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An Objective, Comprehensive and Flexible Statistical Framework for Detecting Early Warning Signs of Mental Health Problems

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The early detection of mental health problems, such as depression or psychosis, is of great scientific and societal interest as it allows for prevention or early intervention. Fueled by dynamical systems theory and grounded in developmental theories [1], research is increasingly focusing on the identification of early warning signs (EWS [2]) preceding the onset of psychopathology (also referred to as prodromal symptoms [3]). The key idea is that transitions between global states, e.g. from not being to being depressed, are foreshadowed by subtle changes in the daily fluctuations and dynamics of individual symptoms [4]. Initial evidence for this EWS hypothesis has been found for depression [5]. Detecting EWS is however not straightforward, and most statistical approaches so far have been mostly univariate, descriptive and rather ad hoc. However, given what is at stake, for the at-risk individual and society, comprehensive, objective and yet flexible statistical tools for accurately detecting EWS are urgently needed.

In this paper, we propose a statistical framework, kernel change point detection (KCP [6–8]), that detects EWS by testing whether summary statistics of repeatedly measured symptoms (e.g., means, variances, correlations, autocorrelations) change across time. The method, a detailed description of which can be found in the online supplementary material (for all online suppl. material, see www.karger.com/doi/10.1159/000494356), features the following key advantages: First, it is flexible, in that it can be easily adapted to any summary statistic that may potentially yield EWS. Second, it is comprehensive, in that multiple variables can be monitored simultaneously. Third, it is objective, in that it implements formal decision procedures, such as a kernel-based algorithm to search for optimal change point locations, a permutation-based significance test to decide whether at least one of the located change points is statistically significant, and a penalty approach to decide on the total number of change points.

We demonstrate the large potential of KCP for studying EWS by reanalyzing experience sampling data that stem from an antidepressant dose reduction experiment tracking a single participant diagnosed with major depression for 239 days over 5 experimental phases [5]. Momentary mood ratings were collected via a smartphone that beeped the participant 10 times a day at random occasions. Importantly, the patient relapsed into depression in the course of the experiment.

Given that Wichers et al. [5] describe changes in the variances, autocorrelations and correlations of these variables before relapse, we monitor the corresponding running statistics (computed in a moving window of size 25; see online suppl. material) with KCP to test for significant change points before relapse. As these statistics quantify affective dynamics linked to psychopathology [9, 10], it makes indeed sense to expect that change points in them can serve as EWS of an upcoming depressive episode.

To enhance specificity of results (i.e., the probability with which changes are attributable to the running statistic monitored) we usually recommend to first implement KCP on the running means and filter the data for significant mean changes, before other changes are searched for. Since the present data are already detrended (see Wichers et al. [5]), we skip this step here and run 3 separate KCP analyses, on the running variances, autocorrelations and correlations (yielding KCP-var, KCP-ac and KCP-corr). Note that we replaced values deviating from the mean by more than 3 SDs with maximum values within 3 SDs. Moreover, we removed observations more than 1 lag apart and overnight lags to keep time intervals invariant for the accurate computation of autocorrelations.

Our results show that each monitored running statistic contains at least 1 significant change point (for the exact *p* values and multiple testing corrections used, see online suppl. material) (Fig. 1). The penalty approach further reveals that, for the running autocorrelation, there is 1 change point observed on day 86 (41 days before relapse), with all variables exhibiting an increase in autocorrelation (max Δ_AC = 0.43 for suspicion). For the running variance, a major change point occurs on day 130, which is already 3 days after relapse. However, if a second change point is searched for, we detect it 53 days before relapse, on day 74. This second change point is mainly characterized by an elevation in the variance of suspicion (Δ_var = 0.62) and mental unrest (Δ_var = 0.58), while the change point on day 130 is marked by drastic variance jumps for worry (Δ_var = 1.01) and suspicion (Δ_var = 0.97). Lastly, for the running correlation, we find a change point on day 116, characterized by all pairwise correlations being strengthened except for the one between positive affect and mental unrest. The largest correlation shifts occur for positive affect and worry (Δ_corr = 0.39), positive affect and suspicion (Δ_corr = 0.39), negative affect and worry (Δ_corr = 0.38), and negative affect and suspicion (Δ_corr = 0.38).

As we are interested in EWS, we repeated the analyses excluding all time points after relapse. This yields very similar evidence. That is, although no significant change point was detected for the running autocorrelation, significant change points were flagged for the running variance on day 88 and the running correlation on day 116. These change points are consistently characterized by upward shifts in the statistics' values.

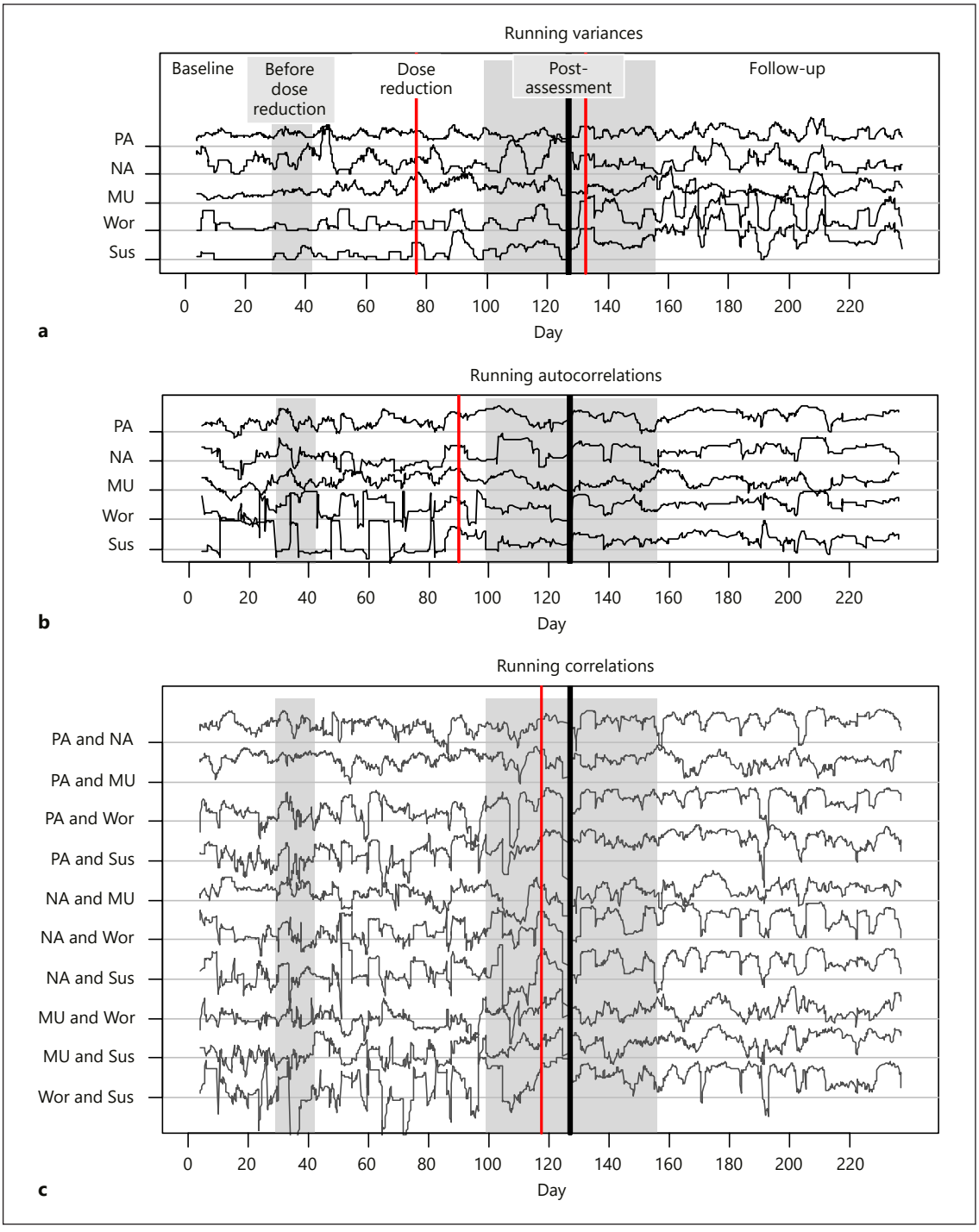
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Fig. 1. Running statistics and the corresponding change points. The first and second panels (**a**, **b**) exhibit the running variances and autocorrelations for the 5 symptoms, while the last panel (**c**) displays the running correlations for the 10 pairwise correlations. All running statistics are computed using a moving window of 25 beeps. The experimental phases are labeled in the first panel and are indicated by varying background shading across all panels. The relapse to depression on day 127 is marked by black vertical lines, while the change points in the running statistics are indicated by red vertical lines. PA, positive affect; NA, negative affect; MU, mental unrest; Wor, worry; Sus, suspicion.

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Summarizing, the proposed KCP approach allows to monitor *different* summary statistics of *multiple* variables simultaneously for change points. The method is statistically sound, well suited for explorative usage and has been shown to identify valid change points in a large variety of applications [6–8]. Here, we were able to reveal change points in a number of running statistics of affective symptoms, detecting EWS before relapse into depression. Specifically, we see that correlation changes occur relatively late, whereas variance and autocorrelation changes occur early (11 days vs. more than a month before relapse). Thus, monitoring these statistics might be more informative and can benefit timely intervention and enable prevention.

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Disclosure Statement

The authors have no conflicts of interest to declare.

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