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Common Practices in Detecting Psychological Early Warning Signals May Lead to Incorrect Results

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Abstract

The past few years have seen a rapid growth in research on early warning signals (EWSs) in psychological systems. Whereas early studies showed that EWSs are associated with sudden changes in clinical change trajectories, later findings showed that EWSs may not be general and have low predictive power. In this study, we demonstrate that two common practices in psychological EWS studies are not warranted by theories and may lead to false-negative or false-positive results, explaining the mixed findings in the literature. These two practices are (1) using loosely-defined time windows for early warning indicators and (2) using different variables for detecting transitions and calculating early warning indicators. We first review the theoretical background of EWSs and current research practices for EWS studies. Two simulation studies with different types of system changes are used to demonstrate the possible consequences of the two practices. In Study 1, we show that when the time window for early warning indicators is not strictly before the transition, the transition process itself and the system dynamics after the transition may confound the result. In Study 2, we show that when the transition and early warning indicators are measured from different variables in the same system, the predictive relationship may not exist. Based on our findings, we provide suggestions for future EWS studies in terms of theory construction, study design, and data analysis.

Keywords: early warning signals, critical transitions, sudden changes, complex dynamical systems, clinical psychology.

Introduction

Human psychology is a complex dynamical system – a proposition that has been claimed for a long time (Granic, 2005; Smith & Thelen, 2003; van Geert & van Dijk, 2021) but has been formalized for psychopathology only in the past few years (Haslbeck et al., 2021; Olthof et al., in press; Robinaugh et al., 2021; Schöller et al., 2018). The appeal of a complex system perspective lies in the fact that this framework is able to provide an explanation for the sudden and abrupt transitions often observed in clinical phenomena (e.g. sudden gains, relapse, see for instance Helmich et al., 2020; Helmich, Olthof, et al., 2021; Olthof, Hasselman, Strunk, et al., 2020; van de Leemput et al., 2014). Researchers in various fields have shown that these sudden transitions for complex systems can be predicted by a collection of indicators, commonly known as *early warning signals* (EWSs, Dakos et al., 2012; Lenton, 2011; Scheffer et al., 2009, 2012). Intuitively, the existence of EWSs can be understood by the following idea: when a certain phase is destabilized, it loses its resilience. The system state is then more likely to fluctuate, and after a perturbation, the system also takes longer to recover. As a result, various indicators, such as increasing variance and autoregressive coefficients, can be observed in the data. At a certain point, the phase that the system previously resides in is no longer stable, the system transitions to another phase abruptly, causing a sudden change in system variables.

For psychological systems, researchers have found empirical evidence that EWSs may exist for clinical changes (e.g., Olthof, Hasselman, Strunk, et al., 2020; Wichers et al., 2016, 2020), and hypothesized that EWSs can potentially be used for detecting vulnerable individuals, determining the suitable time for interventions, and predicting the direction of change (Helmich, Olthof, et al., 2021; Wichers et al., 2019). Later studies, however, found the predictive power of EWSs to be generally weak, EWSs only occurring in some variables different for each patient, and overall not showing a clear consistent pattern (e.g., Bos et al., 2021; Curtiss et al., 2022; Helmich, Smit, et al., 2021; Schreuder et al., 2020). In a recent article, Dablander et al. (2022) showed several example systems for which EWSs may not always exist even if the system experiences a transition (false negative; e.g., when the transition is induced by a strong perturbation or when the dynamic functions or noise have certain mathematical features), and sometimes EWSs exist without preceding a transition (false positive; e.g., for some specific systems EWS can occur before a smooth change or when there is no transitions). They also demonstrated that the measurement noise and sampling frequency can significantly affect the predictive power of EWSs. Further investigations are still necessary to understand in which conditions and how to detect EWSs reliably.

In this paper, we illustrate how two common practices in previous psychological EWS studies can lead to false positive and false negative findings. Those practices are (1) using loosely-defined time windows to calculate early warning indicators, and (2) using different variables to examine early warning indicators and sudden transitions. We will first review the theoretical background on EWSs and the common research methods used in recent psychological EWS studies; in two simulation studies we will then demonstrate how those practices can lead to false positive and negative findings in certain conditions; based on these findings we will discuss the implications and suggestions for future EWS research. We try to involve minimal yet sufficient mathematical details in the current article, readers seeking more rigorous proof and derivations will be provided references in relevant sections.

Theories and Empirical Studies on EWSs

Regardless of their specific nature, many complex systems undergo critical transitions in which the system shifts abruptly from one phase to another. The climate system of the earth, for instance, can transition from a glacial period to an interglacial period (Thompson & Sieber, 2011), the financial system can suddenly go from prosperity to a financial crisis (Gorban et al., 2010; Guttal et al., 2016), and a multispecies ecological system can experience a population collapse (Lever et al., 2020). In many of those systems, EWSs are being observed before the critical transition: the speed with which the system recovers from small turbulence becomes slow (known as *critical slowing down*), and the variance becomes high (known as *critical fluctuations*, Kelso, 2010; Scheffer et al., 2009, 2012).

The theoretical background of EWSs is based on the bifurcation theory (Gilmore, 1993; Scheffer et al., 2009; Thom, 1975; Zeeman, 1976). Here we use the cusp bifurcation, one of the most investigated types of bifurcations, as an example. As shown in Figure 1a, there is a ball on a landscape with two local basins. The position of the ball on the horizontal axis represents the *state* of the system, the basins represent the *phases* of the system[1] and the vertical axis represents the *stability* of the system[2]. When the basin is deeper, the phase is more stable; when the basin is shallower, the phase is more unstable. The stability landscape of the system is often determined by one or more *control parameters*. By adjusting the control parameter, the landscape can be changed smoothly, which destabilizes the left basin and stabilizes the right basin. At a certain point (termed the bifurcation point), the left basin no longer exists, causing the ball to abruptly move to the other basin, which represents that the system experiences a transition. Before the

[1] To avoid confusion, the term “state” is used in this article for the specific condition defined by the values of the system variables, and “phase” is used for the higher-level patterns of the system, which consist of many states that are qualitatively similar (Cui et al., 2021).

[2] Note that the definition of “stability” in this article may not be the same as some other works in this field (e.g., the time that a system spend to go back to its local minimum after a small pertubation, Dablander et al., 2022). See Cui et al. (2021) for the relationships between different stability measures based on a stability landscape.

transition, although the state of the system (i.e., the position of the ball on the horizontal axis) does not change much, the phase's stability (i.e., the depth of the basin) does become lower. As a result, when the system is influenced by a small noise, it is easier for the system to move to another position (i.e., the ball moves further away from the equilibrium point), and it is harder for the system to recover (i.e., the ball returns more slowly to the equilibrium point). For a real-life system, it is often hard to tell how stable a phase is (i.e., the position of the ball on the vertical axis is not easy to measure). However, if we observe that the state of the system (i.e., the position of the ball on the horizontal axis) has a larger variance and higher autocorrelation, we can infer that the stability of the phase has decreased, and a critical transition may happen in the near future.

Many real-life systems are similar to the cusp bifurcation in the sense that one basin of the system disappears at the bifurcation point (in mathematical language, the dominant eigenvalue at that equilibrium becomes zero); under a small white noise, the autocorrelation of the system state will approach 1, and the variance of the system state will approach infinity when the system approaches the bifurcation point (see Box 3 of Scheffer et al., 2009, for the mathematical proof). Therefore, it is reasonable to assume that many real-life systems will show EWSs before transitions, regardless of the specific form of interactions within those systems. This, of course, does not exclude psychological systems, which are well known to be complex, dynamic, and sometimes multistable (Cui et al., 2021; Olthof, Hasselman, & Lichtwarck-Aschoff, 2020; Schiepek et al., 2017). If we describe a patient with depression, the state of the psychological system can be a precise description of the mental state. This can be operationally defined as, for example, how much the person feels down, rated on a continuous scale from "not feeling down at all" to "feeling down very much".[3] Then the two phases of the system can be a depressive phase on the negative mood side (close to "feeling down very much") and a healthy phase on the positive mood side (close to "not feeling down at all"). If the patient is stuck in the depressive phase for a clinically long time, we can say that the person is having a depressive episode; in contrast, if the person is almost always in the healthy phase, the person is not suffering from depression.

Both clinicians' experience and empirical research have shown that many patients do not recover or deteriorate in a gradual way; sometimes they have sudden gains or losses in their symptom levels without any recognizable external stimuli (Hayes et al., 2007; Helmich et al., 2020; Miller, 2004; Olthof, Hasselman, & Lichtwarck-Aschoff, 2020; Tang & DeRubeis, 1999). If we assume the psychological system is simple and linear, this would not be possible because the same amount of change in the independent variable (e.g. treatment) will always lead to the same amount of change in the dependent variable (e.g. depressive symptoms; i.e., a linear dose-response relationship; Stiles & Shapiro, 1994). Thus, if there are no sudden changes in the independent variable, there will not be a sudden change in the dependent variable. However, if we consider psychological systems as complex, nonlinear, and dynamic, just like other complex systems in nature, it is reasonable to assume that a phenomenon like a cusp bifurcation (Figure 1a) can happen, that a gradual change in the stability landscape can lead to an abrupt change in system state through bifurcation, and that EWSs can be detected before the sudden changes. We call this type of transition *bifurcation-induced transition*, or *B-transition*.

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[3] Here we take a simplified way to only use one item to represent the state of the psychological system. Considering the complexity, using a compound measure (e.g., the average activation level of the symptom network, Cramer et al., 2016; Hayes et al., 2007) is probably more realistic.

In the past decade, many researchers have followed this idea and tried to detect EWSs in patients with mental disorders (see Table 1). These empirical studies contain two steps: detecting early warning indicators (EWIs) and transitions. A significant relationship between EWIs and transitions is then taken as evidence of EWSs in psychopathology. Here, we distinguish EWSs and EWIs because EWSs specifically represent critical slowing down and fluctuations before a B-transition, hence making a causal claim, whereas EWIs are simply statistical measures like increasing autocorrelation and variance. As we will show later, sometimes EWIs can also be observed when the system does *not* have a B-transition. Observing these statistical indicators does not necessarily mean they stem from the same underlying mechanism as EWSs. Therefore, we use EWIs for the statistical indicators calculated from the data, and we only label them EWSs when they indicate that a B-transition will happen soon.

We summarize frequently used methods to detect EWIs and transitions in Table 1. This summary demonstrates that these methods do not only differ in statistical indicators (increasing variance, increasing autocorrelation, increasing vector autocorrelation, or high dynamic complexity), but also in the selected variables and time scales. Many studies used a fixed time window to examine if a transition had taken place within that time window. This means that even if those methods can reliably detect whether a transition has taken place, there is no way to determine the exact moment of the transition. For example, the study by van de Leemput et al. (2014) used the difference in depression score before and after treatment (for depressed patients) or observation period (for the general population) to represent if a transition had taken place or not. The result of this study showed that participants with a greater change in their depression scores also had a larger correlation between emotion scores. However, because the depression score was not measured during the treatment or the observation period, it was not possible to detect the exact time point of the transitions. Several other studies used statistical methods to detect both whether a transition has happened and when it happened (see Table 1, transition indicators, unfixed time). Most of those studies, however, used a variable that was sampled more slowly to detect the transition than the variables that were used to calculate the EWIs. This means that the transition point is only roughly determined. For example, in the study by Wichers et al. (2016), the items for EWI detection were measured several times a day, whereas the depression score for transition detection was measured weekly. As a result, it was only possible to determine in which week the transition had taken place, but there was no way to know on which day exactly the transition had happened. Finally, the study by Olthof, Hasselman, Strunk, et al. (2020) used the same sampling frequency for all measures but the variables used for EWI detection and transition detection were not the same. The variables used for transition detections were excluded from the calculation of EWIs.

For conciseness, we will refer to those two practices, namely using loosely-defined time windows for EWIs and using different variables for transition detection and EWI detection, as *the loose-window issue* and *the different-variable issue*. We argue that those two issues may lead to incorrect results because in the mathematical derivation, EWSs and transitions should be observed from the same variable, and EWSs should occur strictly before the transition (Scheffer et al., 2009). This can also be intuitively understood because in the landscape illustration of the cusp bifurcation (Figure 1a), the fluctuation magnitude and return time of the ball only indicate the stability of a basin when the ball is still in this basin, and it is the same ball that shows EWSs and transitions to the other basin. In the following two sections, we use simulations to illustrate that, under certain conditions, both the loose-window issue and the different-variable issue can severely confound the result of EWS studies.

Simulation Study 1: Noise-Induced Transition and the Loose-Window Issue

As introduced above, the theoretical basis of EWS is bifurcation theory, which was developed for deterministic systems. However, real-life systems are always exposed to various forms of noise. For psychological systems, the noise in the system can come from several different sources. The weather, the environment, interpersonal relationships, and randomness in the biological processes of a person can have an impact on his or her psychological system. These factors cannot be fully controlled by the psychological system.[4] Therefore, researchers generally treat them as noises.

For a B-transition, the stability change is the cause for the transition of the system. The system transitions to another phase when its current phase is not stable anymore. Because of the noise in real-life systems, the transitions, however, often do not occur exactly at the same time as the bifurcation point is reached. Even if the noise is small, at a certain point before the bifurcation point, the system is able to escape the shallow basin and transition to the other phase. Nevertheless, as long as the noise of the system is not too large, the bifurcation is still the *dominant* reason for the transition, and the transition point is close enough to the bifurcation point (Boettiger & Batt, 2020). This warrants the use of EWSs for real-life systems. But if the noise strength is larger, the system can still transition to another phase even if the stability of the system has not changed (Figure 1b). This is called a *noise-induced transition*, or *N-transition*.

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[4] Some researchers in the field see psychological processes from a broader view and try to include some environmental factors into the psychological systems (e.g., Lunansky et al., 2021; van Geert, 2019). Taking this view, some factors here may be a part of the system and no longer be noises. However, note that there is almost always something out of a real-life system that can have random influences on it. Therefore, no matter how large the system is defined as, it does not affect our claim that noises should be taken into account.

Because the stability of the system may not change before an N-transition, we cannot expect to observe EWSs anymore (Ashwin et al., 2012; Boettiger & Batt, 2020; Kuehn, 2011).

In this section, we use a simulation study to show the consequence of measuring EWIs in a loosely-defined time window. Both conditions of B- and N-transition were simulated to compare their EWIs. All simulations and parameter estimations were performed in R 4.1.2 (R Core Team, 2021). The replicable R scripts can be found on the OSF repository of this project (https://osf.io/f659u/).

Model setup

We use a simple gradient system with noise by Shi et al. (2016) as the model for our simulation. The model contains one state variable, x, and a control parameter, λ. The potential function of the system, V, is specified as

$$V(x,\lambda) = 100\left(\frac{1}{4}x^4 - \frac{3}{2}x^2 + \lambda x\right). \tag{1}$$

The dynamic functions of the system are then specified as

$$\frac{\mathrm{d}x}{\mathrm{d}t} = -\frac{\partial V(x,\lambda)}{\partial x} + \sqrt{2\sigma}\xi(t) \tag{2}$$

where dx/dt represents the change rate of x, $\partial V(x,\lambda)/\partial x$ represents the gradient of the potential function with respect to x, σ represents the strength of the noise and was set as 10 in this study (as in Shi et al., 2016), and $\xi(t)$ represents standard white noise. The potential landscapes of the system with different λ, as well as the equilibrium points of the system where $\partial V(x,\lambda)/\partial x = 0$, are shown in Figure 2. For simulating the B-transition, the initial value of λ is set as -3, and the changing rate of λ is set as $\mathrm{d}\lambda/\mathrm{d}t = 1$. When the simulation starts, there is only one basin for the system. We refer to this as the *positive phase* because it is in the positive semi-axis of x. As λ increases to -2, the second basin appears, and its stability increases as λ

further increases. We refer to this basin as the *negative phase*. When λ increases to 2, the system reaches its bifurcation point. The positive phase of the system disappears and the negative basin becomes the only possible basin.

To simulate N-transitions, the parameter λ is held constant at 0, which means that the potential function V does not change through the simulation. The parameter σ is set as 10, the same as in the B-transition condition, but there is a strong noise $\Delta x = -3$ at $t = 3$ that pushes the system to the negative phase. This strong noise represents a rare event that is highly unlikely to happen every day but may happen several times in a person's life. This noise is unpredictable and does not change the stability of the system. Therefore, what the system experiences is an N-transition.

All simulations were numerically performed using the Euler-Maruyama method, with 10^{-4} as the step size and 6 as the total time length. The raw simulation data were subsampled by a factor of 10 to reduce the length of the data. Therefore, the time interval between adjunct time points in the output is 10^{-3}. For each condition, the simulation was replicated 10^{3} times and the results and statistical indicators were recorded for further analysis.

Indicators for simulation outputs

Transition point determination. For the simulated model, the transition of the system to another basin can be clearly identified when the system goes over the barrier (the unstable equilibrium in Figure 2) because we know the exact formula of the potential function. Therefore, instead of using the statistical ways that are used in empirical research (Table 1) where the actual transition point is unknown, we use the time that the system first crosses the barrier as the time of the transition (t_{trans}).

Early warning indicators. Here we test three early warning indicators that are commonly used in previous empirical studies (Table 1): increasing variance, increasing autocorrelation function (ACF), and increasing dynamic complexity (DC). Whereas variance and ACF are classical statistical measures, DC is a measure developed by Schiepek and Strunk (2010) for capturing critical instabilities in sparse time series data. It takes both the distribution of the data in the plausible region and the fluctuations into account. DC is higher when the variable fluctuates more frequently and when the variable deviates further from the ideal, uniform distribution. Because we used a simple univariate model, vector autocorrelation cannot be calculated. All three parameters were estimated with the overlapping moving window approach. The window size was selected as 200 time points ($\Delta t = 0.2$), and each time the window moves forward for 20 time points ($\Delta t = 0.02$). Here the number of time points in each window is much more than the typical value in empirical studies. We chose this large value because the main purpose of the current study is to qualitatively show the consequences of the loose-window issue, not to provide a guidance on the window size for empirical studies. A rather large window size can ensure the stability of the results. Within each window, the variance, lag-1 ACF, and DC were calculated. Specifically, the data were linear-detrended within each window before calculating the autocorrelation coefficient, and DC was calculated using the implementation in the casnet package (Hasselman et al., 2022). The right-aligned windows were used, which means that, for example, the variance calculated within the window from $t = 0$ to $t = 0.2$ is regarded as the variance at $t = 0.2$. Thus, no future information is included in the moving windows statistics. After that, Kendall's τ was calculated with the Kendall package (McLeod, 2011) to evaluate the trends of the parameters. The Kendall's τ was calculated in ranges relative to the transition point. We investigated three types of ranges in the current research: (1) strictly before the transition, for which τ was calculated in the range from $t_{\text{trans}} - 1.5$ to t_{trans}; (2) roughly before the transition, for which τ was calculated in the range from $t_{\text{trans}} - 1.5$ to $t_{\text{trans}} + 0.5$; and (3) around the transition, for which τ was calculated in the range from $t_{\text{trans}} - 1.5$ to $t_{\text{trans}} + 1.5$. These conditions were set to mimic different empirical studies where EWIs are calculated strictly before the transition (when the transition indicator is calculated in at least the same frequency as EWIs), roughly before the transition (when the transition indicator is calculated through the whole time period but in a lower frequency as EWIs), and in a large range that may contain a transition (when the transition indicator is only calculated before or after the whole study period). The range sizes are set as roughly one order of magnitude larger than the window sizes for moving window statistics, which is often the case in empirical studies.

Simulation results

Single simulation output. We first present the simulation output (represented as time series of x), the value of λ, and the moving-window statistics of single simulation examples for each condition (Figure 3). As shown in Figure 3a, the B-transition happened at $t = 4.76, \lambda = 1.76$, which was close to the bifurcation point ($t = 5, \lambda = 2$). Before the transition, the variance, ACF, and DC all increased, which is in line with the theoretical prediction. However, the peaks of the three statistical indicators appeared after the transition. This is because the transition itself is a directed movement of x from one region to another, which also increases the variance, ACF, and DC. For the N-transition condition (Figure 3b), the variance, ACF, and DC did not increase before the transition because the stability of the system did not change. Nevertheless, after the transition, there was a peak for all three statistical measures, which were also consequences of the transition itself.

Results from replicated simulations. The distributions of Kendall's τ for each condition are shown in Figure 4, and the descriptive statistics of those distributions can be found in Table S1 in the Supplementary Materials. When the time range for calculating EWIs was strictly before the transition, only the B-transition showed EWIs, manifesting as positive τs of the variance, ACF, and DC. Here positive trends for the B-transition are true positives because they could predict a future transition, whereas the null trends for the N-transition are true negatives because the transition that happened later was not predictable beforehand. When the time range was roughly before the transition, both B- and N-transitions showed EWIs. This is because the effect of the transition itself also falls into the range of the EWIs calculation. Here, the positive trends for the N-transition are false positives because EWIs do not predict a transition but are the result of the transition. Finally, when the range of EWIs was just around the transition, no EWIs could be detected anymore, even for the B-transition. This is because the trend after the transition was also taken into the calculation, which averaged out the EWIs before the transition. Here the null trends for the B-transition are false negatives because the information that can predict the transition was contained in the data, but was not detected.

To summarize, EWIs are only valid measures if they are calculated strictly before the transition. If EWIs are calculated roughly before the transition or just around the transition, it may lead to false positive or false negative conclusions about EWSs.

Simulation Study 2: Distribution Change and the Different-Variable Issue

For this section, we first introduce a situation in which the system noise is even larger, causing the system to easily switch back and forth between two possible phases (Figure 1c). In this case, there are very frequent transition events, hence it is better to use the state distribution, instead of single state values, to describe the system. Because the system has two phases, its state forms a bimodal distribution, and this distribution changes if the stability landscape changes. This type of change is called *distribution change* or *D-change* (Shi et al., 2016)[5]. If the system experiences a D-change, it is no longer possible to pinpoint a single transition point. The same process that leads to the D-change may, however, cause a simultaneous B-transition in another variable of the same system. For example, momentary affect at a specific time point is influenced by multiple environmental factors, thus having stronger noise, whereas depressive symptom severity is more stable over time. It is possible that momentary affect assessed with EMA undergoes a D-change whereas symptom severity measured on a weekly basis shows a B-transition. In this study, we simulate a system that has two associated variables, with one of them experiencing a D-change and the other experiencing a B-transition. We then examine the consequences when we use one variable to calculate EWIs and the other to detect sudden transitions.

Model setup

The model we used for Study 2 is very similar to Study 1, but there are two sets of equations for two variables x_1 and x_2:

$$V_1(x_1, \lambda_1) = 100\left(\frac{1}{4}x_1^4 - \frac{3}{2}x_1^2 + \lambda_1 x_1\right), \tag{3}$$

$$\frac{\mathrm{d}x_1}{\mathrm{d}t} = -\frac{\partial V_1(x_1, \lambda_1)}{\partial x_1} + \sqrt{2\sigma_1}\xi_1(t), \tag{4}$$

$$V_2(x_2, \lambda_2) = 100\left(\frac{1}{4}x_2^4 - \frac{3}{2}x_2^2 + \lambda_2 x_2\right), \tag{5}$$

[5] This type of change was initially proposed by Shi et al. (2016), where they used the term "distribution transition". In the current article, we only use "transition" for a single event in which the system transfer from one basin to another, and we call this type of change "distribution change" to avoid confusions.

$$\frac{\mathrm{d}x_2}{\mathrm{d}t} = -\frac{\partial V_2(x_2,\lambda_2)}{\partial x_2} + \sqrt{2\sigma_2}\xi_2(t). \tag{6}$$

Those equations have different parameters for x_1 and x_2. We set $\sigma_1 = 400$ and $\sigma_2 = 10$ so that x_1 will experience a D-change and x_2 will experience a B-transition when λ_2 approaches 2 (as in Shi et al., 2016; x_1 and x_2 correspond to the mood measure and the depressive symptoms in our example). We further represent the relationship between x_1 and x_2 by associating λ_1 and λ_2.[6] The relationship of λ_1 and λ_2 can, in principle, take any form. We illustrate two simple conditions: (a) $\lambda_2 = \lambda_1$, (b) $\lambda_2 = \lambda_1 + 2$. The starting value and changing rate of λ_1 were set the same as in Study 1: the initial value of λ_1 is -3 and $\mathrm{d}\lambda_1/\mathrm{d}t = 1$. The simulation methods (e.g., simulation length, step size, etc.) are the same as in Study 1.

Indicators for simulation outputs

Transition point determination. The time of the transition (t_{trans}) was determined using the same method as in Study 1, but only the value of x_2 was used.

Early warning indicators. We use the same methods for calculating EWIs as in Study 1, but we only use the time window that is strictly before the transition (from $t_{\mathrm{trans}} - 1.5$ to t_{trans}) and only calculate EWIs for x_1.

[6] Here the association we implemented into the system seems as if we have a causal claim that there is a common cause for both variables (i.e., the association of λ_1 and λ_2 leads to the change in both variables x_1 and x_2). This is not the case because what we focus on here is the transitions of the two variables in the same system are associated with each other, no matter if one variable is the cause of another, they have mutual influences, or they have a common cause. In multivariate systems, many causal mechanisms can lead to the same association in data (Pearl, 2009; Ryan et al., 2019). We chose to link λ_1 and λ_2 in this study mainly for simplicity in model specification and simulation, whereas for the sake of generalizability, we leave open the actual causal mechanism behind this association.

Simulation results

Single simulation output. The single simulation examples for both conditions are shown in Figure 5. For both conditions, the dynamics of x_2 were the same as the B-transition examples in Study 1 (Figure 1a), whereas x_1 experienced D-changes. Because the strength of noise was large, the system was able to travel through the entire possible space almost from the beginning of the simulation. Nevertheless, the distribution only slowly changed throughout the simulation. In the beginning, the system was more likely to be in the positive phase, whereas at the end of the simulation, the system was more likely to be in the negative phase. In the first half of the simulation, there was an increasing trend for all statistical measures, which shows that the distribution of system states became more even, and the system shifted between two phases more often. In the middle of the simulation ($t = 3, \lambda_1 = 0$), the stabilities of the two phases were exactly the same, hence the system was the most evenly distributed in the two phases and can switch between the two phases most easily. After this point, all the statistical measures started to decrease.

Results from replicated simulations. The distributions of Kendall's τ for both conditions are shown in Figure 6, and the descriptive statistics of those distributions can be found in Table S2 in the Supplementary Materials. Although the EWIs were "as expected" for condition (b), the trends of the statistical measures for condition (a) were in the opposite direction: the variance, lag-1 ACF, and DC all decreased before the transition. This is because the trends calculated from x_1 only represent the distribution of x_1, but they do not bear any information about the stability of x_2. The results calculated from two variables depend on an arbitrary relationship specified for λ_1 and λ_2 and could not predict a future transition. Therefore, those positive or negative trends should be regarded as false positives or false negatives.

To summarize, if the variable used for EWI calculation (x_1) is different from the variable used for transition point detection (x_2), there is no reason to assume that the EWIs predict a sudden change in the near future. The positive or negative result of EWIs can merely result from another mechanism in x_1, for example, a D-change in this study.

Discussion

The current article aimed to investigate two issues in the research practice of EWS studies, namely the loose-window and the different-variable issue. In the theoretical review, we showed that early warning signals should precede the transition, and should be observed in the same variable as the variable that undergoes the sudden change. After that, we performed two simulation studies to illustrate the possible consequences of those two issues. In Study 1, we showed that if a system experiences a B-transition, but the EWIs are only measured around the transition point, then a false negative result can be obtained; if a system experiences an N-transition, but the EWIs are measured roughly before the transition point, then a false positive result can be obtained. In Study 2, we showed that when the variable used for EWI calculation is different from the variable used for transition point detection, then both false positive and false negative results can be obtained merely depending on the arbitrary relationship between the two variables. Therefore, we conclude that those two practices should be generally avoided if not justified by additional theories.

The models we used for simulations are radical simplifications of real-life psychological systems because they are unidimensional, gradient, not history-dependent, and not constructed with extensive psychological theories. Despite those limitations, simulations of those systems still provide important information to inform future empirical studies. If those practices already lead to incorrect results in these very simple systems, there is no reason to assume they will yield correct results in a more complex system. Another advantage of using these simplified models is that they align well with the quite often used landscape metaphor. Therefore, the results we obtained are closer to the (implicit) theories of EWS researchers. It is important to point out that our choice to use simple yet unrealistic models for simulations is based on the research aim we had: to qualitatively establish the phenomena and call for a better research methodology. The specific simulation setups (e.g., the window size, the sampling frequency, and the length of observation) should therefore not be taken as quantitative guidelines for empirical studies. In the following sections, we discuss the implications of our research for future EWS studies, and studies on psychological change in general.

Implications and Suggestions for Future EWS Studies

Whereas EWSs have promising prospects in understanding psychological systems and predicting future changes, there may be many potential pitfalls when researchers design and conduct EWS studies. In a previous article, Dablander et al. (2022) provided several general recommendations for EWS studies, including a basic understanding of the system (e.g., using formal models) to warrant the assumption of EWSs, a study design evaluated in terms of measurement frequency and noise, adequate data preprocessing and analysis, and more investigations to determine how and when (psychological) interventions should be applied to avoid a critical transition in the near future. In the current study, we followed the first suggestion by Dablander et al. (2022) by introducing certain types of transitions that are relevant to psychological systems, and by using formal dynamic models for simulations. Moreover, we also connect those theoretical considerations with recent EWS studies (Table 1), yielding more specific perspectives about two common research practices which are highly relevant to the field, conceptually more important than statistical issues, but have not been systematically addressed before. In this section, we discuss the implications with regard to three aspects: theory construction, study design, and data analysis.

Theory construction. Given the complex and dynamical nature of human psychology, it is indeed reasonable to assume that psychological systems are multistable and can sometimes experience transitions between different phases. But researchers should be aware that stating that a system is complex does not necessarily mean that it will experience transitions or that it will experience transitions in the form of a B-transition. The latter seems to be an (implicit) assumption in most previous studies. We encourage researchers to explicate their theoretical claims about the underlying change process. In case of a B-transition there needs to be a specific parameter slowly changing during the study period, leading to the changes in the stability of the different phases in the system. For example, in the study by Wichers et al. (2016), a patient gradually decreased the antidepressants and a transition happened during this process. In this case, researchers may have hypothesized that the gradual change in neurotransmitter level led to the sudden change in symptom level. In general, it may be more valuable to first theorize about the change process (e.g., B- or N-transition or D-change) and then test for EWS when appropriate. A rigorous test of EWS could then also improve theory formation, as it may corroborate or falsify B-transition as an explanation for clinical changes in specific cases. Moreover, such a research program could study whether specific patterns of clinical change (e.g. onset of depression vs. onset of rapid cycling bipolar disorder) are related to specific forms of change.

If a system undergoes another type of change instead of a B-transition, it does not mean that the transitions in those cases are not important, nor does it mean that the EWIs do not bear any information about the system. An N-transition, even without EWSs preceding it, can still be clinically relevant because the system does shift to another phase that is qualitatively different from the previous one, and in cases where the phase is healthier clinical efforts should be devoted to strengthening and stabilizing this new phase. In addition, the inversed-V shape of the variance or autocorrelation for a D-change, although unable to predict a sudden change in the near future, still does show the change of the distribution, and this flexibility or instability of the patient's mental state may be adaptive and be encouraged, or maladaptive and be restrained. The important thing only is that these phenomena are not B-transitions or EWSs and this very fact bears several implications for how we conceptualize mental disorders, therapies, and prevention programs. There have been some studies that used formal models as a way to build theories for psychological changes. Examples include the ones of B-transition (e.g., Cramer et al., 2016; Dablander et al., 2022; van de Leemput et al., 2014), N-transition (e.g., Haslbeck & Ryan, 2021), and other more complex changes (e.g., high-dimensional stochastic models, Burger et al., 2020; Robinaugh et al., 2019; model with chaotic attractors, Schiepek et al., 2017; Schöller et al., 2018). However, there is still a dearth of theories that comprehensively describe the types of psychological changes and their corresponding data features. We encourage future researchers to take this next step and improve theory construction in this field. Only if we have strong enough theories is it possible to design effective empirical studies and meaningfully test those theories (Fried, 2020).

Study design. Based on the theory of EWS and our simulation results two suggestions can be provided. First, we showed that although the choice of statistical measures (variance, ACF, or DC) does not affect the result much, it is important that the EWI assessment period is strictly before the transition because the transition process itself can result in an increase of variance, ACF, or DC. If the transition is included in the time window for EWIs, the results are not purely “early warnings” but also contain the outcome of the transition process itself. The outcome of the transition is theoretically different from EWSs and the EWIs that contain the transition outcome are not able to predict a *future* transition. Moreover, after the transition process, there will be a decrease in statistical measures, which can average out true EWSs. Therefore, this part of the time series should not be included in the time window for EWIs, either.

Next, the same set of variables should be used to calculate EWIs and to detect the transition. In Study 1, x was used both for detecting the transition and calculating the EWIs. This is a natural requirement if we consider the theory of bifurcation, which indicates that the transition and critical stability are different phenomena for the same variables in different periods (Figure 1; also see Ditlevsen & Johnsen, 2010; Kuehn, 2011, for mathematical proves). Although almost all EWS research in other fields uses the same variables for calculating EWIs and sudden transitions (e.g., Gorban et al., 2010; Guttal et al., 2016; Lever et al., 2020; Thompson & Sieber, 2011), this is not the case for previous psychological studies (Table 1). We suspect this practice in psychological research comes from the distinction between “independent variables” and “dependent variables”, and we emphasize that the theories behind EWSs do not include this distinction. As shown in Study 2, EWIs in one variable need not to predict an upcoming transition in a different variable in that system. To summarize, in order to correctly examine EWSs in psychological systems, we suggest that future researchers pinpoint the exact moment of transition, calculate EWIs strictly before the transition, and use the same set of variables for transition detection and EWI calculations. Researchers may also re-analyze existing datasets to check if the EWIs can still be observed with the methods we recommend.

Data analysis. Here we want to highlight the value of descriptive analysis of raw data in EWS studies. Sometimes it is possible to tell the type of transition just by inspecting the raw time series, without sophisticated calculations. Take the simulation outputs in Figure 5, it is easy to see that x_1 does not experience a B-transition because the system did go to the alternative phase at the beginning of the simulation, whereas in case of a bifurcation, the system cannot go to the alternative phase before the bifurcation point. There is a set of descriptive features for catastrophic bifurcations, termed *catastrophe flags* (Gilmore, 1993), which can be used to inspect the raw data and examine if a B-transition can be assumed. Those features include, for example, inaccessibility and bimodality. Here inaccessibility means that the system is not likely to be on the barrier between two phases, and bimodality means that the system variable should show a bimodal distribution, which corresponds to the two phases of the system. In our literature review, not all studies included the raw time series, and in the studies that did, these plots were often not examined with respect to whether they show characteristics of a B-transition. In some studies the raw time series did show a similar pattern as our simulation outputs of B-transitions (e.g., in the data presented by Wichers et al., 2020, the mood time series of the participant had different, although not separated, ranges before and after the hypothesized transition), whereas this is not the case in other studies (e.g., in the data presented by Bos et al., 2022, the mood time series had very similar ranges before and after the hypothesized transition). These differences may partly explain the mixed findings in previous studies because EWSs only exist when a B-transition takes place.

In our simulation studies, different statistical indicators (variance, ACF, and DC) showed similar patterns, but this may not always hold for empirical studies. For example, Bos et al. (2022) found that ACF has better predictive power than the variance for depressive transitions in patients with a bipolar disorder. Several studies have investigated the predictive power of different EWIs (Dakos et al., 2012; Lenton et al., 2012; Weinans et al., 2021), showing that some EWI measures may outperform others under specific conditions. However, if only some EWIs but not others can be found in a data set, it may indicate that the system did not undergo a B-transition (Ditlevsen & Johnsen, 2010). For example, if only the variance but not ACF increased before a transition, it might indicate that the reason for the transition is the increase of noise rather than the change of stability (Chen et al., 2018; Dakos et al., 2013). Therefore, we suggest that future researchers use different EWIs to increase the robustness of their findings.

Conclusion

EWSs can predict future B-transitions in complex systems, but EWIs observed in data are not always true EWSs. False-positive or false-negative results may be observed if researchers (1) use loosely-identified time windows for EWI calculations, or (2) use different variables for calculating EWIs and sudden changes. We therefore suggest future researchers to exactly pinpoint the moment of transition and test for EWSs in the same variable using a time-window defined strictly before the transition. Besides the B-transition, other types of changes can also be important for psychological systems. Future researchers may further investigate such different types of changes in psychological systems and their potential implications.

References

Ashwin, P., Wieczorek, S., Vitolo, R., & Cox, P. (2012). Tipping points in open systems: Bifurcation, noise-induced and rate-dependent examples in the climate system. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *370*(1962), 1166–1184. https://doi.org/10.1098/rsta.2011.0306

Boettiger, C., & Batt, R. (2020). Bifurcation or state tipping: Assessing transition type in a model trophic cascade. *Journal of Mathematical Biology*, *80*(1), 143–155. https://doi.org/10.1007/s00285-019-01358-z

Bos, F. M., Schreuder, M. J., George, S. V., Doornbos, B., Bruggeman, R., van der Krieke, L., Haarman, B. C. M., Wichers, M., & Snippe, E. (2022). Anticipating manic and depressive transitions in patients with bipolar disorder using early warning signals. *International Journal of Bipolar Disorders*, *10*(1), 12. https://doi.org/10.1186/s40345-022-00258-4

Burger, J., van der Veen, D. C., Robinaugh, D. J., Quax, R., Riese, H., Schoevers, R. A., & Epskamp, S. (2020). Bridging the gap between complexity science and clinical practice by formalizing idiographic theories: A computational model of functional analysis. *BMC Medicine*, *18*(1). https://doi.org/10.1186/s12916-020-01558-1

Chen, N., Jayaprakash, C., Yu, K., & Guttal, V. (2018). Rising Variability, Not Slowing Down, as a Leading Indicator of a Stochastically Driven Abrupt Transition in a Dryland Ecosystem. *The American Naturalist*, *191*(1), E1–E14. https://doi.org/10.1086/694821

Cramer, A. O. J., Borkulo, C. D. van, Giltay, E. J., Maas, H. L. J. van der, Kendler, K. S., Scheffer, M., & Borsboom, D. (2016). Major depression as a complex dynamic system. *PLOS ONE*, *11*(12), e0167490. https://doi.org/10.1371/journal.pone.0167490

Cui, J., Lichtwarck-Aschoff, A., Olthof, M., Li, T., & Hasselman, F. (2021). *From metaphor to computation: Constructing the potential landscape for multivariate psychological formal models* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/49xyg

Curtiss, J. E., Fulford, D., Hofmann, S. G., & Gershon, A. (2019). Network dynamics of positive and negative affect in bipolar disorder. *Journal of Affective Disorders*, *249*, 270–277. https://doi.org/10.1016/j.jad.2019.02.017

Curtiss, J. E., Mischoulon, D., Fisher, L. B., Cusin, C., Fedor, S., Picard, R. W., & Pedrelli, P. (2021). Rising early warning signals in affect associated with future changes in depression: A dynamical systems approach. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291721005183

Dablander, F., Pichler, A., Cika, A., & Bacilieri, A. (2022). Anticipating critical transitions in psychological systems using early warning signals: Theoretical and practical considerations. *Psychological Methods*. https://doi.org/10.1037/met0000450

Dakos, V., Carpenter, S. R., Brock, W. A., Ellison, A. M., Guttal, V., Ives, A. R., Kéfi, S., Livina, V., Seekell, D. A., Nes, E. H. van, & Scheffer, M. (2012). Methods for detecting early warnings of critical transitions in time series illustrated using simulated ecological data. *PLOS ONE*, *7*(7), e41010. https://doi.org/10.1371/journal.pone.0041010

Dakos, V., van Nes, E. H., & Scheffer, M. (2013). Flickering as an early warning signal. *Theoretical Ecology*, *6*(3), 309–317. https://doi.org/10.1007/s12080-013-0186-4

Ditlevsen, P. D., & Johnsen, S. J. (2010). Tipping points: Early warning and wishful thinking. *Geophysical Research Letters*, *37*(19). https://doi.org/10.1029/2010GL044486

Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry*, *31*(4), 271–288. https://doi.org/10.1080/1047840X.2020.1853461

Gilmore, R. (1993). *Catastrophe theory for scientists and engineers*. Courier Corporation.

Gorban, A. N., Smirnova, E. V., & Tyukina, T. A. (2010). Correlations, risk and crisis: From physiology to finance. *Physica A: Statistical Mechanics and Its Applications*, *389*(16), 3193–3217. https://doi.org/10.1016/j.physa.2010.03.035

Granic, I. (2005). Timing is everything: Developmental psychopathology from a dynamic systems perspective. *Developmental Review*, *25*(3), 386–407. https://doi.org/10.1016/j.dr.2005.10.005

Guttal, V., Raghavendra, S., Goel, N., & Hoarau, Q. (2016). Lack of critical slowing down suggests that financial meltdowns are not critical transitions, yet rising variability could signal systemic risk. *PLOS ONE*, *11*(1), e0144198. https://doi.org/10.1371/journal.pone.0144198

Haslbeck, J., & Ryan, O. (2021). Recovering within-person dynamics from psychological time series. *Multivariate Behavioral Research*, *0*, 1–32. https://doi.org/10.1080/00273171.2021.1896353

Haslbeck, J., Ryan, O., Robinaugh, D., Waldorp, L., & Borsboom, D. (2021). Modeling psychopathology: From data models to formal theories. *Psychological Methods*. https://doi.org/10.1037/met0000303

Hasselman, F., Olthof, M., & Cui, J. (2022). *casnet: A toolbox for studying complex adaptive systems and NETworks* [Manual]. https://github.com/FredHasselman/casnet

Hayes, A. M., Laurenceau, J.-P., Feldman, G., Strauss, J. L., & Cardaciotto, L. (2007). Change is not always linear: The study of nonlinear and discontinuous patterns of change in psychotherapy. *Clinical Psychology Review*, *27*(6), 715–723. https://doi.org/10.1016/j.cpr.2007.01.008

Helmich, M. A., Olthof, M., Oldehinkel, A. J., Wichers, M., Bringmann, L. F., & Smit, A. C. (2021). Early warning signals and critical transitions in psychopathology: Challenges and recommendations. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2021.02.008

Helmich, M. A., Smit, A., Bringmann, L., Schreuder, M., Oldehinkel, A., Wichers, M., & Snippe, E. (2021). *Detecting impending symptom transitions using early warning signals in individuals receiving treatment for depression*. PsyArXiv. https://doi.org/10.31234/osf.io/vf86s

Helmich, M. A., Wichers, M., Olthof, M., Strunk, G., Aas, B., Aichhorn, W., Schiepek, G., & Snippe, E. (2020). Sudden gains in day-to-day change: Revealing nonlinear patterns of individual improvement in depression. *Journal of Consulting and Clinical Psychology*, *88*(2), 119–127. https://doi.org/10.1037/ccp0000469

Kelso, S. (2010). Instabilities and phase transitions in human brain and behavior. *Frontiers in Human Neuroscience*, *4*. https://doi.org/10.3389/fnhum.2010.00023

Kuehn, C. (2011). A mathematical framework for critical transitions: Bifurcations, fast–slow systems and stochastic dynamics. *Physica D: Nonlinear Phenomena*, *240*(12), 1020–1035. https://doi.org/10.1016/j.physd.2011.02.012

Lenton, T. M. (2011). Early warning of climate tipping points. *Nature Climate Change*, *1*(4), 201–209. https://doi.org/10.1038/nclimate1143

Lenton, T. M., Livina, V. N., Dakos, V., van Nes, E. H., & Scheffer, M. (2012). Early warning of climate tipping points from critical slowing down: Comparing methods to improve robustness. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *370*(1962), 1185–1204. https://doi.org/10.1098/rsta.2011.0304

Lever, J. J., Leemput, I. A. van de, Weinans, E., Quax, R., Dakos, V., Nes, E. H. van, Bascompte, J., & Scheffer, M. (2020). Foreseeing the future of mutualistic communities beyond collapse. *Ecology Letters*, *23*(1), 2–15. https://doi.org/10.1111/ele.13401

Lunansky, G., van Borkulo, C. D., Haslbeck, J. M. B., van der Linden, M. A., Garay, C. J., Etchevers, M. J., & Borsboom, D. (2021). The mental health ecosystem: Extending symptom networks with risk and protective factors. *Frontiers in Psychiatry*, *12*. https://doi.org/10.3389/fpsyt.2021.640658

McLeod, A. I. (2011). *Kendall: Kendall rank correlation and Mann-Kendall trend test* [Manual]. https://CRAN.R-project.org/package=Kendall

Miller, W. R. (2004). The phenomenon of quantum change. *Journal of Clinical Psychology*, *60*(5), 453–460. https://doi.org/10.1002/jclp.20000

Olthof, M., Hasselman, F., & Lichtwarck-Aschoff, A. (2020). Complexity in psychological self-ratings: Implications for research and practice. *BMC Medicine*, *18*(1), 317. https://doi.org/10.1186/s12916-020-01727-2

Olthof, M., Hasselman, F., Oude Maatman, F., Bosman, A. M. T., & Lichtwarck-Aschoff, A. (in press). Complexity theory of psychopathology. *Journal of Psychopathology and Clinical Science*. https://doi.org/10.31234/osf.io/f68ej

Olthof, M., Hasselman, F., Strunk, G., van Rooij, M., Aas, B., Helmich, M. A., Schiepek, G., & Lichtwarck-Aschoff, A. (2020). Critical fluctuations as an early-warning signal for sudden gains and losses in patients receiving psychotherapy for mood disorders. *Clinical Psychological Science, 8*(1), 25–35. https://doi.org/10.1177/2167702619865969

Pearl, J. (2009). *Causality*. Cambridge university press.

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Robinaugh, D. J., Haslbeck, J., Ryan, O., Fried, E. I., & Waldorp, L. J. (2021). Invisible hands and fine calipers: A call to use formal theory as a toolkit for theory construction. *Perspectives on Psychological Science*, 1745691620974697. https://doi.org/10.1177/1745691620974697

Robinaugh, D. J., Haslbeck, J., Waldorp, L., Kossakowski, J. J., Fried, E. I., Millner, A., McNally, R. J., van Nes, E. H., Scheffer, M., Kendler, K. S., & Borsboom, D. (2019). *Advancing the network theory of mental disorders: A computational model of panic disorder*. https://doi.org/10.31234/osf.io/km37w

Ryan, O., Bringmann, L., & Schuurman, N. K. (2019). *The challenge of generating causal hypotheses using network models*. PsyArXiv. https://doi.org/10.31234/osf.io/ryg69

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., Held, H., van Nes, E. H., Rietkerk, M., & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature*, *461*(7260), 53–59. https://doi.org/10.1038/nature08227

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V., van de Koppel, J., van de Leemput, I. A., Levin, S. A., van Nes, E. H., Pascual, M., & Vandermeer, J. (2012). Anticipating critical transitions. *Science, 338*(6105), 344–348. https://doi.org/10.1126/science.1225244

Schiepek, G., & Strunk, G. (2010). The identification of critical fluctuations and phase transitions in short term and coarse-grained time series—A method for the real-time monitoring of human change processes. *Biological Cybernetics*, *102*(3), 197–207. https://doi.org/10.1007/s00422-009-0362-1

Schiepek, G., Viol, K., Aichhorn, W., Hütt, M.-T., Sungler, K., Pincus, D., & Schöller, H. J. (2017). Psychotherapy is chaotic—(Not only) in a computational world. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00379

Schöller, H., Viol, K., Aichhorn, W., Hütt, M.-T., & Schiepek, G. (2018). Personality development in psychotherapy: A synergetic model of state-trait dynamics. *Cognitive Neurodynamics*, *12*(5), 441–459. https://doi.org/10.1007/s11571-018-9488-y

Schreuder, M. J., Hartman, C. A., George, S. V., Menne-Lothmann, C., Decoster, J., van Winkel, R., Delespaul, P., De Hert, M., Derom, C., Thiery, E., Rutten, B. P. F., Jacobs, N., van Os, J., Wigman, J. T. W., & Wichers, M. (2020). Early warning signals in psychopathology: What do they tell? *BMC Medicine*, *18*(1), 269. https://doi.org/10.1186/s12916-020-01742-3

Shi, J., Li, T., & Chen, L. (2016). Towards a critical transition theory under different temporal scales and noise strengths. *Physical Review E*, *93*(3), 032137. https://doi.org/10.1103/PhysRevE.93.032137

Smith, L. B., & Thelen, E. (2003). Development as a dynamic system. *Trends in Cognitive Sciences*, *7*(8), 343–348. https://doi.org/10.1016/S1364-6613(03)00156-6

Stiles, W. B., & Shapiro, D. A. (1994). Disabuse of the drug metaphor: Psychotherapy process-outcome correlations. *Journal of Consulting and Clinical Psychology*, *62*(5), 942–948. https://doi.org/10.1037/0022-006X.62.5.942

Tang, T. Z., & DeRubeis, R. J. (1999). Sudden gains and critical sessions in cognitive-behavioral therapy for depression. *Journal of Consulting and Clinical Psychology*, *67*(6), 894–904. https://doi.org/10.1037/0022-006X.67.6.894

Thom, R. (1975). *Structural stability and morphogenesis: An outline of a general theory of models*. W. A. Benjamin.

Thompson, J. M. T., & Sieber, J. (2011). Predicting climate tipping as a noisy bifurcation: A review. *International Journal of Bifurcation and Chaos*, *21*(02), 399–423. https://doi.org/10.1142/S0218127411028519

van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences*, *111*(1), 87–92. https://doi.org/10.1073/pnas.1312114110

van Geert, P., & van Dijk, M. (2021). Thirty years of focus on individual variability and the dynamics of processes. *Theory & Psychology*, *31*(3), 405–410. https://doi.org/10.1177/09593543211011663

van Geert, P. L. C. (2019). Dynamic systems, process and development. *Human Development*, *63*(3–4), 153–179. https://doi.org/10.1159/000503825

Weinans, E., Quax, R., van Nes, E. H., & Leemput, I. A. van de. (2021). Evaluating the performance of multivariate indicators of resilience loss. *Scientific Reports*, *11*(1), 9148. https://doi.org/10.1038/s41598-021-87839-y

Wichers, M., Groot, P. C., & Psychosystems, ESM Group, EWS Group. (2016). Critical slowing down as a personalized early warning signal for depression. *Psychotherapy and Psychosomatics*, *85*(2), 114–116. https://doi.org/10.1159/000441458

Wichers, M., Schreuder, M. J., Goekoop, R., & Groen, R. N. (2019). Can we predict the direction of sudden shifts in symptoms? Transdiagnostic implications from a complex systems perspective on psychopathology. *Psychological Medicine*, *49*(3), 380–387. https://doi.org/10.1017/S0033291718002064

Wichers, M., Smit, A. C., & Snippe, E. (2020). Early warning signals based on momentary affect dynamics can expose nearby transitions in depression: A confirmatory single-subject time-series study. *Journal for Person-Oriented Research*, *6*(1), 1–15. https://doi.org/10.17505/jpor.2020.22042

Zeeman, E. C. (1976). Catastrophe Theory. *Scientific American*, *234*(4), 65–83.

Table 1. An overview of commonly investigated early warning indicators, sudden change indicators, and assessment periods.

Type	Specific indicator	Examples of empirical studies
Early warning indicators		
Critical fluctuation	Increasing variance	(Bos et al., 2022; Curtiss et al., 2021; Helmich, Smit, et al., 2021; van de Leemput et al., 2014; Wichers et al., 2016, 2020)[1]
Critical slowing down	Increasing autocorrelation	(Bos et al., 2022; Curtiss et al., 2019, 2021; Helmich, Smit, et al., 2021; Schreuder et al., 2020; van de Leemput et al., 2014; Wichers et al., 2016, 2020)
	Increasing vector autocorrelation/network connectivity	(Curtiss et al., 2021; Wichers et al., 2016, 2020)[1]
Critical fluctuation & slowing down	High dynamic complexity (Schiepek & Strunk, 2010)	(Olthof, Hasselman, Strunk, et al., 2020)
Transition indicators		
Fixed time	Mean level difference	(Curtiss et al., 2019, 2021; Helmich, Smit, et al., 2021; Schreuder et al., 2020; van de Leemput et al., 2014)
Unfixed time	Change above a threshold	Slowly sampled: (Bos et al., 2022)[2]
	Change point analysis	Slowly sampled: (Wichers et al., 2016, 2020)[2]
		Same frequency, different items: (Olthof, Hasselman, Strunk, et al., 2020)[3]

[1] Curtiss et al. (2021) tested increasing variance and network connectivity as early warning indicators but did not find significant relationships of them with sudden change indicators. Other studies at least find statistically significant results for each indicator for some items or patients.

[2] Slowly sampled: the variable for detecting transitions was sampled in a slower frequency than the variables used for calculating EWIs.

[3] Same frequency, different items: the variable for detecting transitions was sampled in the same frequency than the variables used for calculating EWIs, but two sets of variables were distinguished.

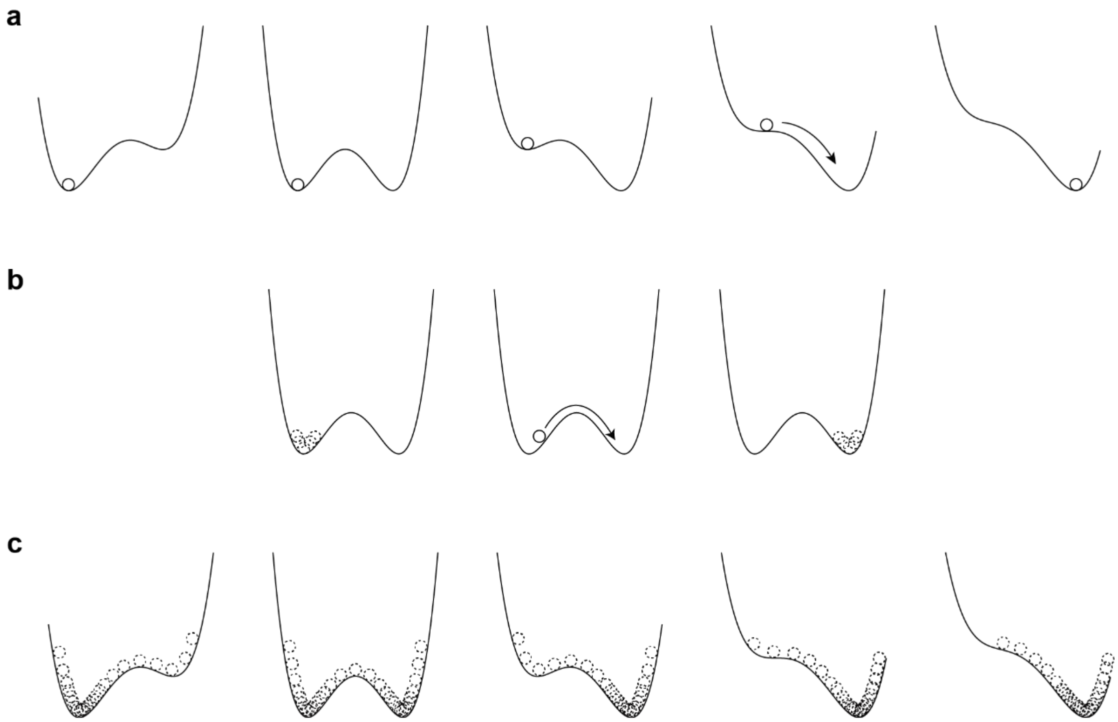

Figure 1. Diagrams of (a) bifurcation-induced transition (B-transition), (b) noise-induced transition (N-transition), and (c) distribution change (D-change).

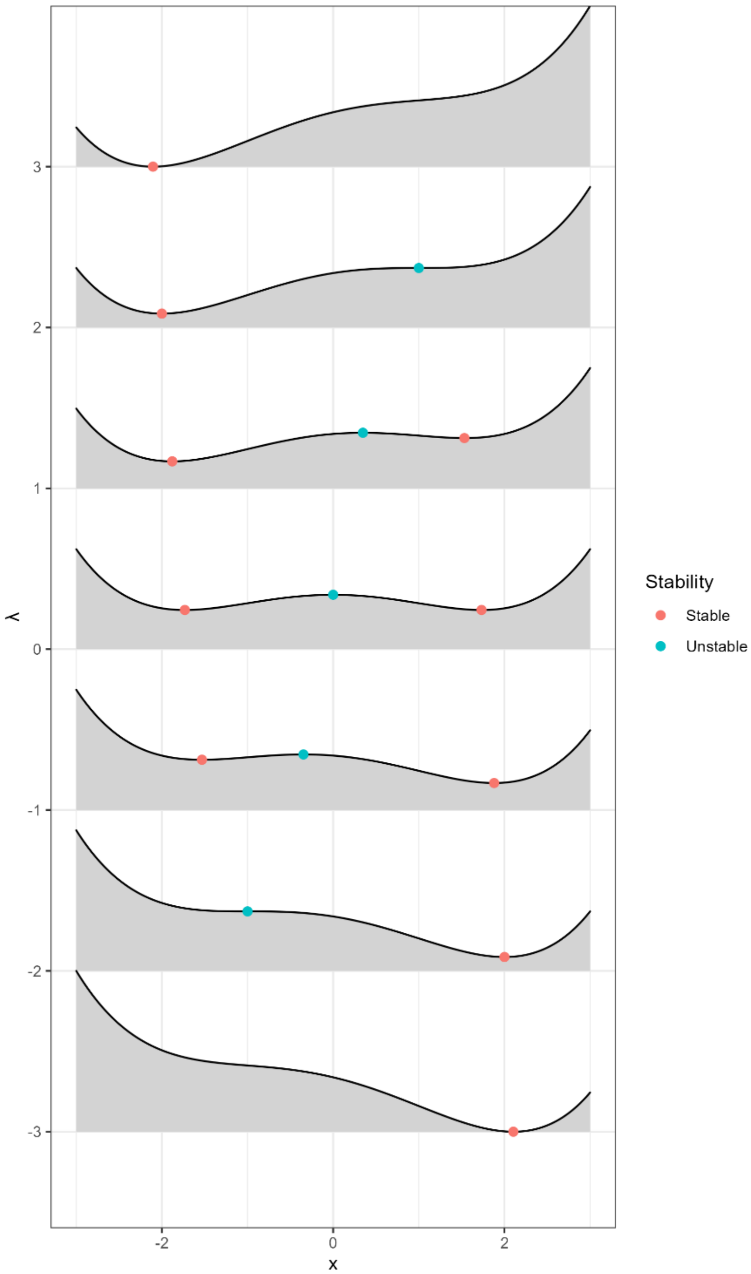

Figure 2. The potential function of the model (Equation 1) for different λ values. The red dots represent the stable equilibrium points and the blue points represent the unstable equilibrium points.

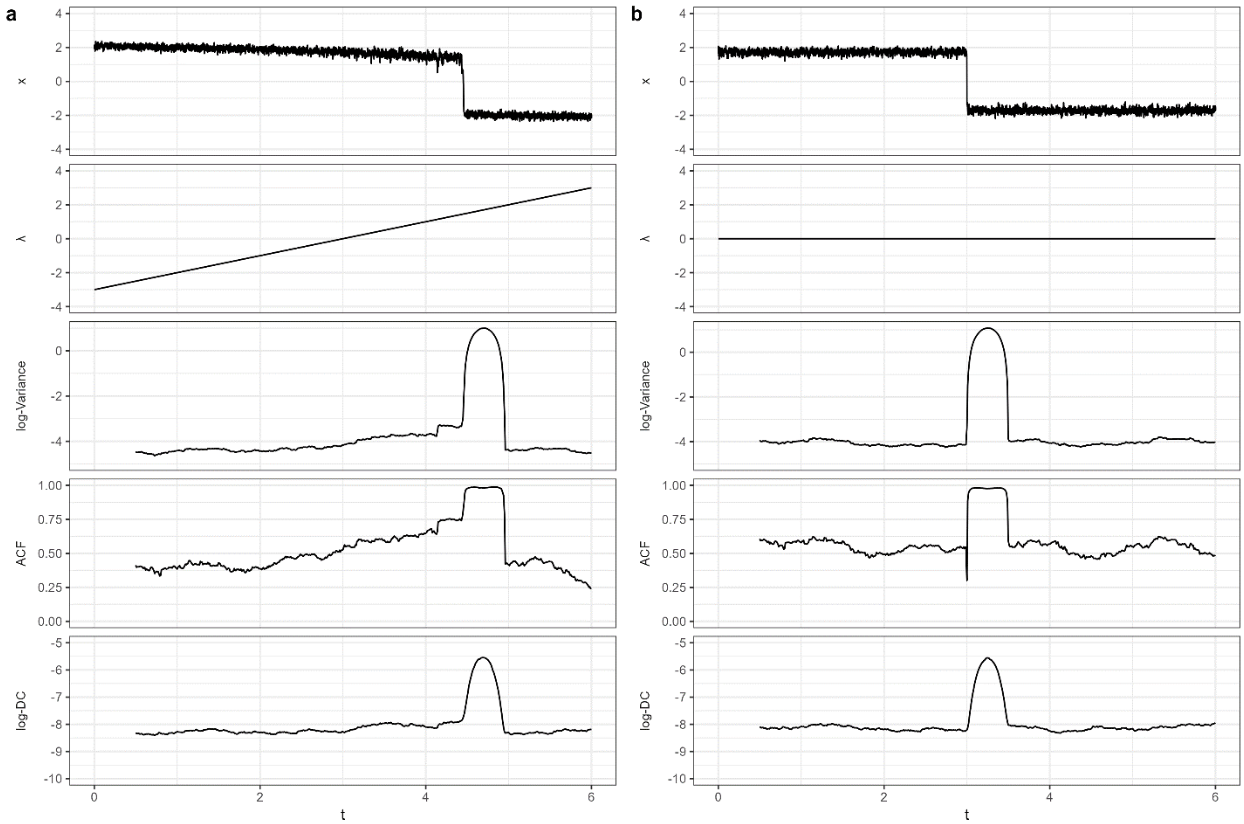

Figure 3. Simulation examples for (a) B-transition and (b) N-transition. Variance and DC were log-transformed to better show the trends before the transitions.

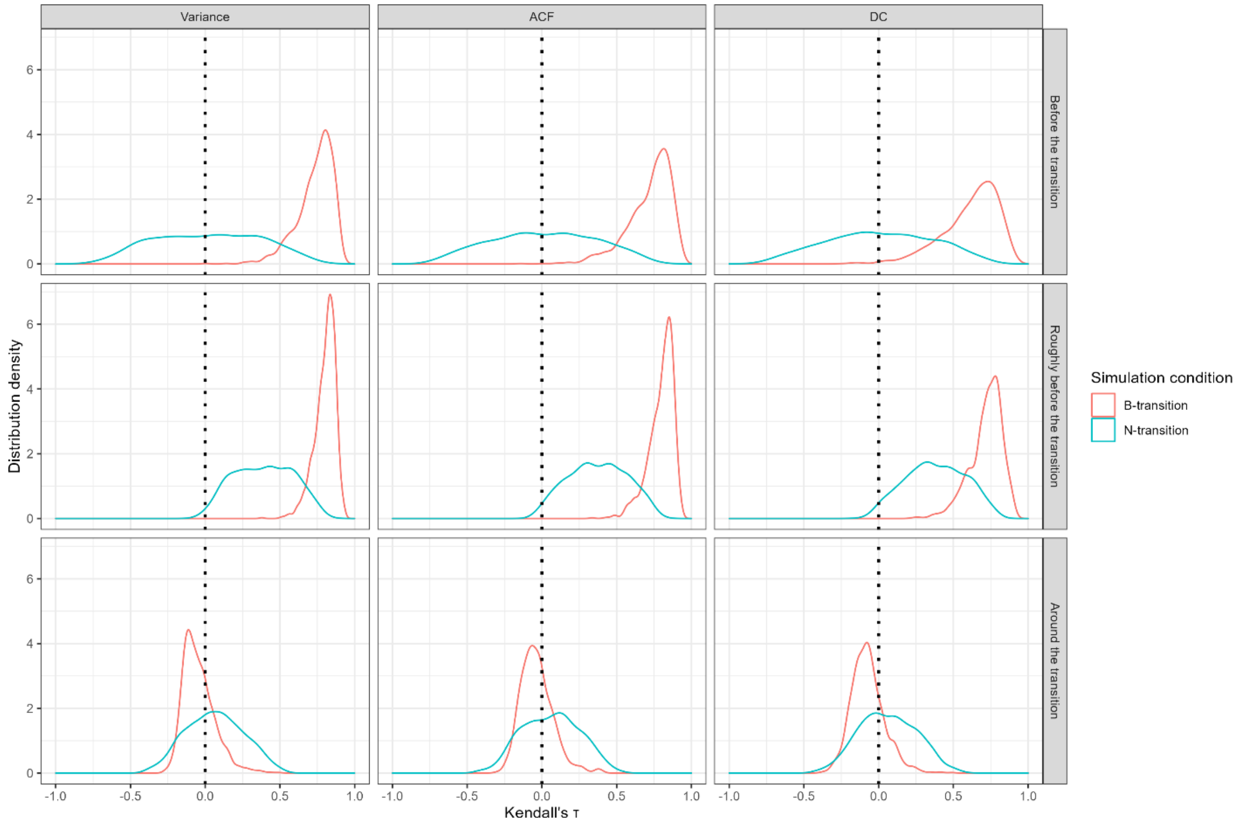

Figure 4. Trends of variance, ACF, and DC, represented with the distribution of Kendall's τ from 10^3 simulations, for B- and N- transitions and different periods.

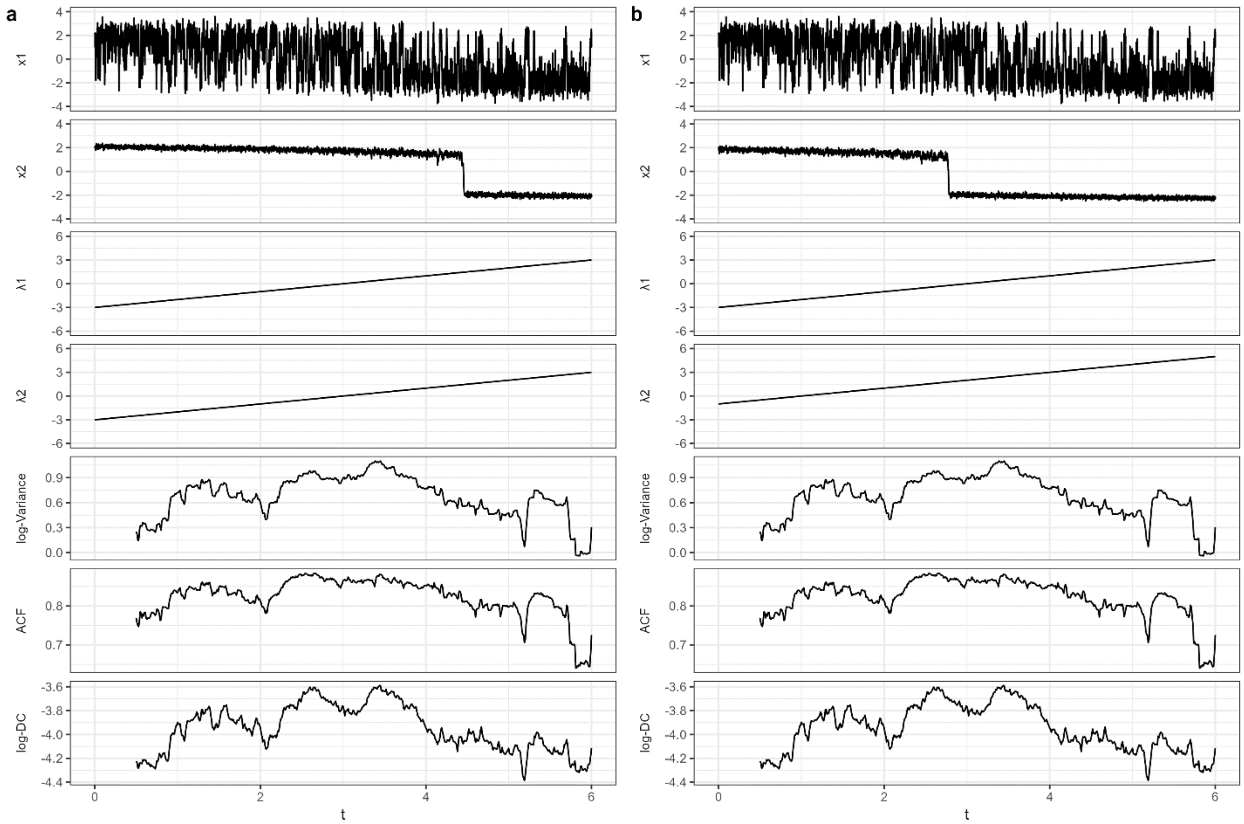

Figure 5. Simulation examples for (a) $\lambda_2 = \lambda_1$ and (b) $\lambda_2 = \lambda_1 + 2$. Variance and DC were log-transformed to better show the trends before the transitions.

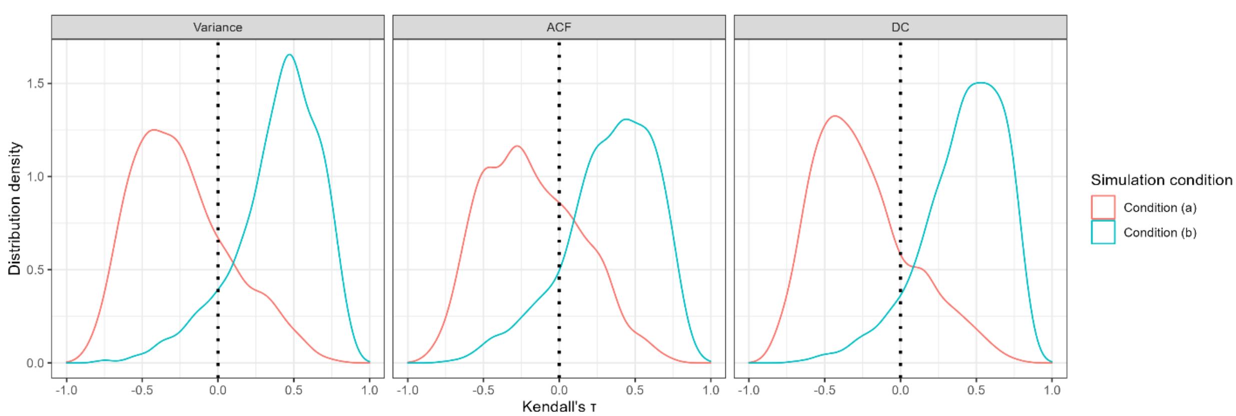

Figure 6. Trends of variance, ACF, and DC, represented with the distribution of Kendall's τ from 10^3 simulations, for two conditions.