

The Patient as a Dynamic Network, Not a Laboratory Report

Absurd Health Institute · Volume Nine · Expanded medical concept paper

Abstract

Clinical medicine depends on measurements, yet most measurements are captured as isolated observations: one blood draw, one blood-pressure recording, one sleep questionnaire, one office visit. These snapshots are essential for identifying urgent abnormalities and monitoring established disorders. They are less informative about dynamics: how physiology responds to stress, how quickly recovery occurs, whether two signals change together, or whether the patient's baseline is quietly drifting. This paper proposes a **dynamic-patient model** in which health is described not only by the values of separate variables, but also by their timing, covariation, response to perturbation, and recovery trajectories. The model draws on longitudinal molecular profiling, wearable measurements, and resilience research while emphasizing a critical limitation: a correlation between two time series is not sufficient to establish that one causes the other. Dynamic data can generate better questions, but will only improve clinical decisions when its predictions are reliable, interpretable, and associated with actionable outcomes.

1. The limitation of the single encounter

A blood result has several meanings simultaneously. It is a measurement obtained under specific laboratory conditions. It is one point within a person's distribution of measurements. It can be compared with a reference population. It may also represent a response to recent behavior, medication, inflammation, exercise, sleep or illness. A typical laboratory report communicates the first and third meanings well, often says little about the second, and may not contain enough contextual information to interpret the fourth.

This is not a defect in laboratory medicine. Many measurements are highly useful as single observations: severe hyperkalemia, markedly elevated troponin in an appropriate clinical context, or an alarming blood count may demand immediate attention. The mistake is to assume that every question about chronic illness has the same information structure. When a patient asks why fatigue varies by day, why symptoms worsen after exertion, or why a previously tolerable exposure has become difficult, a normal laboratory result obtained at rest cannot address the entire question.

There is a difference between **what state is present now** and **how the organism behaves over time**. Some illnesses are characterized less by a fixed abnormal concentration than by altered feedback, excessive reactivity, reduced adaptive reserve, or unusually slow return toward baseline. To investigate these possibilities, temporal information is essential.

2. The organism is coupled, but coupling does not imply one cause

Cardiovascular, endocrine, immune, neural, renal, and metabolic processes continually influence one another. Physical activity changes heart rate, ventilation, glucose use and temperature. Sleep alters autonomic regulation and inflammatory signaling. Meals change glucose, gastrointestinal motility, hormonal output and subjective energy. These relationships are expected physiology. The presence of coupling is not evidence of pathology.

For a dynamic-patient model, the central question is whether the **structure or strength of coupling** changes in a way relevant to a patient's symptoms. Does heart rate remain elevated long after activity ends? Does a change in sleep duration precede worsening pain? Does a rise in measured glucose coincide with a change in symptoms because glucose is causal, or because both are consequences of stress, illness, or a medication? These possibilities require different inferences.

A simple network diagram can suggest connections between variables. But a dense diagram made from correlations will almost always look biologically impressive, especially when dozens of signals are collected. Many apparent

connections arise from common daily rhythms, shared measurement artifacts or simple features of time-series autocorrelation. A meaningful network model therefore requires deliberate decisions about temporal alignment, missing data, confounding variables and measurement reliability.

3. Three kinds of individual baseline

A useful starting distinction is between a population reference interval, a person's usual baseline, and the response the person is expected to show under a defined challenge. The population interval helps identify patterns that are unusual in the general population. A personal baseline may reveal substantial change even while values remain within population limits. A challenge response can reveal reduced reserve that is not evident at rest.

For example, a resting heart rate that increases relative to a person's usual pattern may reflect fever, dehydration, reduced conditioning, stress, medication, sleep loss, altered endocrine status, or changing cardiovascular status. The trend is a signal deserving interpretation, not a diagnosis. Conversely, a stable heart rate does not exclude illness. Personal baselines are valuable only when their sources of variability are understood.

The same logic applies to repeated laboratory measures. Someone with stable hematologic or metabolic values may develop a persistent within-person shift that remains technically normal compared with the reference population. Such a shift may be relevant, but meaningful change should be evaluated against biological variation, analytical uncertainty, and the possibility of regression to the mean. A precision-medicine system that treats every deviation as danger will quickly become an engine of false alarms.

4. Recovery kinetics may reveal more than peak responses

A characteristic of a resilient system is not merely that it resists disturbances, but that it returns toward an effective operating range after disturbances occur. The dynamics of this return can sometimes be measured. Heart rate after exertion, glucose after a meal, sleep following a disrupted night, and functional performance after an illness represent different recovery processes. They cannot be compressed into a single universal score without validation.

Pyrkov and colleagues analyzed longitudinal physiological and blood-marker data in relation to age and inferred a progressive loss of resilience reflected in recovery dynamics. Their research makes recovery time an interesting scientific target, not an immediately validated patient-care metric. Two people may experience comparable short-term changes but differ in how quickly they stabilize. If that difference predicts clinically meaningful outcomes beyond conventional measures, dynamic recovery metrics could have independent value.

The strongest version of the hypothesis therefore asks whether *response and recovery curves* provide predictive information after adjusting for baseline disease severity and known risk factors. A marker that merely changes with age, stress or fitness may be informative but not causally diagnostic.

5. What longitudinal profiling has already demonstrated

Longitudinal multi-omics projects offer a useful precedent. Schüssler-Fiorenza Rose and colleagues followed a cohort enriched for type 2 diabetes risk using repeated clinical, molecular and wearable observations. The study identified clinically relevant signals and illustrated how repeated measurement can reveal changes that single snapshots would not. This is an existence proof for the value of dynamic profiling, but it is not evidence that unconstrained data collection improves outcomes in every clinical setting.

The source of insight was not simply gathering more variables. It was relating new measurements to a person's evolving clinical context. A time series without valid clinical interpretation can multiply uncertainty rather than reduce it. Worse, dense longitudinal data often contain missingness that is informative: patients may stop wearing devices when they feel ill, complete symptom surveys only during flares, or change behaviors in response to what the device reports. Those feedback loops create selection and measurement biases.

Wearables also differ in their ability to measure physical quantities. Heart rate may be estimated relatively reliably under some conditions, while sleep stages or stress labels are often indirect algorithmic inferences. A model that feeds weak sensor estimates into a confident disease-prediction engine can magnify rather than eliminate error.

6. A clinical thought experiment: two identical blood panels

Imagine two hypothetical patients whose conventional laboratory panels are nearly identical at today's appointment. The first has stable physical capacity, consistent sleep, ordinary post-exertional recovery, and no major change in daily function. The second reports that comparable exertion now produces prolonged tachycardia, disrupted sleep, and two days of reduced function. The blood panels offer no obvious distinction, but the clinical trajectories are different.

A dynamic approach would not automatically conclude that the second patient has dysautonomia, mitochondrial failure or a hidden infection. It would begin by verifying the observations and asking which relevant mechanisms could produce them. It would distinguish subjective fatigue from measured impairment; investigate medication effects, infection, sleep and mood contributors; and, when clinically appropriate, use established diagnostic pathways for cardiovascular, autonomic or other abnormalities.

The network model adds a question: *which changes are consistent across episodes, and which lead or follow the symptoms?* If sleep deterioration reliably precedes reduced exertional tolerance, one causal hypothesis becomes plausible. If exertion comes first and sleep disturbance follows, a different interpretation is needed. If both are driven by an unrecorded medication or infection, the apparent coupling may be confounded. Recording order does not by itself settle causation, but it narrows the possibilities.

7. The counterfactual problem

Longitudinal measurement invites a tempting but hazardous inference: "I changed X, then Y improved, therefore X cured Y." The body changes continuously, symptoms fluctuate, patients alter several habits together, and disease trajectories may regress toward their usual mean. These factors are especially troublesome when interventions are chosen during symptom peaks.

A dynamic model should therefore distinguish **description, prediction, and causal inference**. Description captures what happened. Prediction estimates what may happen next under similar conditions. Causal inference asks what would have happened had one intervention or exposure differed while relevant other factors were held comparable. High-resolution measurement improves the first two categories but does not automatically solve the third.

In selected low-risk contexts, repeated within-person observations and preplanned contrasts may strengthen inference. But even carefully structured time-series comparisons can be confounded by trend, expectation, learning effects, seasonal changes and delayed responses. Clinical decisions must not be based on apparent patterns that have not survived those challenges.

8. What a responsible dynamic medical record should contain

A useful system would retain ordinary diagnoses, medication history, laboratory data and red-flag findings. It would also preserve the timing and conditions of measurements; distinguish sensor estimates from direct measurement; display baseline uncertainty; represent meaningful personal trends; and let clinicians examine temporal relationships rather than flattening everything into a single wellness score.

It should communicate its limitations. Missing values should be visible. The model should not issue a confident conclusion when the evidence is weak or contradictory. It should distinguish an acute safety signal from a speculative chronic-disease hypothesis, and avoid recommending high-risk interventions on the basis of an unverified network pattern.

The practical objective is not to replace physicians with a graph. It is to build better context for clinical reasoning and to identify specific questions that conventional episodic care may not capture. Such a system may be particularly useful for following recovery after illness, detecting changes from personal baseline, and evaluating conditions whose manifestations vary substantially over time. Whether it improves health outcomes remains an empirical question.

9. What would change our minds?

The dynamic-patient hypothesis would be weakened if personal trends and cross-signal features offered no meaningful incremental prediction beyond established clinical factors, or if their apparent benefits disappeared in external validation. It would also be weakened if the added alerts created substantial unnecessary testing, anxiety, cost or treatment harm without demonstrating net benefit.

Network complexity should not be celebrated for its own sake. If a simple model involving symptoms, age, medication history and a few reliable measurements performs as well as a complex multisensor algorithm, the simple model is preferable. Dynamic data are justified when they solve a real decision problem, not merely because more data can be collected.

Conclusion

The patient is not a laboratory report, but laboratory reports are indispensable observations of the patient. The task is to combine accurate snapshots with trustworthy trajectories. A biological measurement acquires additional meaning through its time course, its relationship to relevant functional demands, and its connection with other physiological processes. The result can be a more discriminating form of clinical reasoning—but only if the model remains disciplined about measurement quality, confounding, causality and the harms of false confidence.

The central proposition is narrow and testable: **in selected clinical settings, within-person trajectories and physiologically interpretable interactions among signals may reveal clinically meaningful changes that are not captured by isolated measurements.** That is more scientifically useful than claiming that a network can explain every unexplained illness.

Selected scientific literature

1. Schüssler-Fiorenza Rose SM, et al. A longitudinal big data approach for precision health. *Nature Medicine*. 2019. Full article. 2. Pyrkov TV, et al. Longitudinal analysis of blood markers reveals progressive loss of resilience and predicts human lifespan limit. *Nature Communications*. 2021;12:2765. doi:10.1038/s41467-021-23014-1. 3. Tebani A, et al. Integration of molecular profiles in a longitudinal wellness profiling cohort. *Nature Communications*. 2020. Full article. 4. Babu M, et al. Multi-Omics Profiling for Health. *Molecular & Cellular Proteomics*. 2023. Full article.

Editorial disclosure: This article advances a conceptual interpretation of longitudinal medicine. It is not a description of a validated clinical screening product, a demonstrated treatment effect or an original cohort study. Rewritten and substantially expanded 16 October 2026 for Absurd Health Institute.