Making Self-Report Ready for Dynamics: the Impact of Low Sampling Frequency and Bandwidth on Recurrence Quantification Analysis in Idiographic Ecological Momentary Assessment

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ABSTRACT

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Keywords: complex dynamics, data quality

1 INTRODUCTION

Self-report scales have a long historical precedent in psychology. Ecological momentary assessment (EMA) is a technique meant to construct time series based on self-report instruments. This approach allows mapping within-person fluctuations of psychological constructs in a systematic manner (1). While traditional statistical methods are frequently and fruitfully employed to analyze data generated using EMA, these methods are not suitable for capturing complex temporal within-person patterns (6).

The methods to study chaotic behavior are still in infancy within a psychological context (4). They are often imported from complex dynamical systems theory, which is an area of mathematics that concerns itself with the study of the time-dependent dynamics of complex systems. A popular analysis technique is called Recurrence Quantification Analysis (RQA). It results in the identification of recurrent patterns, or repetitions, in time series analysis (7). One can then derive several indicators of the stability, predictability, and dynamical behavior of data from these recurrences. This method was developed in the physical sciences under the assumption that measurements can be retrieved at great frequency and at high resolution, to an extent that is impossible when relying on self-report scales. Hence, it is necessary to systematically assess the consequences of utilizing EMA data on the quality of RQA output (3).

We postulate that there is an underlying continuous trajectory of the constructs that EMA devices aim to measure. In other words, we assume that ordinal likert type-scales reflect an underlying continuous measure.

We also assume that the trajectory of the time series is chaotic, which means that the data generating mechanism is very sensitive to changes in the initial parameters: it is only predictable in the short-term, and observations are dependent on the state of the system and its externalities at earlier time points (5). Hence, chaotic behaviour can be easily mistaken for random behaviour, but can (yet does not have to be) fully deterministic. Finally, we suppose that self-report measures are accurate measures at a certain timepoint of this continuous measure, but with lower bandwidth and more coursegraining. Working from these assumptions, we first simulate a potential continuous trajectory of a dynamical system, coursegrain and ordinalize it, and then test the deviation of recurrence measures from a segment of the full dataset to its degraded alternatives.

We choose to generate the data through a set of coupled differential equations that lead to chaotic behaviour. Note that while randomness does have a part to play in the generation of the data, most of the variance is created determinalistically through four broadly modeled influences. These influences consist of symptom intensity, the modelling of the person's internal factors, influences of the perceived environment, and the influence of time. Many alternative models could be formulated that could result in similar behavior or would be as or more realistic.

Our choice for this way of modelling is based on a variety of interesting characteristics. The most important of these is that self-report data cannot be measured consistently and continuously with high ecological validity in almost all use cases where self-report is used. We note that if it were possible to measure these variables directly, then researchers would not have to rely on the instrument in the first place. Therefore, theory-based simulation is a necessary starting point for further research. We hope that the models, in turn, can be refined using empirical data that takes into account time dependence, and that is where the recovery of complex characteristics can be used in ways that would be hard to do if one were to study the trajectory statistically. Furthermore, we chose for this model because it is one of the only ones (if not the only one) that has the stated goal of emulating the trajectory of psychological constructs over time (in the form of symptomatology of psychiatric illness), thus being a good starting point .

This brings us to a natural place to introduce the goal of this project. Right now, there is often no empirical feedback system for theoretical models that aim to recover the time-dependent characteristics of constructs that are measured using EMA. We hope that studying the stability of complexity characteristics under data degredation can help us recover certain aspects empirically of the trajectory of the system under study. E.g., incompatibility of the theoretical time development of disease symptomatology contrasted with the recovered complexity characteristics of a patient can be used as a counterfactual against the choice of one model over another. A more concrete example: say that a patient is postulated to have a disorder where a particular symptom oscillates predictably and repeatadly for a period of 12 hours. A more fine-tuned understanding of that trajectory can then be used to optimize treatment times. If their symptoms were to oscillate more irratically, then this would be reflected in the recurrence indicators of the patient. If it would show dampened oscillations instead where the bandwidth becomes lower with the passage of time, then that would be reflected in the recurrence inidicators in a different manner. This is, of course, only true if those characteristics can be picked up reliably from the degraded data.

2 MATERIALS AND METHODS

2.1 Software

We used the Julia languages, and in particular the 'DynamicalSystems.jl', 'RecurrenceAnalysis.jl', and 'Statistics.jl' packages to implement the toy model and run the recurrence analyses. Full information about dependencies and version numbers can be found in a human-readable format in the Manifest.toml file in the Github-repository. Instructions for running the analysis through a sandboxed project environment identical to our system can be found on the main page of the github repository.

2.2 Toy Model

For this study, we will use the ”3 + 1 dimension model” introduced by (2). The original aim of this toy model is to simulate the trajectory of symptomatology over time, but it can be used for our project by reformulating some of the model . It uses four coupled differential equations to model the effect of time on symptom intensity. It is explained quite well in the aforementioned paper. We give a basic explanation of each equation, and note some interesting behaviour that might be more or less suitable for use in this project. I will use identical terminology where possible

2.2.1 Symptom intensity

The first equation is supposed to represent symptom intensity. For our study,

$$\tau_x \frac{dx}{dt} = \frac{S_{\max}}{1 + exp(\frac{Rs-y}{\lambda_s})} - x \tag{1}$$

2.2.2 Modelling of internal elements

$$\tau_y \frac{dy}{dt} = \frac{P}{1 + exp(\frac{R_b-y}{\lambda_b})} + L - xy - z \tag{2}$$

2.2.3 Modelling of perceived environment

$$\tau_y \frac{dy}{dt} = \frac{P}{1 + exp(\frac{R_b-y}{\lambda_b})} + L - xy - z \tag{3}$$

2.2.4 Temporal specificities

$$\tau_z \frac{dz}{dt} = S(ax + \beta y)\zeta(t) - z \tag{4}$$

2.3 Recurrence Indicators

The **Recurrence rate** is the proportion of points in the phase space that reoccur at later times. A flat line would mean a recurrence rate of 1. **Determinism** is the share of recurrent points that are part of diagonal lines, which indicate that the structure is deterministic. **Average and maximum length of diagonal structures** is the average length of diagonal lines. A longer average length means more predictable dynamics, the maximum also indicates that there are long predictabe segments. **Entropy of diagonal structures** concerns the Shannon entropy of diagonal line lengths. It quantifies the amount of randomness, or information, in the data. **Trapping time** is the average length of vertical lines in the plot. It is a measure of how long a system stays in a particular state. **Most probable recurrence time** is the mode of the length of the vertical lines in the plot.

3 RESULTS

4 DISCUSSION

The results of this study suggest that applying recurrence methods in

One of the ways that researchers can strengthen their idiographic inferences is through asking whether their

The limitations of this study are

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$$\sum x + y = Z \tag{5}$$

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```
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```
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```

e.g.

```
\textgamma
```

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FUNDING

Details of all funding sources should be provided, including grant numbers if applicable. Please ensure to add all necessary funding information, as after publication this is no longer possible.

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SUPPLEMENTAL DATA

Supplementary Material should be uploaded separately on submission, if there are Supplementary Figures, please include the caption in the same file as the figure. LaTeX Supplementary Material templates can be found in the Frontiers LaTeX folder.

DATA AVAILABILITY STATEMENT

The code, all additional material, and generated data for this study can be found in the [NAME OF REPOSITORY].

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