A control theoretic approach to evaluate and inform ecological momentary interventions

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Funding information
European Union's Horizon 2020 Programme (IMMERSE), Grant/Award Number: 945263; Deutsche Forschungsgemeinschaft, Grant/Award Numbers: 389624707, TRR-265 (project A06); Ministerium für Wissenschaft, Forschung und Kunst Baden-Württemberg, Grant/Award Number: 31-7547.223-7/3/2; Hector II Foundation

Abstract

Objectives: Ecological momentary interventions (EMI) are digital mobile health interventions administered in an individual's daily life to improve mental health by tailoring intervention components to person and context. Experience sampling via ecological momentary assessments (EMA) furthermore provides dynamic contextual information on an individual's mental health state. We propose a personalized data-driven generic framework to select and evaluate EMI based on EMA.

Methods: We analyze EMA/EMI time-series from 10 individuals, published in a previous study. The EMA consist of multivariate psychological Likert scales. The EMI are mental health trainings presented on a smartphone. We model EMA as linear dynamical systems (DS) and EMI as perturbations. Using concepts from network control theory, we propose and evaluate three personalized data-driven intervention delivery strategies. Moreover, we study putative change mechanisms in response to interventions.

Daniel Durstewitz and Georgia Koppe contributed equally to this work.

Results: We identify promising intervention delivery strategies that outperform empirical strategies in simulation. We pinpoint interventions with a high positive impact on the network, at low energetic costs. Although mechanisms differ between individuals - demanding personalized solutions - the proposed strategies are generic and applicable to various real-world settings.

Conclusions: Combined with knowledge from mental health experts, DS and control algorithms may provide powerful data-driven and personalized intervention delivery and evaluation strategies.

KEYWORDS

computational psychiatry, control theory, ecological momentary assessment, ecological momentary intervention, mobile health

1 | INTRODUCTION

Mobile devices, such as smartphones and sensors, facilitate the rich and dynamic collection of information pertaining to an individual's mental state (Myin-Germeys et al., 2009; Schick et al., 2021; Shiffman et al., 2008; Trull & Ebner-Priemer, 2009). Specifically, ecological momentary assessments (EMA) afford the acquisition of high-dimensional data related to positive and negative affect, physical needs, and social interaction multiple times throughout the day (Myin-Germeys et al., 2018), extending to periods of several months (Reichert et al., 2021). A central advantage inherent in these approaches is the sampling of mental health states within the natural context of an individual's everyday life. Through these ecologically valid assessments, a more granular understanding of the reasons and moments at which mental health deteriorates becomes attainable (Myin-Germeys et al., 2018; Schulte-Strathaus et al., 2022).

Ecological momentary interventions (EMI) constitute a distinct category of mobile health (mHealth) interventions designed to fill this crucial gap in the treatment of mental health conditions. EMI are administered via smartphone devices and are designed to intervene in an individual's natural environment, precisely targeting moments when mental health is at risk (Heron & Smyth, 2010; Myin-Germeys et al., 2016; Schulte-Strathaus et al., 2022). For instance, EMI have been employed to enhance resilience in response to stress in youth at risk to develop, or with first episodes of, severe mental disorders (Rauschenberg et al., 2021; Reininghaus et al., 2023; Schick et al., 2021), and to reduce depression and anxiety (Schueller et al., 2017; Seppälä et al., 2019).

Although the integration of EMA and EMI holds significant promise for mitigating the burden of mental health, it concurrently poses several conceptual and data-analytic challenges. Specifically, the selection and delivery of an effective EMI requires determining its proximal utility. However, determining the utility based on EMA can become challenging, particularly for high-dimensional recordings, as EMA are inherently dynamic and interdependent. Due to interdependencies and feedback loops among various psychological variables, it is conceivable, for instance, that seemingly modest immediate effects accumulate over time, or immediate favorable effects backfire over an extended period (Borsboom, 2017; Henry et al., 2022; Rabbi et al., 2019). Thus, evaluating intervention deliveries requires accounting for the temporal dynamics and interdependencies among the sampled EMA variables (e.g., Borsboom, 2017; Boruvka et al., 2018; Schueller et al., 2017). In addition, when designing personalized EMI delivery strategies, we may need to factor in inter-individual differences into these dynamics (Bidargaddi et al., 2020; Nahum-Shani et al., 2018). Finally, different researchers may have different definitions of utility (e.g., some may want to reduce negative affect while others aim to increase activity levels Rabbi et al., 2019). It is therefore desirable to have an independent data-driven framework to obtain personalized EMI delivery schemes.

One way to address these challenges is to understand and treat the psychological variables collected within an EMA as nodes in an interconnected dynamic network (Borsboom, 2017; Bringmann et al., 2022; Hamaker et al., 2015; Henry et al., 2022; Hofmann et al., 2016; Stocker et al., 2022; Wigman et al., 2013). By operating on such networks, network control theory (NCT) offers guidelines and insights on how to address current questions in EMI research (Henry et al., 2022). NCT is a contemporary branch of dynamical systems theory that concerns itself with quantifying the control an external input (such as an intervention) exerts over a dynamical system (DS). Specifically, NCT studies how a network behaves under perturbation both immediately and over time, and how to place input to achieve some goal or desired state (Brunton & Kutz, 2022). In this way, NCT provides insight into which individuals are particularly sensitive to which external inputs based on their network structure, and which network nodes (e.g., which EMA variables) are best to target in order to effect change.

In a proof-of-concept study, we aimed to illustrate these principles on a dataset of individuals that underwent several weeks of EMI for the improvement of emotional resilience in youth with early mental health problems (Rauschenberg et al., 2021). Our contributions are two-fold: First, we used NCT to gain insights into network mechanisms by studying how the network behaves in response to real and hypothetical interventions. Second, we used concepts from control theory to propose and test three viable and personalized online strategies to guide the EMA-based delivery of EMI.

2 | MATERIALS AND METHODS

2.1 | Linear dynamical system models

Ten participants underwent several weeks of EMA with interleaved EMI (see Rauschenberg et al. (2021) and Supplement 1.1 in Supporting Information S1). The EMA consisted of 7 point Likert scales that were centered on 0, ranging from −3 to 3, prior to analysis (see Supplement 1.2 in Supporting Information S1 for details on all preprocessing steps). Table S1 lists the $M = 15$ assessed EMA variables. To extract their dynamics and the associated network structure, we modeled the EMA time series as a linear dynamical system (LDS), where the EMI constitute external inputs, that is, perturbations, to this system. The dynamics and network structure of each participant are described by the following map:

$$x_{t+1} = Ax_t + Bu_t + \epsilon_t \tag{1}$$

Here, x_t is a (state) vector collecting all EMA scores at time t, A is an adjacency matrix which describes how different vector elements (linearly) affect each other from one time point to the next (i.e., A describes the network structure), u_t are binary vectors that code for the presence of a specific external input at time t, B is a matrix specifying the degree to which each external input perturbs the system state, and ϵ_t is Gaussian white noise with 0 mean and covariance Σ. Each element of u_t indicates the delivery of one of three types of EMI (with a 1 indicating a delivery), or whether the individual was currently alone or in the presence of social company (a 1 indicating company). This model delineates a vector-autoregressive (VAR) model of first order with external inputs that was inferred separately for each participant via regularized least squares using Ridge regression. For further details on model estimation and code see Supplement 1.3 in Supporting Information S1.

2.2 | Average controllability

Average controllability (AC) determines interventions u_t that can cause large state changes with little (input) energy (Gu et al., 2015). It is assessed here via the so-called controllability Gramian W_T as

$$\mathrm{AC} = \mathrm{trace}(W_T)$$

with $T = M$ (Pasqualetti et al., 2014; Summers et al., 2015). The controllability Gramian is computed based on matrices A and B (see Supplement 1.4.2 in Supporting Information S1 for intuition and details on Gramian).Through matrix A in Equation (1), the EMA nodes $x_{:,i}$ form an interconnected network. The four columns of B specify the nodes which are targeted and the degree to which they are targeted by the four inputs. While B is derived from the data, we could replace it by an arbitrary matrix $\tilde{B}$ with the same number of rows. In doing so, we can simulate the effect of any *hypothetical* set of inputs. For instance, we can simulate an input that targets only a specific node i by setting $\tilde{B}$ to a column vector of zeros with a one at position i. To assess the AC of the empirical inputs (including the EMI), we set $\tilde{B}$ to the inferred columns of B (Equation 1). To assess the AC of simulated hypothetical interventions targeted at single network nodes, we set $\tilde{B}$ to unit (canonical) vectors (multiplied by −1 to account for positive effects on mental health).

2.3 | Cumulative impulse response

The CIR quantifies the isolated response of every system node (e.g., EMA variable) in response to an initial input (e.g., EMI), integrated over time. Essentially, it integrates the system trajectory along each dimension after initial perturbation. We compute the CIR as

$$\mathrm{CIR_T} = \sum_{t=0}^{\mathrm{T}} A^t \tilde{B}$$

where the j-th component of $\mathrm{CIR_T}$ represents the total effect on observable j of the intervention defined by control vector $\tilde{B}$ after applying a control input once at time $t = 0$, and accumulating effects over time (see also Henry et al., 2022). As such, the CIR captures a system's immediate change in response to an intervention, as well as the prolonged deviation away from its equilibrium point, and may therefore be understood as the total "benefit" (or harm) induced by an intervention over a specific time period. Once more, we set $\tilde{B}$ to columns of B to compute CIRs for the presented inputs, and to $-e_j$ (i.e., to canonical unit vectors multiplied by −1) to compute CIRs for simulated interventions which target single network nodes. The minus sign accounts for simulating interventions with *positive* effects on mental health. T was set to 100 to account for a sufficient temporal horizon.

2.4 | Control strategies

Equation (1) defines a DS that models the future fate of the network of EMA variables, and relatedly, the system's future response to any proposed sequence of interventions represented by $u_1, \ldots, u_{T-1}$ (also termed a control policy), where each u_t represents one external input available in the original study. By adjusting this sequence, we may thus *control* the system state. We evaluated three model-based control strategies that each propose a distinct control policy, with the goal of driving the system toward a desired target (here, the most positive EMA state, cf. Supplement 1.2.1 & 1.5 in Supporting

Information S1), while minimizing the required effort to do so. That is, we evaluated three policies to select interventions so as to improve mental health.

Optimal control strategy. The first control strategy was derived from the linear quadratic regulator (LQR). The LQR is a well-defined approach toward computing an optimal solution to a linear control problem, under circumstances in which we can dimensionally vary inputs u_t (i.e., we have no input constraints). For these settings, the LQR returns an optimal control sequence $u_1^*, \ldots, u_{T-1}^*$ as a function of speed of convergence to the desired state (i.e., how quickly do we wish a system to converge to the target), and enforced input energy (i.e., how much energy do we want to exert to get there), regulated by a parameter ρ. However, the LQR cannot be applied directly, because our admissible input is restricted to the finite set of available interventions. We therefore defined an adjusted strategy by first obtaining the optimal control input proposed by the LQR (therefore termed 'optimal control strategy' here), and then selecting the element u_t from the set of interventions with minimal squared Euclidean distance to the former (see details in Supplement 1.6.2 in Supporting Information S1).

Brute force strategy. The second strategy is a brute-force strategy. It simulates the effect of all combinations of available inputs forward in time and selects the intervention with lowest predicted loss (where we used the LQR loss; details in Supplement 1.6.3 in Supporting Information S1).

Max AC strategy. Finally, we tested a third comparatively simple strategy, based on the AC of each intervention. The max AC strategy selects the intervention with highest AC. All three strategies were implemented in an offline and an online evaluation (see Supplement 1.6.5 in Supporting Information S1).

2.5 | Software

All calculations were done using self-developed Python code, using the open source packages Numpy (Harris et al., 2020), Scipy (Virtanen et al., 2020), Pandas (McKinney, 2010), NetworkX (Hagberg et al., 2008), and Matplotlib (Hunter, 2007).

3 | RESULTS

3.1 | Gaining mechanistic insights with control-theoretic approaches

3.1.1 | Average controllability

After verifying that our LDS models explained a significant amount of variation in the data, validly capturing intervention effects (Supplement 2.1 in Supporting Information S1, Figure S1), we analyzed their control to gain mechanistic insights. We first explored the AC, as a marker of interventions that may cause large state changes with little input energy (Gu et al., 2015; Karrer et al., 2020; Pasqualetti et al., 2014), of the empirical interventions. We observed statistically larger AC values for the three EMI compared to the input that indicated the mere presence or absence of social company (T (38) = −2.09, p = 0.043, Figure 1a), indicating that the inputs which were specifically designed to improve mental well-being were also indexed by comparatively large ACs.

Next, we assessed the AC of hypothetical interventions targeted at single network nodes (i.e., EMA variables). Nodewise ACs showed high variations across participants (see Figure 1b left for interquartile ranges). This variation was consistent with a high degree of inter-individual differences in network structure. That is, network edge weights also exhibited high variance with no consistent pattern for positive or negative weights across individuals (all p_{Bonf} > 0.05 Bonferroni corrected; but see supplementary Figure S3). Nonetheless, we also found evidence for a few common nodes with high AC across individuals. For instance, "social unpleasant", "agreeable*", and "rather company" (reflecting an individual's desire to rather be with company when alone) were frequently identified among the four nodes with highest AC in each individual (identified in 5 out of 10 individuals, Figure 1a right). Moreover, "anxious" was the node with highest median AC (Figure 1b left), also exerting a high degree of average control over the inferred DS.

Nodes which exert high average control are typically hub nodes (Gu et al., 2015), that is, nodes with strong connections to other nodes. This could be confirmed here as well, with AC being positively associated with node centrality (the log net magnitude of incoming and outgoing edge weights of a given node, see Figure 1c; r = 0.71, p < 0.001 over all participants and nodes).

3.1.2 | Cumulative impulse response

Since AC is an average descriptor of network control, it provides little insight into the dimensions of change that an experimenter is commonly interested in. We therefore also examined the CIR. CIR_T quantifies the network connectivity-dependent effect an input exerts on each network state, accumulated over a fixed number of time steps T (cf. Methods 2.3).

First off, we assessed whether CIR_T returns reasonable results for the empirical inputs. Figure 2a shows the predicted median CIR_{100}, that is, accumulated over 100 time steps, for the three EMI and the social external input (indicating the presence or absence of social company). EMI-I and EMI-II resulted in a temporary improvement across the assessed psychological variables, predicted by a significantly negative median CIR (EMI-I: T (14) = −4.15, p_{Bonf} = 0.004, EMI-II: T (14) = −6.55, p_{Bonf} < 0.001, EMI-III: T (14) = −2.0, p_{Bonf} = 0.261). Simulating an increase of company did not improve the mental state (T (14) = −1.58, p_{Bonf} = 0.547). The specific temporary improvements observed for the EMI are thus largely consistent with expectations.

We then assessed CIRs for the single node interventions, by perturbing them with −1, toward higher mental well-being. Figure 2b

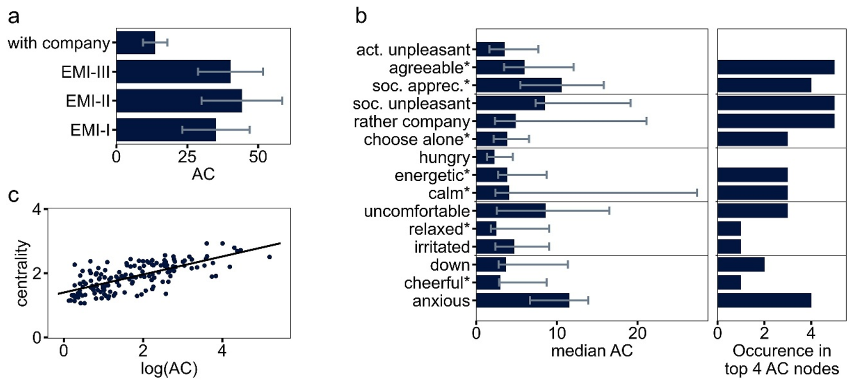

FIGURE 1 Node-wise AC. (a) AC of presented inputs (mean and SEM are displayed) (b) left: AC of single network nodes (median and interquartile range are displayed). Right: Distribution over the number of times each node was identified as one of the 4 nodes with highest AC in each individual. (c) Relationship between log-transformed AC and node centrality, measured by the sum of absolute incoming and outgoing weights, for each participant and node.

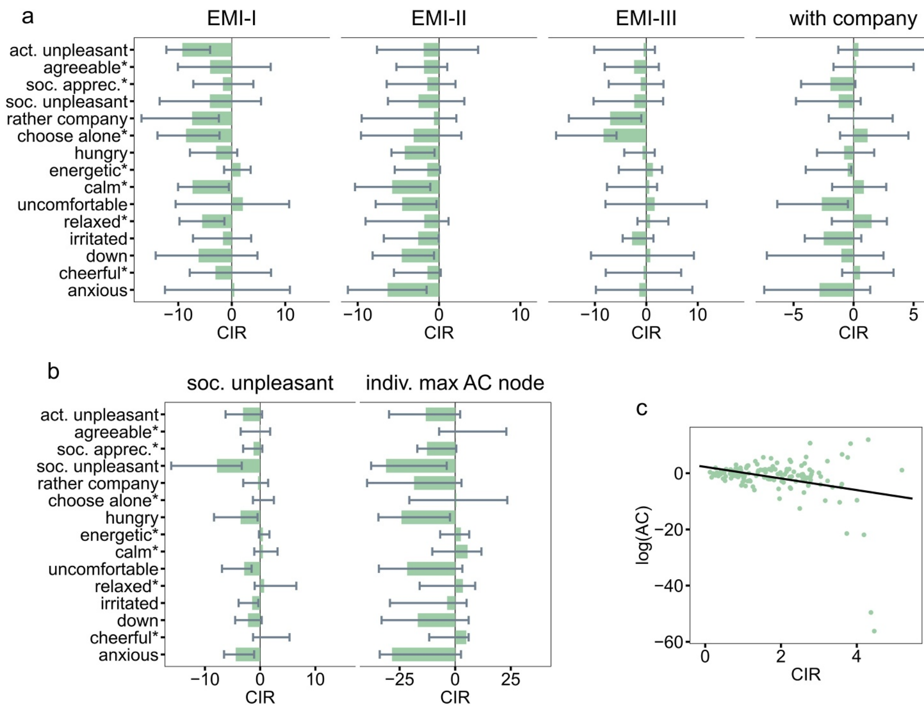

FIGURE 2 Cumulative impulse responses. (a) Predicted CIR for 100 time steps in response to the four presented inputs (median and 25-75 percentile range are displayed). Negative values always indicate an improvement in observed variables since an unfavorable mental health state is reduced. Asterisks mark inverted scales. (b) Left: CIR_{100} of node "soc. unpleasant," which was frequently found to have high AC. Right: CIR of participant specific node with highest AC. In each frame, median and interquartile range are displayed. (c) Relationship CIR_{100} and log AC for each participant and node.

delineates CIR_{100} for simulated interventions that target the EMA node "social unpleasant" which frequently was among the top AC nodes (Figure 2b left) and the personalized node with highest AC in each participant (Figure 2b right). Interventions on the identified high AC nodes yielded significantly negative CIR scores ('social unpleasant': T (14) = −2.77, p_{Bonf} = 0.046, personalized AC nodes: T (14) = −3.07, p_{Bonf} = 0.025). Among these two interventions, a 'personalized intervention' which targeted the highest AC node in each individual was superior in improving mental health than targeting "social unpleasant" (T (14) = 3.04, p = 0.009). The results are consistent with the notion that decreasing social unpleasantness results in a favorable mental health state, and that personalized interventions which target high AC nodes in each individual can be (even more) effective in temporarily improving mental health (also confirmed by a sample mean negative correlation between AC and CIR_{100}; $r = -0.50 \pm 0.24$, see Figure 2c).

3.2 | Control strategies to inform the ambulatory selection of EMI

Finally, we aimed at exploring different strategies to obtain personalized intervention selection schemes and guide intervention selection in empirical settings with a finite number of pre-defined interventions (see Figure 3a for proposed approach). We explored three strategies, one based on the LQR referred to as "optimal control," one based on a brute-force search strategy termed "brute force," and one based on selecting inputs with high AC, termed "max AC." These three strategies were evaluated as an alternative to the empirical strategy (Rauschenberg et al., 2021), and were deployed to select inputs at the time the empirical interventions were administered.

To evaluate intervention selection based on these control strategies, we compared the model-predicted improvement in mental well-being in response to the selected inputs, to the empirical improvement. More specifically, we assessed the predicted mean change $\hat{D}$ in EMA values before and after an intervention, and compared it to the empirical change D (Supplement 1.6.1 in Supporting Information S1). The control strategies were implemented in both an "offline" and an "online" version. The offline versions provide control inputs based on models inferred on the entire time series, while the online versions iteratively infer models up to the decision point, closely mimicking the empirical application setting (Supplement 1.6.5 in Supporting Information S1). See Figure 3d–e for two example trajectories, intervention selection points, and empirical and predicted improvement in EMA state for the online version of the max AC and brute force strategy.

3.2.1 | Offline control strategies

Optimal control strategy. The optimal control strategy had a large predicted effect size (Hedge's $g = 1.03$), with a mean change of $\hat{D} = -0.38 \pm 0.35$. The predicted mean change was larger than the empirical change across participants on a marginally significant level ($T\,(9) = -2.14$, $p = 0.061$), despite the small sample (see Figure 3b).

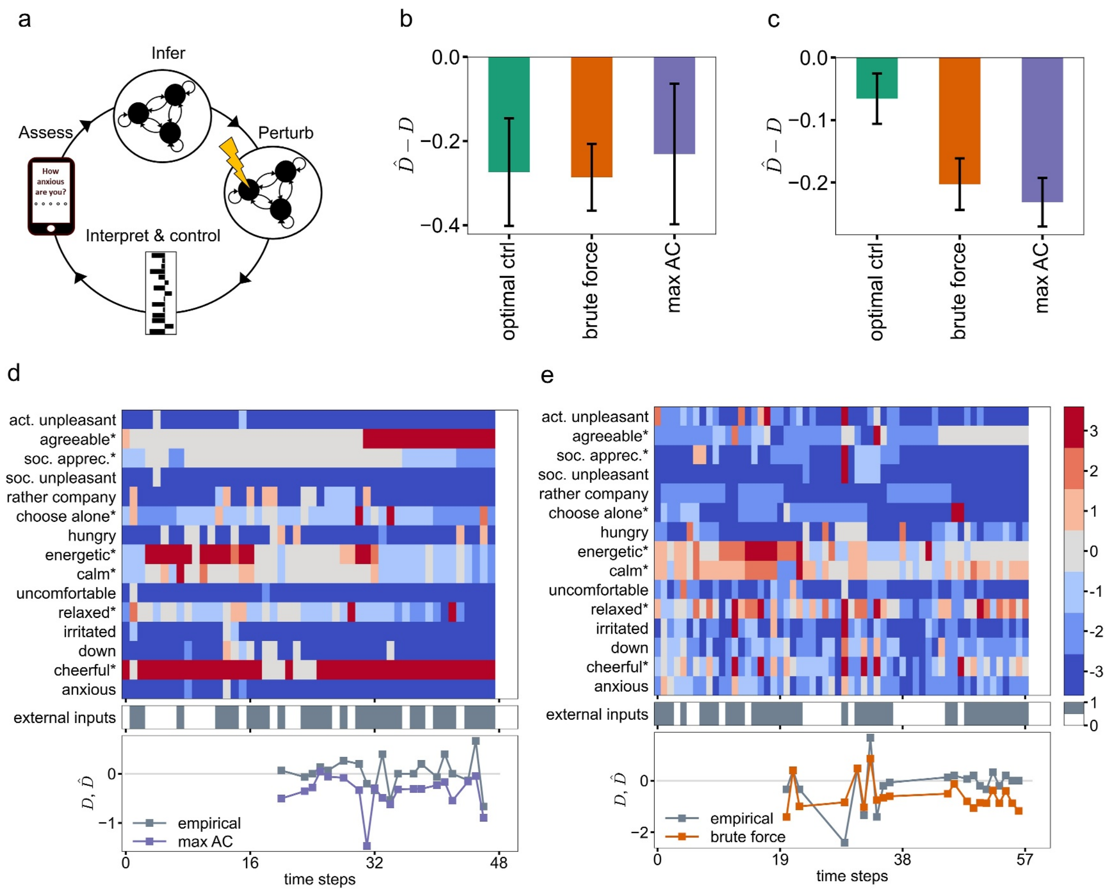

FIGURE 3 Control strategy results. (a) Proposed analysis approach. After assessing ecological momentary assessments (EMA) and Ecological momentary interventions (EMI) time series, we infer dynamical systems models on these time series and conduct perturbation analyses to obtain insights into network control and future system behavior. (b) Predicted improvements in EMA states, $\hat{D}$, for optimal control, brute force, and max AC selection strategies minus the empirically observed effects D (mean and standard error over participants are displayed) for offline strategy. Negative values indicate a relative improvement. (c) Same as (b) for online strategy. (d) Empirical time series (top panel) and intervention time points in empirical data and control strategy (middle panel). Bottom panel shows improvement in EMA state for empirical strategy (gray) and predicted improvement for online control strategy of one participant. Effect of max AC control strategy is displayed. Effects were computed from time step 20 onward. (e) Same as (d) for the brute force strategy.

Brute force strategy. The brute force strategy had a large effect size (Hedge's $g = 1.58$), and resulted in a significantly larger improvement in EMA variables when compared to the empirical prediction (T (9) = 3.59, $p = 0.006$, $\hat{D} = -0.39 \pm 0.23$; see Figure 3b). While this may be expected, as both the evaluation and the selection strategy are based on model simulation, it is not necessarily trivial. The improvement in EMA variables is assessed based on the one-step ahead prediction, the brute force scheme selects its control based on iterating $\tau = 5$ steps forward in time. A significant finding here thus requires models that are valid several steps into the future. Also, the results demonstrate that the models predict there even *exist* superior personalized control sequences to the empirical one, in the first place.

Max AC strategy. Interventions with high AC are interventions that cause relatively large state changes with little input energy (c.f. Methods Section 2.2). While the AC is a marker of change, and does not differentiate between positive and negative state changes per se, the results (Section 3.1.1, 3.1.2) indicate that in the current setting, the AC was associated with positive state changes. Additionally, we observed the LQR consistently invested more energy in high AC inputs for $\rho > 10$ (Supplement 2.4 in Supporting Information S1). Thus, the AC may provide a simple marker of an intervention's efficacy. As a third strategy, we therefore implemented a scheme that selects the intervention with maximum AC.

On average, the max AC strategy had a medium effect size (Hedge's $g = 0.64$), with a descriptively greater mean improvement ($\hat{D} = -0.33$ +/− 0.48), although this was not statistically significant compared to empirical improvement in this small sample (T (9) = −1.38, $p = 0.201$, see Figure 3b).

3.2.2 | Online control strategies

For the online setting, results are displayed in Figure 3c. Although the optimal control strategy did not statistically differ from the empirical selections (T (8) = −0.73, $p = 0.48$), it yet exhibited a positive effect size (Hedge's $g = 0.37$). Interestingly, when excluding decision points $t < 40$, we observed a moderate negative correlation between the number of time steps used for model estimation and the optimal control strategy's predicted effect $\hat{D}$ ($r = -0.3$, $p = 0.026$), possibly indicating that this strategy may improve upon additional data. The brute force and max AC strategies, moreover, showed large effect sizes and statistically significant reductions in target state deviation in this setting as compared to the empirical reduction (brute force: Hedge's $g = 1.32$, T (8) = 3.67, $p = 0.006$, max AC: Hedge's $g = 1.3$, T (8) = 3.86, $p = 0.005$).

4 | DISCUSSION

The delivery of EMI in naturalistic settings holds significant potential for mental health promotion and treatment (Myin-Germeys et al., 2016; Schulte-Strathaus et al., 2022). However, assessing the impact of interventions, identifying change mechanisms, and optimizing EMI delivery strategies is challenging due to the dynamic nature of psychological states (Boruvka et al., 2018; Henry et al., 2022; Koppe et al., 2019). To address this, we propose control-theoretic approaches, unexplored in EMA and EMI contexts, which view EMA variables as interconnected states and interventions as perturbations to these states (Borsboom, 2017; Bringmann et al., 2015, 2022; Henry et al., 2022). We furthermore propose three online control strategies for data-driven personalized EMI delivery that show promising efficacy in initial tests.

In an offline evaluation, all data-driven computational strategies for personalized EMI selection demonstrated moderate to substantial effect sizes. In online evaluations, the brute force and max AC strategies demonstrated potential for real-world applications. The proposed strategies offer a versatile data-driven control-theoretic framework adaptable to various experimental protocols. However, experimental validation is required to ascertain their superiority over existing delivery schemes.

An analysis of empirical and simulated inputs revealed mechanistic insights, with intervention effects generally aligning with expectations. For instance, empirical EMI resulted in an overall pattern of improvement across predicted psychological variables, and exerted a stronger degree of system control than the mere passive indication of social presence and absence. This aligns well with previous observations of immediate EMI-driven mental health improvements (Rauschenberg et al., 2021), as well as the general motivation behind delivering these specific EMI (Paetzold et al., 2022; Reininghaus et al., 2023). However, the observed inter-individual differences in dynamical systems and responses also imply personalized intervention approaches are necessary. Personalized interventions targeting participant-specific nodes with high AC predicted larger mental health improvements, indicating the potential effectiveness of individualized interventions based on network dynamics and control.

4.1 | Implications for EMI delivery schemes and evaluation

The study suggests innovative directions for EMI research, emphasizing the integration of energetic considerations and individual dynamics into intervention design. Integrating psychotherapeutic research focusing on real-time state changes with dynamical systems and control theory could further enhance future EMI delivery schemes. As an example, the EMI selected in the current data set are based on principles of CFT that rest on cultivating and enhancing compassion in individuals. These compassion focused interventions (CFIs) are particularly designed to act on three interacting emotional systems (Paetzold et al., 2022). By capturing the dynamics of these emotional systems and integrating CFIs into personalized EMI selection based on proximal prediction of effects and energetic constraints, interventions could be strategically placed and utilized.

AC and CIR provide interpretable measures of intervention effects and offer insights into behavioral contingencies and network mechanisms (Gu et al., 2015; Lynn & Bassett, 2019). These could be used for personalized feedback to increase awareness of individual behavioral patterns. For instance, one could inform on interactions between psychological variables (e.g., 'when you are not relaxed, you tend to feel less appreciated'), educate on the effects of a given CFI (e.g., 'positive imagery relaxes you'), and raise awareness for effects of other recorded external factors (e.g., 'spending time in nature had a positive effect on your mood'). In blended care settings, such evaluations could moreover guide therapists in identifying effective intervention points (e.g., high AC nodes).

4.2 | Limitations

The success of the proposed approaches hinges on the DS model's ability to accurately reconstruct dynamics, as highlighted in (Henry et al., 2022; see also Durstewitz et al., 2023). However, the linear VAR(1) model used is limited by a single fixed point, causing perturbations to decay exponentially and limiting its capacity to represent long-term changes induced by interventions. An alternative employed by Henry and colleagues (2022) is the integrated VAR model. While this model is theoretically capable of capturing long-term dynamical changes, we found it to explain significantly less variance in the present data.

While linear models may thus not fully reflect reality, they remain effective approximations for many systems (Hamaker et al., 2015; Kirk, 2004; Peralta et al., 2020). However, more powerful nonlinear approaches exist, which can better account for permanent stable changes in mental health states but require longer time series for accurate generalization. Future studies should focus on validating proposed approaches on longer time series, using methods such as inferring models on part of the time series to predict statistics for the left-out part, thus enabling validation on a personalized level (Koppe et al., 2021; Thome et al., 2023).

5 | CONCLUSION

The proposed approach aligns with network theories of mental disorders, emphasizing the interaction between mental health symptoms or latent variables (Borsboom, 2017; Bringmann et al., 2018; Fried & Cramer, 2017). In digital mental health research, the goals of administering personalized mHealth interventions and understanding inter-individual variations in intervention responses are eminent. EMA offers opportunities to study intervention effects by tracking psychological variables over time. By integrating these variables into a dynamic system responsive to perturbations, NCT facilitates personalized intervention delivery and identifies key drivers of change.

AUTHOR CONTRIBUTIONS

Janik Fechtelpeter: Conceptualization; formal analysis; methodology; software; validation; visualization; writing—original draft preparation; writing—review and editing. **Christian Rauschenberg**: Data Curation; investigation; writing—review and editing. **Hamidreza Jalalabadi**: Writing—review and editing. **Benjamin Boecking**: Resources; writing—review and editing. **Therese van Amelsvoort**: Resources; writing—review and editing. **Ulrich Reininghaus**: Data Curation; funding acquisition; investigation; resources; writing—review and editing. **Daniel Durstewitz**: Funding acquisition; methodology; supervision; writing—review and editing. **Georgia Koppe**: Conceptualization; funding acquisition; methodology; project administration; supervision; writing—original draft preparation; writing—review and editing.

ACKNOWLEDGMENTS

This work was funded by a living lab grant by the Federal Ministry of Science, Education and Culture (MWK) of the state of Baden-Wuerttemberg, Germany (grant number 31-7547.223-7/3/2) and the European Union's Horizon 2020 research and innovation program under grant agreement 945263 (IMMERSE) to DD, GK, and UR, by the German Research Foundation (DFG) within the collaborative research center TRR-265 (project A06) to DD and GK, by a DFG Heisenberg professorship (No. 389624707) to UR, and by the Hector II foundation.

Open access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data sets analysed during the current study are available from the corresponding author upon reasonable request. The underlying code for this study is available on GitHub and can be accessed via https://github.com/JMFechtelpeter/control_theory_for_emi.

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How to cite this article: Fechtelpeter, J., Rauschenberg, C., Jalalabadi, H., Boecking, B., van Amelsvoort, T., Reininghaus, U., Durstewitz, D., & Koppe, G. (2024). A control theoretic approach to evaluate and inform ecological momentary interventions. *International Journal of Methods in Psychiatric Research*, e70001. https://doi.org/10.1002/mpr.70001