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Perspective

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Slow down and be critical before using early warning signals in psychopathology

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Abstract

Early warning signals are considered to be generic indicators of a system's accumulating instability and 'critical slowing down' prior to substantial and abrupt transitions between stable states. In clinical psychology, these signals have been proposed to enable personalized predictions of the impending onset, recurrence and remission of mental health problems before changes in symptoms occur, thereby facilitating timely therapeutic interventions. In this Perspective, we question the idea that early warning signals in a person's emotion time series can predict changes in mental health symptoms. Using the empirical findings to date and the theoretical and methodological limitations inherent in their application, we argue that there is little support for the use of early warning signals based on critical slowing down in clinical psychology. Deepening our knowledge of the theoretical foundations of these predictors and improving their measurement are key to clarifying the potential and boundaries for their use in psychopathology. It is necessary to build on the insights gained from early warning signal studies and to improve and evaluate alternative methods, keeping in mind that clinical applications require prospective, real-time predictions that not only indicate whether, but also when, a specific person is likely to experience changes in their mental health.

Sections

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Introduction

Change is an inherent and vital part of nature and of being human. People change as they develop and age, and vary in their moods, thoughts, interpersonal relationships, habits, mental health and interests over the span of years, months, weeks, days and moments[1–4]. Dynamical systems theory offers a framework for studying the dynamics and nonlinearities of human change[5–7] and for understanding and predicting transitions in mental health[8–12]. Within this framework, humans are conceptualized as changeable systems with a tendency towards stability. Methods involving intensive monitoring of momentary experiences, such as ecological momentary assessment[13] (Box 1), enable changes in the system's elements (a person's emotions, cognitions and behaviours) to be investigated over time. Such data provide not just a single, static observation of a measured construct, but a time series of observations in which natural variation (for example, daily emotional ups and downs) as well as pronounced shifts can be captured. Studying these meaningful observable temporal dynamics could deepen our understanding of how individuals change over time[14–17] and could have predictive value for anticipating relevant change[18,19].

One hypothesis based on dynamical systems theory is that large, abrupt shifts from an initial stable state to a new equilibrium ('critical transitions') are preceded — and can therefore be predicted — by a period of accumulating instability in the system[5,20,21]. This phenomenon, in which the attraction to return to the system's initial state weakens over time, is known as 'critical slowing down' and can be detected in intensive time series data through statistical indicators known as early warning signals (EWS) (also termed 'dynamic indicators of resilience'). Examples include increasing autocorrelation (degree of similarity between adjacent assessments) and variance. A remarkable property of EWS is that they are proposed to be generic and expected to precede sudden, impactful, otherwise unpredictable transitions in a large variety of complex systems[20], including ecosystems, ocean currents, disease emergence and the brain[21–25].

The parallels between the dynamical systems phenomenon of critical slowing down and clinical observations of sudden symptom changes and periods of instability[16,26,27] have fuelled the idea that EWS could also be useful for personalized predictions in clinical psychology[5,19,28,29]. The search for methods to predict changes in the course of symptoms for individual patients and to obtain timely warnings of mental health risk and recovery is urgent and ongoing in the field of psychopathology[30–35]. Clinically, a method such as EWS (which promises to facilitate personalized early detection of destabilization) could be extremely valuable for timely intervention in relapse prevention, or for reinforcement when the patient is most receptive in the context of therapy[10,36–40]. Consequently, many researchers have been inspired to adopt ambitious intensive longitudinal data collections (for example, measuring a patient's momentary emotions for 239 days[41]) to study EWS and to improve clinical predictions.

In this Perspective, we question the field's enthusiasm for EWS and their clinical utility in predicting mental health symptom changes. We first elaborate on the process of destabilization and clinical change in mental health from a dynamical systems standpoint, describe how EWS are hypothesized to be useful in anticipating clinical symptom shifts, and discuss the burgeoning empirical literature in psychopathology to date. Throughout, we consider 'the system' to be the person and their experiences. We focus especially on the system 'elements' of emotions, cognitions and behaviours, because these are central to diagnostic descriptions of mental disorders and everyday functioning[18,19,42]; for ease of reading, we refer to the system's elements generically as emotions throughout. Then, we consider the implications of the reviewed empirical studies, which leads us to take a step back and evaluate fundamental theoretical and methodological difficulties related to the use of EWS as predictors of clinical change. Next, we discuss the need to pursue timely, prospective clinical warnings and consider alternative methods for early change prediction. We conclude that the quest for EWS is entering a new stage, having sparked several directions for further research, such as improving the theoretical understanding and measurement of psychological systems, investing in the real-time detection of prodromal states, and prioritizing the clinical utility of risk indicators by uncovering their temporal properties as well as their person-specificity.

We centre our Perspective around rising autocorrelations and variances, because these are by far the most studied EWS across scientific domains[43] and have been investigated in ecological momentary assessment data with clinical applications in mind. However, EWS based on critical slowing down include other statistical indicators[21,44] such as rising skewness and kurtosis, multivariate indicators[45] (such as cross-correlations, which are sometimes referred to as network connectivity[9,11]) and spatial indicators[46]. Other closely related phenomena that can be used as EWS are recurrence-based indicators and critical fluctuations[47–51]. Likewise, passive sensing data offer an alternative to subjective emotion ratings gathered with ecological momentary assessment or daily diaries. However, these metrics and data sources have not yet been studied empirically in a way that allows their potential for clinical applications to be evaluated, and there is a lack of insight into their sensitivity, specificity and predictive values for detecting clinical change (or related criteria that could indicate predictive performance, such as concordance and calibration). We therefore do not include them in our Perspective.

The dynamics of clinical change

In this section, we delve deeper into dynamic stability and the process of system destabilization that might precede clinical change. We expound on the phenomena of critical slowing down and EWS and summarize the empirical work on EWS in psychopathology.

From stability to change

Although changeable, dynamical systems have a tendency towards stability. In the context of mental health, the system can be broadly defined as the person and their experiences, but it is most readily understood by the elements that describe how someone is doing — their emotions, thoughts and physiological needs, such as hunger and tiredness. Contextual factors, such as recent social interactions, current surroundings and hormonal balance, interact with this system and can affect momentary states and the dynamical system's behaviour (a person's tendencies). Stressors (or perturbations), which can be perceived as positive, negative or mixed, might evoke a temporary reaction that affects several system elements, but once the stressor is gone, the system is attracted to return to its original equilibrium or set point[52–54]. As a simple illustration, challenges and impactful moments in daily life might cause a person's emotions (such as anger or happiness) to rise and fall, but after a while those feelings tend to dissipate and settle back to their usual levels. This personal equilibrium around which a system tends to fluctuate and restabilize is known as an 'attractor' in dynamical systems theory.

For many people, their attractors are resilient to change: even after facing major life events, most people eventually regain their balance without developing clinical symptoms[55]. Thus, a person's mental states

Box 1 | Ecological momentary assessment

The ecological momentary assessment[13,185] methodology — often referred to interchangeably as the experience sampling method[186,187] or ambulatory assessment[188] — was developed to gain a detailed and ecologically valid understanding of how people experience "life as it is lived"[189–192]. Participants are repeatedly asked to report on their momentary emotional and cognitive experiences, behaviour or (social) contexts, throughout the natural course of their daily lives. Examples of typical ecological momentary assessment questions include "Right now, I feel happy" and "Since the last measurement, I have been worrying," with agreement measured on a Likert or visual analogue scale ranging from "Not at all" to "Very much."

Although ecological momentary assessment data collection started with pen-and-paper questionnaires and beeps from digital wristwatches[189,190], the widespread use and improved quality of smartphones and wearables has greatly increased the feasibility of these methods. Nowadays, ambulatory assessment[35,191,192] represents an umbrella term that can be applied to a collection of methods that gather intensive (repeated or continuous) within-individual measurements of current or recent experiences in real-world environments, including repeated subjective self-reporting (through ecological momentary assessment, experience sampling and daily diaries) and passively collected mobile sensing data (such as step counts, ambient noise levels, GPS information or heart rate[193–196]).

The key advantage of these methods compared to a single retrospective assessment — in which, for instance, questions are asked about experiences over the past week or month — is that asking about the person's experiences in the present moment or the last few hours reduces recall bias and increases ecological validity[197]. Furthermore, ecological momentary assessment allows the natural fluctuations of emotions, cognitions, behaviour and context to be captured across the day and thereby moment-to-moment variations and their associations to be studied[66,67,198]. For example, with this method it is possible to assess to what extent adjacent assessments are similar to one another (autocorrelation, also called inertia or rigidity, which is associated with worse mental health[65,199,200]), the strength of moment-to-moment fluctuations (a key feature in borderline personality disorder[76,201,202]), and to what degree assessments of one variable — for example, tiredness — predict assessments of another variable — for example, sad mood — at a subsequent moment in time (cross-correlations[203–206]).

Ecological momentary assessment is usually used for a relatively short period of time (for example, a week) with a high number of assessments within the day (for example, ten per day) at semi-random moments, to get a representative snapshot of an individual's emotion dynamics, typical symptom levels or behaviour patterns[187,207,208]. The use of this method has been expanded to capture more long-term changes as well, to shed light on how momentary experiences and slower-changing processes (for example, the onset of a disorder) or infrequent occurrences (for example, panic attacks) relate. To balance the burden of having a longer overall study duration (several weeks or months), these studies tend to use fewer assessments per day (or only one, a daily diary), and set fixed, evenly spaced timings[209,210].

Finally, ecological momentary assessment has also been considered for applied, clinical use[211]. For instance, self-monitoring one's core problems prior to therapy might be used for intuitive visualizations in feedback reports that inform patients and clinicians how often and in what contexts symptoms manifest in daily life. Ecological momentary assessment can be a excellent tool for case conceptualization and might provide tangible starting points for conversation between patient and therapist[173,212–214]. Even outside therapeutic settings, completing the repeated self-reports can have a positive effect in itself, improving self-awareness and providing people with a sense of control and empowerment[125,215–218].

can vary meaningfully, even drastically, around their own stable equilibrium (the attractor) without such variation necessarily constituting a true systemic change (Fig. 1a).

When systemic change does occur, a person's equilibrium shifts so substantially that their experience of and interaction with the world around them become noticeably altered[1,8,26,56,57]. To illustrate, a person who becomes depressed progressively loses interest in things they used to enjoy and becomes more sensitive to small criticisms and setbacks, which leads to a transformed emotional response pattern (a new stable equilibrium) in which sadness lingers while joy is fleeting and rare. The constituent elements of the system do not necessarily change, but their intensity, duration and interrelations are changed and together form a new stable equilibrium[9,58]. Thus, the systemic change is revealed in the altered dynamics of these elements[14,59].

In the context of mental health, some system elements, such as momentary emotions and thoughts, are more likely to change meaningfully as symptoms develop or remit and are also more easily observed than others[18]. Monitoring these elements and their dynamics over time might therefore offer a way to discern early on when the system starts to become less stable and consequently more vulnerable to abrupt systemic changes (such as the onset of an anxiety disorder).

Critical slowing down and EWS

In brief, critical slowing down refers to a dynamical system's increasingly reduced ability to return to its original stable equilibrium after experiencing stressors (also described as a gradual build-up of instability, a loss of resilience or a weakening of the attractor). This process can be detected by observing the dynamics of the system elements over time and testing for the presence of EWS: rising trends in certain statistical metrics. For instance, the more volatile responses to perturbations and slowed return to a person's stable equilibrium can be expressed statistically as a rising trend in the variance (increasingly strong deviations away from equilibrium) and rising autocorrelations (increasingly high similarity between consecutive observations) in intensive longitudinal data[21]. Naturalistically, these effects could appear as follows: a person who typically (within their usual equilibrium state) shows mild symptoms of anxiety after stressful social encounters becomes more and more distressed after such occasions (rising variance) and maintains a heightened degree of restlessness and rumination throughout the day, holding on to that feeling much longer than they usually would (rising autocorrelation).

As the initial attractor weakens, even minor stressors can have major effects (Fig. 1b). Specifically, as the person gradually becomes more vulnerable, they could reach a point at which recovering from

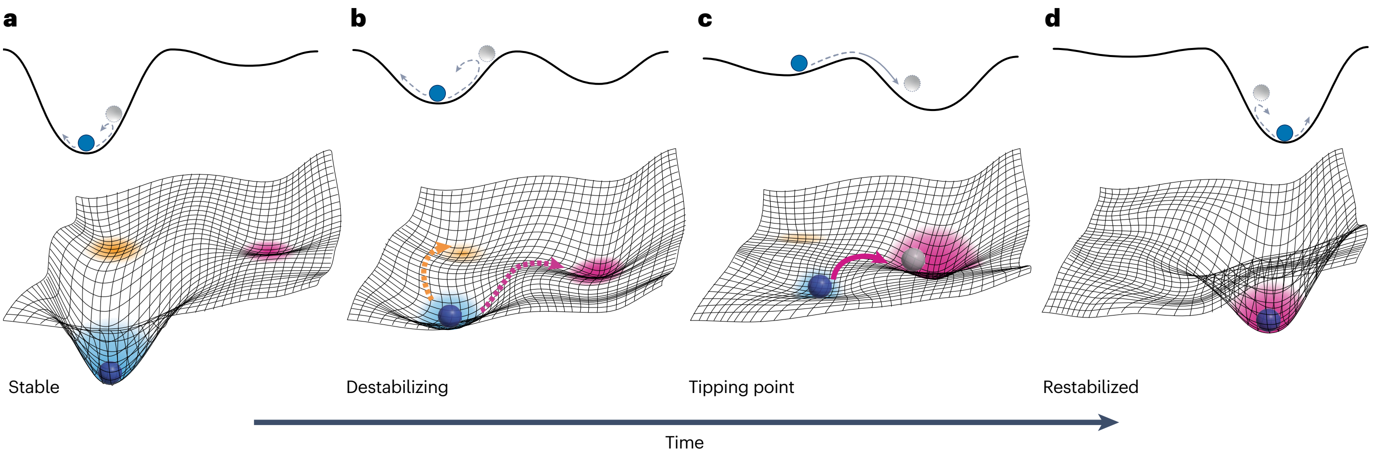

Fig. 1 | Changing system stability landscapes during critical slowing down. A dynamical system (top, two-dimensional; bottom, three-dimensional) changes throughout critical slowing down. Within the initial equilibrium state of the system (dark blue ball), the momentary state of the system can vary over time (light grey ball). The stability of the system is linked to the attractor's strength (the depth of the basins). A system can have various directions (arrows) and alternative attractors of varying strength (pink and orange areas) to which it could shift[114]. **a**, The system is stable, with a strong, deep attractor (blue basin) enabling quick recovery from small perturbations. **b**, The system is destabilizing and the initial attractor has become weaker and shallower. Compared to the stable system, perturbations are more likely to result in stronger deviations away from equilibrium, which take longer to recover from. **c**, The system has destabilized so much that even a small perturbation might cause it to tip over and undergo a system-wide shift into an alternative stable state (the pink basin, which has strengthened over time). **d**, The end point of the process is the loss of the initial attractor and the system's restabilization into a new stable state.

even the slightest perturbation is no longer possible, and a transition to an alternative state becomes inevitable: a tipping point (Fig. 1c). After a tipping point has been crossed and the system has shifted and restabilized into a new attractor state (Fig. 1d), more effort (for instance, with therapeutic intervention) is often required to revert the change, a phenomenon known as hysteresis[5].

Clinical examples of these critical transitions in psychological states are relatively abrupt symptom shifts[16,60,61], such as symptom relapses from a state of remission[62,63], or sudden gains and losses within the course of therapy[27,55,64]. Anticipating such transitions in a personalized way has traditionally remained elusive: psychopathology has proved to be too complex (with many interacting causes, which differ between individuals) for any straightforward prediction method to work. Unsurprisingly, then, the possibility of using generic signs of vulnerability, namely EWS, to anticipate major changes in mental health in a person-specific way was met with great optimism. Indeed, EWS were hypothesized to enable personalized predictions of major symptom changes, possibly weeks before changes in symptom levels are reported[41], and without needing to know the precise causal factors that drive the change.

Empirical findings

Initial studies exploring the idea that EWS might precede relevant symptom changes compared emotion dynamics – including autocorrelations and variances – between different groups. These studies typically collected ecological momentary assessments of emotional states of people with and without mental health conditions for about one week and subsequently computed, separately for each person, their emotion dynamics. Used in this way, ecological momentary assessments provide a 'snapshot' impression – a single statistical estimate – of a person's emotion dynamics as observed during the study period. Results generally showed that people with mental health problems or more severe symptoms had higher autocorrelations and variances in their momentary emotions than people with no or fewer mental health problems[65–72]. Additionally, some studies found that higher autocorrelations and variances predicted worsening of mental health several months and up to 2.5 years later[73–75] – although not all longitudinal studies confirmed this result[76–79].

Such a longitudinal association could imply that the autocorrelations and variances found in these kinds of emotion data represent early markers of instability that indicate a person's risk for upcoming mental health problems. However, such between-individual differences rely on a single snapshot of an individuals' emotion dynamics and therefore cannot reveal critical slowing down. Instead, the hypothesis that EWS can predict transitions in mental health can be tested only by individually monitoring trends in autocorrelations and variances (revealed through repeated snapshots) of each person's momentary emotions in the period before the transition[37,80,81]. Moreover, the proposed generic nature of EWS is supported only if these signals precede symptom transitions consistently across diverse individuals.

Within-individual investigation of EWS is an ambitious quest: it requires recruitment of participants who are likely to undergo transitions in their mental health and are willing to collect intensive longitudinal data for several consecutive months. Not surprisingly, the first within-individual study into EWS described a single case[41]. The studies that followed included more individuals, but adopted suboptimal sampling designs, lasting a relatively short time (8 weeks) with only one assessment a day[82] or using more frequent measurements (ten per day) but on only three days a week interspersed with days with no data collection[83], which impaired the discrete-time models used in their analyses. These first studies reached partly contradictory conclusions regarding the potential utility of EWS. One study of 22 individuals with recurrent depression did not detect EWS, and therefore questioned their clinical relevance[83]. By contrast, another study[82] found associations between EWS (and particularly, rising autocorrelations) and changes in depressive symptoms across 8 weeks. However, this study was limited by low statistical power, did not disentangle the temporal order of EWS and depressive changes in their data (rising autocorrelations could have been driven by, rather than preceded, changes in depressive symptoms)[76,84], and showed substantial between-individual differences, indicating a limited utility of these EWS to predict large changes in symptoms.

A next set of empirical studies adopted a more rigorous approach to investigating EWS, leveraging ecological momentary assessment or daily diary data collected over four to twelve months[85–91]. These studies included participants who were likely to experience changes in their mental health, for instance because they had decided to taper off their antidepressant medication, because they were considered at-risk young adults after experiencing childhood mental health problems, because they had been diagnosed with bipolar disorder, or because they had begun psychological treatment for depression and their symptoms were expected to improve. To detect whether these individuals indeed experienced large, abrupt symptom changes, most studies used change-point analyses (a method for finding points in a time series at which distributional characteristics, such as the mean level, significantly differ in value before and after the point), a criterion informed by cut-offs from validated clinical questionnaires, or a combination of both. Naturally, not all participants in these studies experienced large, abrupt symptom shifts, and EWS were therefore only expected for the subsets of participants who experienced transitions. Across the board, these studies consistently reported low sensitivity (a low proportion of true alarms), indicating that most symptom changes were not preceded by EWS. For instance, only 36% of transitions towards worsening mental health in youths were preceded by EWS[88]. Recurrence and remission of depression were preceded by EWS in less than 50% of cases[86,89].

The low sensitivity of EWS presents a challenge to clinical implementation and is especially concerning in the presence of low specificity. For example, if the sensitivity is around 40% (40% chance of a true positive) and the specificity is around 60% (40% chance of a false positive), EWS would be equally likely to occur in individuals with and without transitions in their mental health, and therefore they provide no information regarding the probability of a transition. Thus, it is the balance between sensitivity and specificity that determines how practically useful EWS can be expected to be. Assessing this balance requires investigating EWS not just in individuals experiencing changes in their mental health, but also in individuals without such changes – indeed, empirical studies outside psychopathology often ignored the possibility of false alarms, which led to an overly optimistic idea of the predictive utility of EWS[92]. The reviewed studies (Table 1) mostly reported a moderate to high specificity, which nevertheless meant EWS were (incorrectly) detected in around 25% of non-transitioning individuals. In sum, transitions were often missed (limited sensitivity) and sometimes incorrectly predicted (limited specificity), and therefore the presence – or absence – of EWS provides limited information about the presence – or absence – of ensuing symptom transitions.

Stepping back from EWS

Although empirical support for the use of EWS for personalized prediction of clinical symptom changes is rather weak, absence of evidence should not be taken as evidence of absence. In this section, we reflect on the expectations around the predictive utility of EWS in psychopathology in light of both theoretical complexities and the methodological challenges that come with collecting the data needed to evaluate EWS.

Grounding the theory

Enthusiasm for using EWS for the prediction of changes in mental health was fuelled by the idea that these signals manifest in all sorts of systems. Yet EWS are less generic than is often implied[24,93–95], which complicates their application not just in psychology, but also in other fields[24,96–100]. To illustrate, a meta-analysis of 126 ecosystems showed that EWS were detected prior to only 13% of the transitions[96]. To understand why EWS are so often absent or undetected, it is imperative to consider the theoretical foundations of critical slowing down.

A first theoretical explanation is that critical slowing down precedes some, but not all, sudden shifts in complex dynamical systems[101,102] (Fig. 2a), and is not limited to sudden shifts, but also precedes certain gradual shifts[103,104]. The fact that only certain types of transition show EWS can be understood through bifurcation theory[5], which is the theoretical basis of critical slowing down. Bifurcations are points at which a system crosses a threshold to a new organization of its attractors and their stability, such as when a critical transition occurs from one stable state towards an alternate state. Diverse bifurcation points have been described for smooth or gradual shifts (for example, Hopf, Transcritical and Pitchfork bifurcations) and for sudden transitions (for example, Fold, Cusp and Butterfly bifurcations)[101,105], only a selection of which are preceded by critical slowing down[101,106]. It is quite possible that many transitions in mental health do not show EWS because they involve a bifurcation point that is not preceded by critical slowing down – because it is the wrong type of bifurcation, or because the transition occurs faster than critical slowing down can manifest. For instance, EWS would not be expected prior to transitions that are due to abrupt changes in a control parameter (a variable that directly affects the behaviour of the system) (Fig. 2b). Moreover, some transitions in mental health might occur without the involvement of a bifurcation, and therefore without EWS. For example, EWS are not expected when transitions are caused by external forcing (a particularly strong perturbation) (Fig. 2c) or when the attractor gradually evolves from healthy to disordered, without destabilizing (Fig. 2d). The fact that EWS are neither generic nor unique to sudden transitions in dynamical systems poses a challenge for psychology, because typically very little is known about the processes that govern upcoming symptom changes, let alone whether or how bifurcation points are involved[93,107]. As a consequence, it remains uncertain whether critical slowing down should be expected before clinical change at all, and labelling EWS as true or false alarms is ambiguous.

A second theoretical argument for the absence or lack of detection of EWS prior to sudden changes in clinical symptoms is that the measured variables might not be fit to capture critical slowing down[108–110]. EWS are usually investigated in the variables in which a transition is expected to occur. For example, transitions in depression could be anticipated by EWS in depressive symptoms[19,84]. However, at least theoretically speaking, EWS are not guaranteed to be present in the variables that undergo a transition. Instead, EWS are present only in variables that match the direction in which a system loses its resilience (corresponding with the eigenvector associated with the dominant eigenvalue of the system), which does not always align with the direction in which the system transitions[109,111,112]. For instance, precursors to a transition toward a depressive episode would be expected in core depressive symptoms such as feeling down and listless[56,113,114], but might be more strongly expressed in heightened anxiety and irritability for some individuals[115]. Moreover, although appropriate directions could be captured by momentary emotions or symptoms, it is possible that other (heretofore unstudied) variables might be better suited for monitoring EWS. A further consideration is that the variables might not be fit to capture critical slowing down if their response to perturbations occurs at a rate that eludes observational monitoring and the calculation of EWS (for example, emotions might recover faster than they can be measured). In the absence of a more fundamental understanding of how critical slowing occurs, it remains unclear which variables are best suited to detect EWS.

Table 1 | Empirical studies of within-person rises in the autocorrelation or variance of intensive longitudinal data preceding symptom changes

Sample	EMA design	Detection methods		Transition		Early warning signals				Conclusion
		Transitions	EWS	Present (*N*)	Absent (*N*)	Autocorrelation		Standard deviation		
						Sensitivity	Specificity	Sensitivity	Specificity	
122 at-risk young adults[88]	183 days, once per day	Change-point analysis	TV-AR, MWT	26	71	TV-AR=6–10% MWT=24–30%	TV-AR=95–98% MWT=70–76%	MWT = 30–38%	MWT = 60–67%	EWS hardly predict transitions towards mental health conditions
20 adults with bipolar disorder[85]	122 days, 5 times per day	Minimum change score	MWT	7 towards depression, 8 towards mania	9	25–36%	75–84%	15–38%	67–72%	False positives and negatives complicate the clinical usage of EWS
29 adults with bipolar disorder[87]	365 days, once per day	Clinical interviews	MWT	29 towards depression, 20 towards mania or hypomania	–	[b]	[b]	–	–	AR is increased in the late prodromal phase of mania and hypomania and during (not before) depressive episodes
42 adults with major depressive disorder in remission[83]	24 days, ten times per day[a]	Clinical interviews	TV-AR	22	20	0%	100%	–	–	EWS have doubtful relevance for depressive relapse in recurrent depression
6 adults with major depressive disorder in remission[91]	95–183 days, three times per day	Change-point analysis	MWT	1	4	Support for EWS in one participant	75%	Inconsistent support for EWS in one participant	[b]	If replicated, EWS might prove useful to foresee recurrence of depressive symptoms
43 adults with major depressive disorder in remission[89]	122 days, five times per day	Minimum change score, qualitative evaluation	MWT	19	18	37–42%	78–94%	26–37%	89–94%	The low sensitivity of EWS poses a substantial challenge for clinical applications
4 adults with major depressive disorder in remission[90]	196 days, once per day	Clinical interviews, minimum change score	TV-VAR, DFA	1	3	Support for EWS in one participant	[b]	–	–	EWS might be sensitive but not specific to depressive relapse
30 adults with major depressive disorder[82]	56 days, once per day	None	MWT	[c]	[c]	People with larger increases in depressive symptoms had steeper increases in AR	[b]	Changes in depressive symptoms were not related to within-person changes in SD	[b]	Rising AR was more reliable than other EWS but results varied between individuals; unclear whether EWS preceded transitions
41 adults with major depressive disorder[86]	122 days 5x/day	Minimum change score	TV-AR, MWT	9	32	TV-AR=6% MWT=44%	TV-AR=97% MWT=73%	MWT = 11%	MWT = 88%	EWS have limited value as a personalized prediction method

Most studies applied a range of statistical models (for example, systematically changing window sizes) to investigate changes in predictive values. The different detection methods and model settings of the studies mean that the summarized findings are not directly comparable and require cautious interpretation. DFA, detrended fluctuation analysis; EMA, ecological momentary assessment; EWS, early warning signals; MWT, moving window technique; TV-AR, time-varying autoregressive model; TV-VAR, time-varying vector autoregressive model. [a]The EMA period in this study was interspersed across 8 weeks (each with 3 days per week EMA). [b]Sensitivity and/or specificity was not or could not be computed for this study. [c]This study related EWS to increases in depressive symptom scores over 8 weeks, not to individually detected transitions.

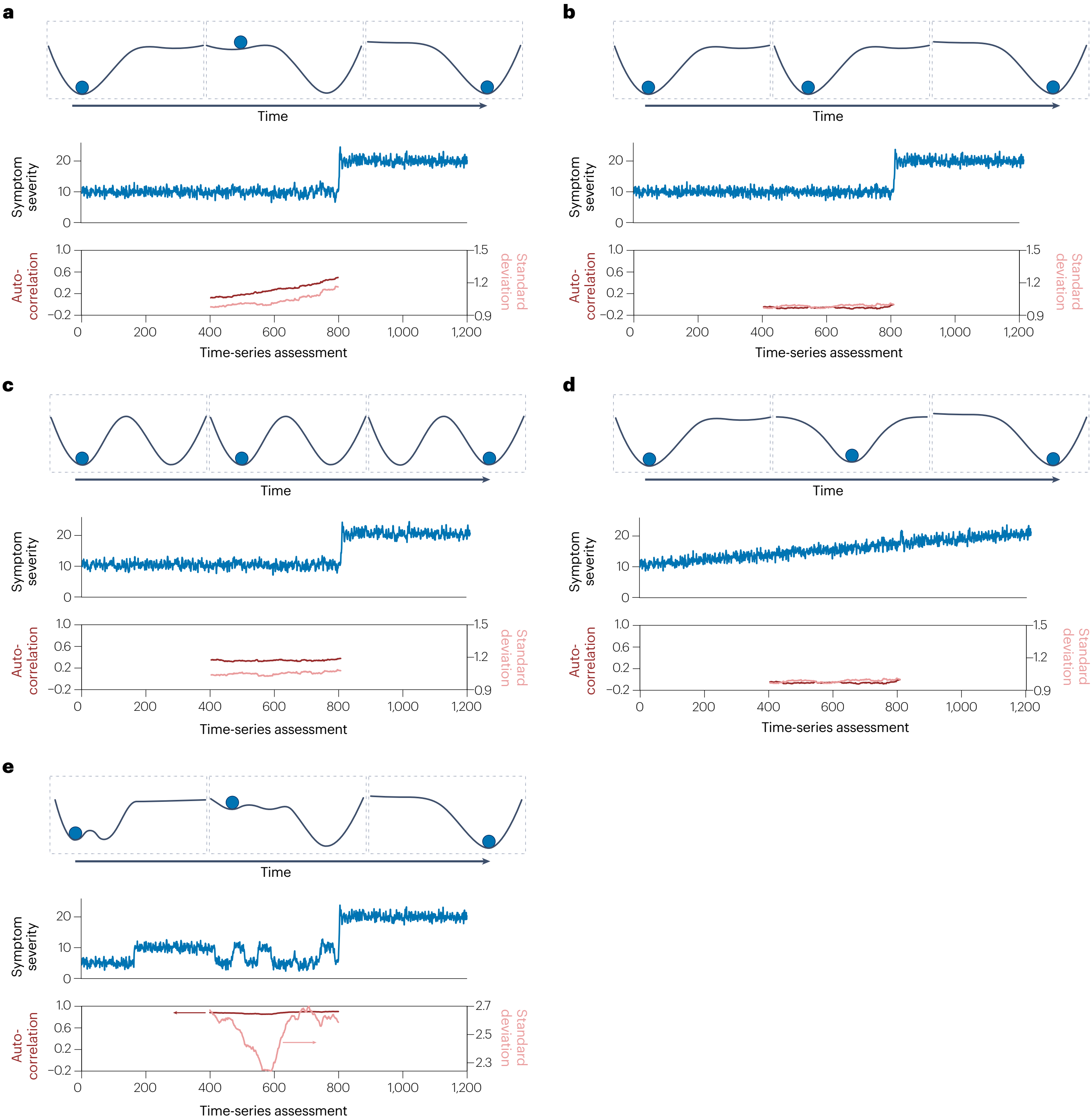

Fig. 2 | Example transitions in psychopathology. a, Critical slowing down precedes sudden shifts in a dynamical system (top); for example, if the gradual tapering off of antidepressant medication results in changing dynamics of symptoms captured with ecological momentary assessment (middle), a rising variance (standard deviation; pink line) and rising autocorrelations (red line) reflect early warning signals (EWS, bottom). **b**, EWS would not be expected if a variable that affects the stability of the system (the control parameter) abruptly changes prior to transition; for example, if a treatment is suddenly discontinued. **c**, EWS are not expected if the shift from the initial attractor towards the new attractor is caused by large perturbations (such as the death of a loved one) with no changes in the stability of the attractors. **d**, EWS are not expected when a system gradually shifts its location without destabilizing; for example, when gradual reduction of antidepressant medication also gradually increases symptom levels. **e**, EWS might not be detected if a system shows changes in dynamics that are more prominent than the signs of rising variance and autocorrelations caused by critical slowing down; for example, swings between manic and depressed attractors might result in strong emotion dynamics that obscure potential signs of the attractors' destabilization (Supplementary Note 1).

A third and final theoretical argument that might explain the absence of EWS is the fact that, even in cases in which EWS would theoretically be expected, their presence might be obscured by other processes influencing emotion dynamics (Fig. 2e). Periods of physical illness or vacation could also affect emotion dynamics in ways that do not relate to underlying system change, potentially clouding the EWS. Similarly, response shifts in emotion ratings (a pattern of declining variance due to participants using a smaller range of the response scale over the course of long ecological momentary assessment studies[89,116]) might cancel out the rising variance that is indicative of critical slowing down.

In sum, EWS are not generic indicators of upcoming transitions in any and every system, but instead imply several auxiliary assumptions that are in practice difficult to verify: the transition should involve a bifurcation that is preceded by critical slowing down; assessments should involve the 'right' variables at the 'right' timescale; and the effect of critical slowing down must not be obscured by other, more pronounced processes influencing the data. The successful application of EWS therefore requires a more complete understanding of the dynamics of a system, which poses a considerable challenge to empirical studies.

Measurement matters

Detecting EWS in empirical data is not straightforward. The hypothesis that EWS anticipate transitions in symptoms can be tested only in intensive longitudinal designs that can capture clinically relevant transitions in people's mental health. The investigation of EWS is therefore hampered by common issues pertaining to psychological measurement[117,118] and ecological momentary assessments, such as floor effects[119], measurement error[120] and measurement invariance[121]. To illustrate, individuals are likely to differ in how they rate their own momentary emotions[122] (for instance, a score of 80/100 or the emotion 'angry' could be interpreted in unique ways by different individuals), and they might change how they answer the questions over the course of a study (owing to response shifts[123], increased self-awareness[124,125] or measurement reactivity[116]). These measurement issues can make it extremely difficult to detect meaningful changes (such as a marked difference in symptom levels or emotion dynamics) in ecological momentary assessment data generally[126–128], and thus impede the study of EWS as well.

Additionally, there are several measurement challenges that are uniquely relevant to studying EWS in psychopathology. A crucial first challenge is to define robust outcomes (transitions) that occur frequently enough to offer a valid test and evaluation of the predictors (EWS)[129]. Statistically, this requires data that capture the course of symptom change closely, yielding sufficient power to detect and pinpoint transitions accurately[130]. However, defining critical transitions not only presents a statistical challenge, but also a conceptual one. Not every statistically detectable change is clinically relevant; not all clinically relevant changes can be detected statistically; and even changes that are both clinically relevant and can be detected statistically might not represent the type of critical transition preceded by EWS. It is therefore necessary not just to define transitions on the basis of momentary assessment data and/or quantitative symptom score cut-offs, but also to consider qualitative information[62,131]. At a minimum, including the person's lived experiences[132] could help to identify which processes are truly relevant precursors and expressions of change for them. Participants do not always recognize their symptoms as relevantly improved even if a clinical score indicates that a statistically significant decrease has occurred, and conversely, they might report a qualitatively important change in mental health that remains below threshold and undetected by a questionnaire[133–136]. Only when they anticipate clinically meaningful changes in a person's experiences could EWS have clinical value[135,137,138].

The collection of high-resolution data in a large sample of individuals (for example, through active or passive ecological momentary assessment) is another relevant challenge to the detection of EWS in psychopathology. Even though EWS are detected within single individuals, a scientific evaluation of EWS requires between-individual comparisons. To illustrate, when computing the sensitivity, specificity and predictive values of EWS, researchers essentially compare the presence of EWS in individuals with versus without a transition in symptoms. Both the sensitivity and specificity of EWS should be high to warrant clinical utility. However, sensitivity and specificity indices are likely to be imprecise if based on small sample sizes, as is common in ecological momentary assessment studies. For instance, when 10 out of 15 individuals with a transition in symptoms show EWS, sensitivity would be equal to 0.67. Adding only one individual with EWS would change the sensitivity to 11/15 = 0.73. Large sample sizes are therefore needed to evaluate EWS, but gathering data of sufficient quality to detect EWS and transitions is a challenge in itself[137].

The optimal ecological momentary assessment study design for EWS detection in multiple individuals must reconcile two competing design choices: sampling frequency and overall study duration. On the one hand, a high sampling frequency is recommended to ensure sufficient temporal resolution for detection of transitions and EWS[93,137]. In particular, EWS metrics such as the autocorrelation, which reflect a statistical relation between successive assessments, are sensitive to sampling frequencies. Long time intervals between assessments inevitably lead to lower autocorrelations, which threatens the detectability of such EWS[139]. An additional problem is that low sampling frequencies limit the detectability of EWS that arise within a short time period (Fig. 2b). On the other hand, monitoring people for a long period of time is imperative to optimize the chances of capturing transitions. To illustrate, recurrent depression might develop over long periods of time (weeks to months), and therefore would be captured only with long-term monitoring[61,140]. However, combining long-term monitoring with a high sampling frequency might place an unrealistically high burden on participants. Most empirical studies reported impressive durations, but also accepted several hours or even an entire day in between assessments to reduce the load on participants, which probably impaired their ability to detect EWS. In sum, designing an ecological momentary assessment study with a sampling frequency that is high enough to detect EWS, but also long enough to detect transitions in mental health, is decidedly challenging[137,141].

At face value, searching for EWS in passively collected mobile sensing data (such as physiological time series) might be an answer to the call for long, high-resolution time series data for detecting EWS and psychological transitions. Collecting such data is less burdensome than collecting self-report data (such as momentary assessments of emotions) and could offer a solution to the issue of statistical power in EWS detection. However, the results of some efforts to detect EWS in actigraphy[142,143] and heart rate complexity[47] were similar to the results of EWS in self-reported momentary emotions. Indeed, verifying critical slowing in mobile sensing data presents comparable challenges, the most prominent one being that processes other than critical slowing down – such as physical activity, smoking or medication – strongly affect the dynamics of physiological variables such as heart rate, skin conductance and activity counts[144]. Given that these processes might outweigh critical slowing down, and the signal-to-noise ratio consequently lowers, EWS in actigraphy or physiological data can easily remain undetected[47,142–146]. A second limitation of this method is that passive sensing data might not map well enough onto changes in clinical symptoms and mental health (or, more formally, the direction in which a system loses its resilience[111]). Thus, high-resolution, passively collected time series data are not free of conceptual and statistical challenges and do not eliminate the need to further understand the timescales of critical slowing down and transitions in clinical symptoms. In short, investing in formal theories and statistical approaches that can address the core principles of dynamical systems in psychopathology remains paramount[14,93,139,147].

The promise of prospective warnings

A large part of the popularity of EWS for psychological applications can be ascribed to the expectation that EWS could provide individuals with timely warnings of imminent symptom changes so that action can be taken before a transition has taken place. Indeed, the question that prompted the search for EWS in psychopathology was not just for whom, but also at what moment in time, symptom changes are more likely to occur. However, so far, EWS have not been studied in a way that would support such prospective monitoring. All empirical studies retrospectively (after data collection was completed) identified which individuals showed symptom transitions and then looked for the presence of rising trends in EWS before or around those transitions. This post-hoc practice does not align with eventual clinical applications, in which incoming data should be monitored prospectively for rising EWS without already knowing whether and when a symptom transition will occur.

Unsurprisingly, prospective monitoring is statistically more challenging than testing for EWS post hoc because it requires EWS to be evaluated regularly and repeatedly for every individual while data collection is ongoing. Such a procedure entails multiple tests for each monitored individual, resulting in a higher number of false alarms compared to post-hoc investigations, in which the significance of a specific EWS is tested only once per individual. The number of false alarms could be controlled using a correction for multiple testing, but this would cause a proportional reduction in the sensitivity, which ultimately hampers the predictive value of the EWS.

Until empirical support is found for practically applicable prospective procedures that detect EWS, it would be pragmatic to consider alternative ways to monitor people's risk and resilience based on intensive longitudinal data. A viable option might be assessing statistics that are simpler, more reliable and perhaps also more informative than the relatively complex dynamics used as EWS. On a between-person level, metrics capturing complex emotion dynamics have shown limited utility for predicting well-being and mental ill health[66]; simply assessing the mean and variability of people's momentary emotions might suffice[148]. If such findings translate to the within-person level, worsening or remitting mental health problems could be foreseen by unusually high or low levels in the mean or variability of emotions. Although rises in variability are also considered in the EWS framework, rising mean levels are not. Instead, the process of critical slowing down presumes that transitions cannot be anticipated by rising mean levels (the equilibrium position of the initial stable attractor remains unchanged, even as the system loses resilience; see Fig. 1). However, it makes sense from a clinical perspective that, prior to remission of symptoms, patients might feel less negative (down or stressed) and more positive (content or happy)[149,150]. Vice versa, worsening symptoms could be preceded by increasingly negative and decreasingly positive mental states. This change in mean levels is also reflected by prodromal states of the earliest stages of mental health disorders. For instance, many individuals report heightened levels of restlessness, negative thoughts about the self and worrying prior to the onset of core symptoms of depression[151]. Prospectively monitoring mean levels of such prodromes might therefore enable a timely detection of full-blown mental disorders.

Statistical process control is a method that enables real-time monitoring of simple emotional change[152–154]. This method can be used to prospectively detect statistically significant deviations from a person's usual mean or variability in emotions, which in turn could facilitate timely intervention (Fig. 3; Supplementary Note 2). First, statistical process control requires determining person-specific thresholds, or control limits, based on ecological momentary assessment data collected during a stable baseline period of several weeks or even months (for example, during symptom remission). These control limits define

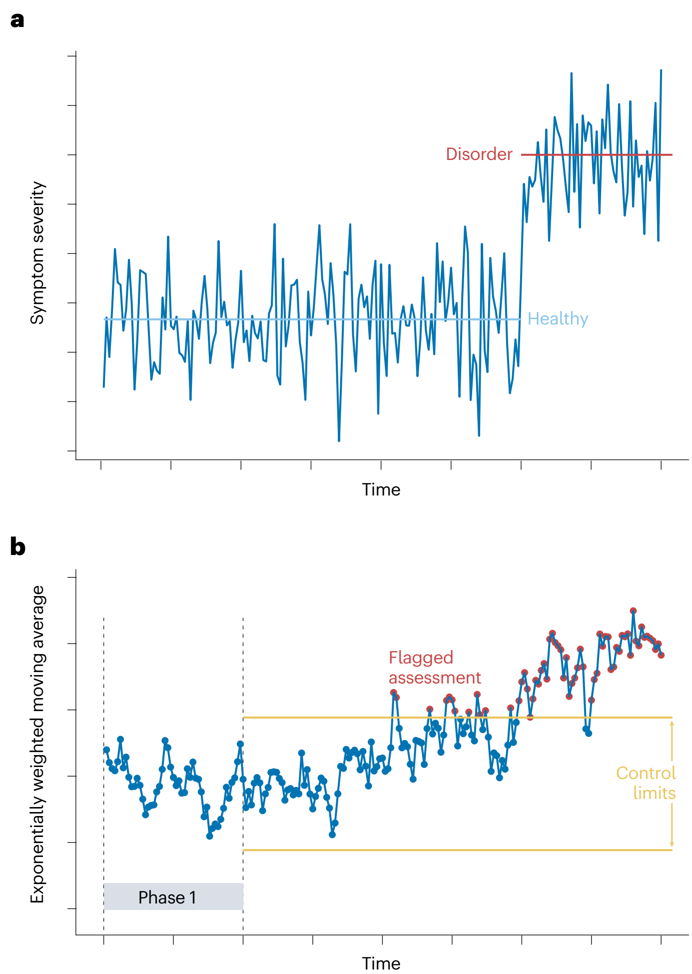

Fig. 3 | Statistical process control method. a, A time series of momentary assessments of the severity of symptoms shows two stable states: stability around a 'healthy' attractor (blue line) and stability around a 'disorder' attractor (red line). **b**, Statistical process control uses the mean and standard deviation of the momentary assessments (baseline phase) to compute control limits (yellow lines). Exponentially weighted moving averages are monitored across time, with values exceeding the upper control limit (flagged assessments, red dots) indicating a warning sign for possible clinical change prior to the observed symptom transition.

the range within which emotion levels are expected to remain as long as mental health does not drastically change. Next, newly collected ecological momentary assessment data can be compared against these control limits, and will be flagged when the limits are exceeded, to indicate a statistically significant change compared to baseline. A key strength of this approach is that it enables prospective monitoring, essentially yielding a new prediction (presence or absence of significant change) with each new incoming observation[155,156].

The initial empirical studies of statistical process control in mental health show promise. A post-hoc application of statistical process control applied to ecological momentary assessment data (previously collected to evaluate EWS) showed that 45–82% of transitions towards depression were preceded by repeatedly assessed mental states that exceeded the control limits[157]. Such extreme scores were less prevalent (11–42%) in people with depression who remained in remission. The sensitivity and specificity of the predictions generated through statistical process control were further improved by monitoring not just mean levels, but also the variability of emotions[158]. Thus, investigating the potential of statistical process control for timely individualized change predictions could be fruitful.

Nevertheless, implementing statistical process control in clinical practice will come with several challenges, perhaps the most urgent one being that (just like EWS detection) the method is quite 'data-hungry' — particularly when considering the baseline period. To calculate reliable control limits, long-term ecological momentary assessment data must be collected when individuals are experiencing relatively stable mental health — applying this method once individuals are already at increased risk for worsening symptoms (for example, while waiting for psychological treatment) might be too late. Yet it is usually only after the identification of some kind of risk that clinicians and patients might wish to start daily symptom monitoring. Therefore, looking into alternative methods for estimating the aforementioned control limits and thereby circumventing the need for baseline data is imperative[159–161]. Further, the first prospective application of statistical process control in empirical data is yet to be carried out.

Moving ahead with predictions based on ecological momentary assessment data, whether using statistical process control or other techniques, tailoring the temporal resolution and the person-specificity of the predictions to the outcome at hand is critical. Predictions on the level of days or hours might only be useful to monitor fast-fluctuating processes. Examples of such processes are suicidal ideation[162,163], panic attacks[164], and symptoms of substance-use disorders (such as craving)[165] and eating disorders (such as binge-eating episodes)[166]. In these cases, closely monitoring signs of risk might be crucial for effectively timing preventive interventions (for example, ecological momentary interventions or just-in-time adaptive interventions[167–171]). By contrast, less fine-grained prediction would perhaps suffice to monitor slowly evolving psychological processes (for example, recovery from a burn-out). Additionally, many psychological processes differ between individuals and therefore each individual might have their own, unique predictors of changes in mental health[172]. At the same time, such person-specificity complicates generalizability[30–33]. A compromise is to look for relatively homogeneous subgroups of individuals with similar indicators of risk and resilience[173,174]. Ultimately, insight into such subgroups combined with an improved understanding of the temporal properties of predictions could help to make ecological momentary assessment a demonstrably useful tool for timely detection of clinical change.

In sum, further research into the use of intensive longitudinal assessments for predicting clinical changes might benefit from focusing on simpler statistics (such as the mean and variability of prodromal symptoms), further evaluating and improving statistical methods that enable real-time predictions (such as statistical process control) and considering the temporal resolution and person-specificity of predictions.

Moving forward

Despite the long-standing interest in complex dynamical systems principles in clinical psychology[5] and the methodological rigour of empirical studies, findings to date do not sufficiently support the use of EWS to predict worsening or remitting mental health conditions. Moving forward, it will be necessary to broaden the methodological repertoire for investigating EWS, to account for the theoretical restrictions that limit the generality and clinical usefulness of EWS, and, finally, to prioritize feasibility of current clinical prediction efforts.

Empirical research into the use of EWS for clinical change prediction has only just begun, and there are still various ways the predictive properties of EWS could be improved. One possible avenue is to investigate whether clinical transitions are anticipated by distinct combinations of EWS. Combining different metrics (for example, autocorrelation and variance) might yield a better predictive performance compared to isolated metrics[86,89]. Similarly, multivariate EWS (for instance, based on multiple emotion variables), which include the explained variance of principal components and the cross-correlation between different variables (also termed network connectivity), might be more predictive of upcoming change than univariate indicators[93,110,112,175]. A rigorous evaluation of combined and multivariate EWS will be possible only with sufficiently rich data, which calls for innovative sampling designs to capture within-person changes in emotion dynamics without imposing an unrealistically high burden on participants[176]. Another option is to explore whether experimental perturbations could offer a more controlled and low-burden way to gain insight into the dynamic responses and resilience of an individual[177,178]. For example, using repeated micro-interventions to evoke temporary emotional responses and monitoring how long it takes for the system to recover could help to map changes in the stability of the system over time. These interventions could be delivered via ecological momentary intervention, or through multiple (for example, weekly) laboratory or virtual reality sessions, which would provide a way of studying critical slowing down that is fundamentally different from using intensive longitudinal ecological momentary assessment data.

Irrespective of any empirical advances, several theoretical complexities are likely to impede the proposed clinical usefulness of EWS. The fact that EWS are not as generic as sometimes implied[24,93–95] underscores the importance of a more nuanced understanding of how to measure, define and model psychological systems. Without knowing whether the theoretical conditions for critical slowing down are met, lack of EWS in empirical studies can always be attributed to misspecification of the system. For instance, the presence of false alarms can be explained and dismissed as a failure to detect transitions that are actually present. Thus, the hypothesis that EWS precede major transitions is extremely difficult, if not impossible, to falsify in empirical data without better system specification[179]. The need for such system specification is somewhat ironic, given that part of the interest in EWS in the field of psychopathology originated in the hope that these signals could enable person-specific predictions without necessitating fundamental insight (for example, information about the biological, psychological or social causes of mental disorders). Yet, although insight into the underlying causes of mental disorders might indeed not be crucial for implementing EWS[75], improved understanding of the dynamics of mental health will be invaluable to shape expectations around the predictive value of EWS.

One way to gain the necessary insight into the system is to look for markers indicating that the system might undergo the types of transition that are anticipated by EWS, so-called catastrophe flags[24]. Support for dynamical systems principles and the potential presence of EWS is substantiated only upon detecting multiple different catastrophe flags[3,180], and therefore developing statistical methods to detect them in empirical data might be a relevant line for future research. Catastrophe flags include – but are not limited to – the presence of two or more stable states (bimodality or multimodality), states with distinct tipping points (hysteresis), and sensitivity to certain initial conditions[181]. Statistically detecting such properties is not straightforward, but some studies have already made progress in this direction[3,182]. For instance, models have been proposed to detect hysteresis in psychological time series[147], and methods of detecting bimodality include the computation of bimodality coefficients, hidden Markov models and drift-diffusion models[180,183,184]. Eventually, such work could help to determine whether EWS should be expected in a particular system and thereby improve the falsifiability of the hypothesis that EWS herald clinical change.

Finally, the clinical implementation of EWS is conditional on whether timely, person-specific prediction is possible. A crucial step is therefore to evaluate EWS in real time, with each new incoming ecological momentary assessment triggering a new (or updated) risk evaluation. This design in turn raises the question of within what timeframe changes in clinical symptoms and their timely warnings (EWS or otherwise) are expected to occur. For instance, it is unclear whether warning signs that occur one to two months prior to transitions should be considered true or false alarms. There is no simple answer to this question – it depends on the outcome that is being anticipated, the given individual, and the timeframe of interventions that could potentially influence the outcome (for example, promoting remission or preventing relapse). Certain mental health disorders (such as rapid-cycling bipolar disorder) manifest on faster timescales than others (such as depression), which will influence the optimal timeframes of eventual momentary interventions. A one-size-fits-all solution to the optimal timeframe for considering EWS is also unlikely, as there are substantial individual differences with respect to the onset and course of prodromal symptoms[151]. Thus, although EWS have the reputation of offering timely warnings of people's resilience, there is still much to learn about what exactly 'timely' means for EWS in psychopathology.

The challenge of implementing EWS for clinical change prediction in psychopathology highlights the difficulty of translating theories derived from other fields (such as ecology and physics) to the social sciences, in which measurement is far less straightforward and change mechanisms are poorly understood. Concepts such as emotions and mental health are inherently hard to define, and even harder to measure. Researchers and clinicians should slow down, be critical and focus on improving theoretical clarity, psychological measurement and their interconnections, to have a better chance at predicting individual clinical change using EWS.

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Competing interests

The authors declare no competing interests.

Additional information

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