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Detecting and Redirecting Critical Transitions in High-Need, High-Cost Patient Trajectories: An Instability–Plasticity Theory for Longitudinal Care

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Abstract

Background: Patients described as high-need, high-cost (HNHC) represent a subset of individuals with complex multimorbidity whose healthcare trajectories are characterised by recurrent instability and intensive use of acute care services. Concepts such as trajectory disruption, resilience, and complex adaptive behaviour are widely discussed in health systems research, yet linking these ideas to longitudinal patient care remains limited. The PaJR (Patient Journey Record) relational system was designed using principles from complex adaptive systems theory, enabling longitudinal observation of patient trajectories in real-world care. **Objective:** This study develops a middle-range theory grounded in longitudinal relational monitoring data. **Methods:** Two datasets (MonashWatch and Irish cohorts) provide empirical grounding through descriptive analysis of signal clustering, distribution, and multi-domain patterns. Monitoring calls capture structured patient-reported signals across multiple domains, including illness, medication, healthcare utilisation, social support, environmental factors, and self-care. **Results:** Results demonstrate long-tail signal distributions, temporal clustering, and multi-domain instability preceding admission. Alerts frequently occurred in clusters across consecutive monitoring calls 88% of alert calls were part of a consecutive alert sequence, with approximately 64% of alert calls occurring immediately after a previous alert. Alerts were also commonly multi-domain, with approximately 64% involving disturbances across more than one domain simultaneously. **Conclusions:** Longitudinal relational monitoring reveals instability patterns in patient journeys that are not visible in episodic health-system data. Recognising these instability phases may enable earlier, more adaptive responses for patients with complex healthcare needs and provides empirical grounding for emerging theories of healthcare trajectories within complex adaptive systems. Although grounded in relational monitoring data, the instability–plasticity framework may extend to inform interpretation across physiological and connected health monitoring systems.

Keywords: complex adaptive systems; patient trajectories; multimorbidity; high-need high-cost patients; telehealth monitoring; relational monitoring; resilience; instability; patient journey

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1. Introduction

This paper positions instability–plasticity as a middle-range theory linking complex adaptive systems to empirical patient journey data. Within this framework, clusters of patient-reported signals preceding hospital admission are interpreted as indicators of declining resilience and increasing trajectory plasticity, suggesting that healthcare journeys periodically enter instability phases in which transitions to acute care become more likely.

This manuscript is a theory-building and conceptual integration study grounded in previously published empirical analyses from the Irish [1] and MonashWatch [2] PaJR longitudinal monitoring programs. It develops an explanatory middle-range theory [3] informed by longitudinal observational patterns. Quantitative validation of the framework is provided in a companion empirical study which reports outcomes from 621 instability windows across 157 patients and the pre-admission signal cascade across 175 patients with emergency admissions [4].

1.1. Background

People who frequently use acute health care services often have complex multimorbidity beyond a single disease, with multiple bodily and social system concerns, whose needs are frequently unmet, and are termed high-need, high-cost patients [5,6]. Multiple interventions have focused on such patients as Superutilizers who consume 'excessive health care costs' with little attention to improving their experiences of care, Ref. [7] nor the complex systems of personal trajectories and health and social from which they emerge [8,9]. Multimorbidity in high-need, high-cost patients, therefore, represents not simply the coexistence of multiple diseases, but the emergence of interactions among biology, psychosocial, environmental and health service dynamics [10,11]. When the capacity of these interacting systems to absorb disturbance declines, trajectories may become increasingly unstable and may transition into acute care events such as hospital admission.

Conventional care records and episodic encounter data often provide clinicians with limited visibility into the evolving lived experience of illness between clinical encounters and events [11]. Consequently, deterioration may remain largely invisible until it culminates in an acute care episode.

Research across fields including ecology, climate science, and social interactions demonstrates that systems approaching critical transitions often exhibit early warning signals [12]. These signals reflect declining resilience within the system as it approaches a tipping point [13–16]. Underlying biological processes, psychological coping capacity, social support networks, and health-system responses interact continuously to shape patient journeys. Work on multimorbidity resilience offers a useful frame for thinking about plasticity in patient trajectories beyond disease counts [16]. Early warning systems have arguably become mid-level theories widely adopted in health care. Longitudinal studies of older adults with multimorbidity suggest that trajectories are plastic—capable of bending toward better or worse outcomes—depending on how these biopsychosocial and environmental resources are engaged over time [17–19].

1.2. Relational Monitoring Systems

Patients with complex multimorbidity often experience healthcare as a series of fragmented encounters, despite their conditions evolving through continuous and interconnected processes over time. Conventional models of care, including disease-specific management and episodic clinical review, are not well suited to capturing these dynamics. As a result, important changes in health status, function, coping, and social context frequently occur between clinical encounters and remain unrecognised until deterioration culminates in acute care. There is increasing recognition that such patients are better understood

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through the concept of *patient journeys*, in which healthcare trajectories evolve non-linearly through interactions across biological, psychological, and social domains.

Relational monitoring in patient journeys refers to a longitudinal approach in which repeated, structured interactions capture evolving, multi-domain signals across illness, functional activity, coping, and social context, enabling observation of healthcare trajectories as dynamic processes over time. This approach extends established models such as case management and patient-reported outcome monitoring by emphasising continuity, multi-domain signal capture, and the temporal evolution of change. A distinguishing feature of relational monitoring is that signals are not treated as isolated measurements, but as patterns that emerge through ongoing relationships and repeated interactions. This creates the opportunity to detect early changes in trajectory before they become clinically overt.

These considerations suggest that deterioration in complex multimorbidity may be better conceptualised not as sudden events, but as transitions preceded by periods of instability within patient trajectories. Drawing on concepts from complex adaptive systems and resilience theory, this study develops an instability–plasticity framework to explain how such transitions emerge and how they may be detected through longitudinal relational monitoring.

1.3. Core Proposition of This Paper

This paper proposes an instability–plasticity framework that interprets clusters of patient-reported signals as indicators of declining resilience and increasing trajectory plasticity within healthcare journeys. Unstable multimorbidity care trajectories exhibit detectable instability signals preceding critical transitions to acute care. These instability phases represent plasticity windows during which relatively small ongoing relational interventions (nudges in health care, biopsychosocial and environmental domains) may redirect patient trajectories toward stabilisation or resilience. To avoid conceptual slippage, we use the following definitions consistently throughout:

Relational monitoring: a method of sensing trajectories in complex care that shares elements with case management, telehealth follow-up, and patient-reported outcome monitoring, but differs in its explicit focus on trajectories clinical encounters as the unit of observation. Through repeated interactions within longitudinal therapeutic relationships, it captures evolving, multi-domain signals from a patient's lived experience, enabling identification of instability phases as they emerge.

Resilience: the capacity of the person-in-context to absorb disturbance while maintaining function (remaining in community-based management rather than transitioning to acute care, or other services).

Instability: a phase in which fluctuations and clustering of distress/alert signals increase, indicating reduced capacity to absorb perturbations and increased sensitivity to stressors.

Plasticity: the capacity of the trajectory to be redirected by relatively small inputs. Plasticity is not "improvement" per se; it is *responsiveness* to perturbation (helpful or harmful).

Complex (adaptive) systems Complex adaptive systems are characterised by networks of interacting agents whose behaviour adapts in response to changing conditions and feedback from other system components. Such systems exhibit non-linear dynamics, emergent patterns, and evolving trajectories over time.

See Figure 1 for theoretical framework.

Healthcare trajectories in complex adaptive systems move dynamically between states of relative stability and instability. Instability phases are characterised by increased variability and sensitivity to perturbation, reflecting reduced system resilience. These phases may also represent periods of trajectory plasticity, during which relatively small influences may redirect the trajectory toward stabilisation or escalation. The framework illustrates how transitions to acute care emerge within evolving trajectories rather than as isolated events.

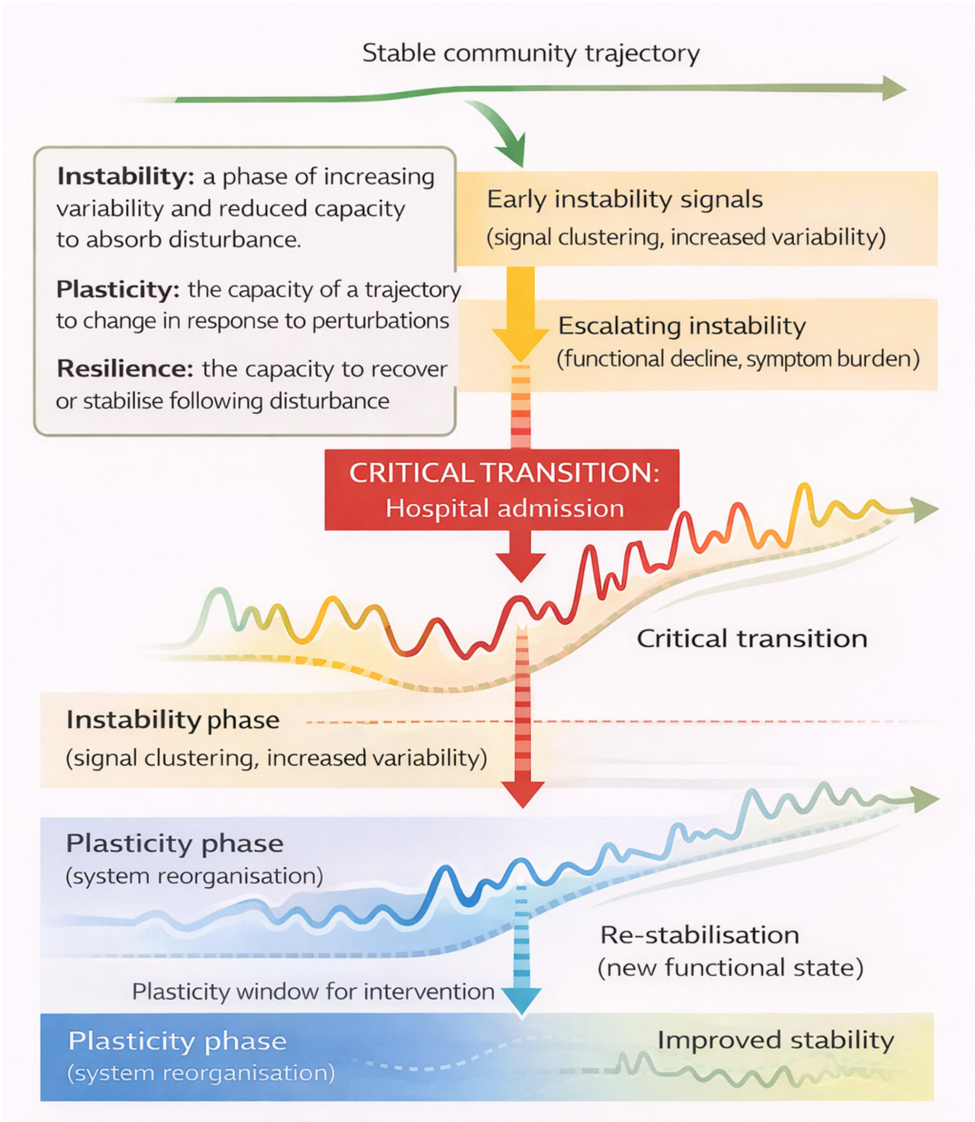

Figure 1. Conceptual framework of relational monitoring of instability, plasticity, and resilience within multimorbidity trajectories.

2. Materials and Methods

2.1. Approach

This study presents a conceptual systems analysis informed by previously published empirical observations derived from the Patient Journey Record (PaJR) (version 1.0) telehealth monitoring system [1,2]. The aim to interpret reported trajectory patterns through the lens of complex adaptive systems and resilience theory, not to test hypotheses.

The analytical approach combines implementation observation, longitudinal trajectory interpretation, and conceptual theory development. Data derived from the PaJR system are used to illustrate patterns of instability preceding acute care events. These observations provide the empirical foundation for the instability–plasticity framework proposed in this paper.

The methodological approach reflects an iterative cycle of theory, observation, and theory refinement, characteristic of complexity-informed health systems research. Initial theoretical ideas about instability in multimorbidity trajectories informed the design and

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implementation of the relational monitoring system. Subsequent empirical observations generated through longitudinal monitoring revealed instability patterns preceding hospital admission, which then informed further theoretical development.

2.2. Program Context and Data Source

Patient Journey Relational Monitoring and Data Sources

The empirical data analysed in this study are part of a suite of PaJR programs that have been previously evaluated in 3 pragmatic trials, and qualitative studies across 9 sites with statistical reductions in ED visits and hospital bed days [1,2,20].

In this study, relational monitoring is operationalised through the PaJR platform. These patterns arise from the structure of the monitoring process. Data are generated through regular, structured interactions between patients and trained peer health navigators, typically conducted via weekly telephone contacts and increased in frequency during periods of instability [1,2,17].

Peer health navigators are non-clinical personnel who provide continuity, practical support, and facilitation of access to care. During each interaction, patient-reported information is systematically elicited across multiple domains, including symptom burden, functional activity, coping capacity, healthcare utilisation, and social circumstances [21].

Two PaJR monitoring datasets were used for analytic purposes. Together, the MonashWatch and the Irish independent datasets—collected in different health-system contexts and time periods—provide complementary perspectives on patient trajectory dynamics within a common longitudinal monitoring framework.

All call data were de-identified and analysed with appropriate ethical approval. Dataset characteristics are summarised in Table 1.

Table 1. Two datasets representing independent PaJR monitoring cohorts collected in different health system contexts and time periods. They are analysed here for complementary purposes: to illustrate individual trajectory dynamics, examine population-level signal distributions, and explore variability across patient journeys within complex health systems.

Dataset/Site	**Health System Context**	**Patients (*n*)**	**Monitoring Calls (*n*)**	**Observation Period**	**Analytic Purpose**
MonashWatch (Victoria, Australia)	Urban hospital–community integrated care program	244	16,383	18 months	Illustrate example patient trajectories and escalation dynamics
Irish PaJR monitoring cohort	National health service community monitoring program	286	11,108	18 months	Examine signal distributions and instability patterns across a large longitudinal dataset

2.3. Monitoring Data

During each telephone interaction, navigators engage participants in structured but conversational discussions about their current health and circumstances. These conversations begin with open-ended narratives and include directed prompts designed to elicit information about the participant's current state. From these conversations, several types of longitudinal signals are generated, including:

1. Acute red alerts of perceived symptom burden triggering an acute red alert when the intensity is high
2. Continual red alerts with various subcategories
    - coping capacity and emotional state

- functional activity and daily participation
- emerging health concerns or symptom changes
- social or practical challenges affecting care

These signals are translated into structured risk indicators within the PaJR monitoring system, often represented through graded alert levels indicating different levels of concern. Because navigators interact repeatedly with the same individuals over extended periods, the monitoring system captures fluctuations in illness burden, coping capacity, and social context that may precede clinical deterioration and acute care utilisation.

2.4. Trajectory Observation

Previous analyses of the PaJR dataset examined temporal relationships between patient-reported signals and acute care events such as acute hospital admission [2,20,22]. Trajectory signals were aligned relative to admission events to examine patterns occurring in the days preceding hospitalisation. These analyses demonstrated clustering of deterioration signals in the days before admission, suggesting that patient journeys often enter phases of increasing instability prior to acute care events.

The trajectory figures referenced in this paper—including both individual case trajectories and aggregated signal patterns—are derived from data in these previously published observational analyses.

2.5. Statistical Analysis for Conceptual Development

No inferential statistical modelling was undertaken; analyses are descriptive and support theory development.

An instability window was defined as $\geq$2 consecutive monitoring calls in which total alerts were $\geq$3. This threshold was selected to capture sustained, multi-signal elevation across domains while excluding isolated fluctuations. Duration was measured in monitoring calls, representing the natural unit of the monitoring process. For interpretive context, approximate calendar duration was derived assuming a median inter-call interval of 7 days (range 1–247 days) and should be interpreted cautiously.

Descriptive statistics are reported as medians [IQR] for skewed distributions and means (SD) for approximately normally distributed variables.

All analyses were conducted in R (R Foundation for Statistical Computing) (version 4.5.3 (2026-03-11)), using base R functions for descriptive analyses.

This is an observational study, and findings should be interpreted as hypothesis-generating and theory-building rather than confirmatory.

2.6. Conceptual Analysis

The instability patterns observed in PaJR trajectories were interpreted using concepts from complex adaptive systems and resilience theory. Within this perspective, healthcare trajectories are understood as emergent phenomena shaped by interactions among biological, psychological, social, and organizational factors.

Periods of clustered deterioration signals were interpreted as trajectory instability phases, potentially representing early indicators of declining resilience within the patient's care system.

These observations informed the development of the instability–plasticity framework, which conceptualises such instability phases as potential plasticity windows during which relatively small relational interventions may influence the direction of the trajectory. Methodologically, this approach aligns with the development of middle-range theory [4].

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2.7. Ethics and Data Governance

The data referenced in this study originate from previously published analyses of the MonashWatch telehealth service, which received approval from the Human Research Ethics Committees of Monash Health and the Irish College of General Practitioners.

The present manuscript does not involve access to identifiable patient-level data or new data collection. All figures and trajectory patterns presented are used here illustratively to support conceptual theory development. Instead, it provides a conceptual secondary interpretation of previously published observations and figures. The illustrative case trajectory included in this paper is fully de-identified and cannot reasonably be linked to an identifiable individual. Accordingly, additional ethical approval was not required.

3. Results

The results are derived from descriptive analyses of two longitudinal monitoring datasets, as described in the Methods section: a MonashWatch cohort (100 patients, 1137 monitoring contacts) and an Irish cohort (286 patients, 11,108 monitoring contacts). These data were examined to identify patterns of instability, including signal clustering, multi-domain activity, and temporal relationships to acute care events.

3.1. Population Context: High-Risk Multimorbidity Trajectories

The analyses relate to a subgroup of patients characterised by complex multimorbidity, functional vulnerability, and recurrent use of acute care services. The observed patterns should therefore be interpreted within the context of high-risk patient trajectories in which health status fluctuates over time.

3.2. Observing Healthcare Trajectories Through Relational Monitoring

Analysis of longitudinal trajectories identified recurring patterns in which clusters of deterioration signals precede acute care events, including hospital admission and emergency department attendance. These patterns reflect changes across multiple domains of patient experience and occur over varying timeframes within individual trajectories.

3.2.1. Patient Trajectories

The observed journeys are characterised by multiple longitudinal signals—including illness burden, functional activity, and self-rated health—plotted alongside hospital admission events. Signals fluctuate over time, reflecting the dynamic nature of patient trajectories, with periods of increased volatility emerging in the days or weeks preceding admission. These periods are typically marked by rising symptom burden, reduced activity, and worsening self-rated health.

Following hospital admission, signals often show temporary stabilisation before further fluctuations occur as patients return to community care.

Figure 2 illustrates these patterns within individual trajectories. Periods of increased signal variability are observed prior to admission events, although the timing, duration, and intensity of these periods vary between patients.

Figure 3 shows that similar patterns are present across multiple patients when signals are examined at the population level. However, not all instability periods are captured through routine monitoring. Some reflect rapid events or changes in social and environmental context, and the timing of detection may be influenced by monitoring frequency and system responsiveness.

Longitudinal patient-reported signals across multiple domains are plotted over time, with hospital admissions indicated. Periods preceding admission are characterised by increased variability and clustering of signals, consistent with trajectory instability. Not all periods of instability result in admission, illustrating the heterogeneous and dynamic nature of trajectory evolution.

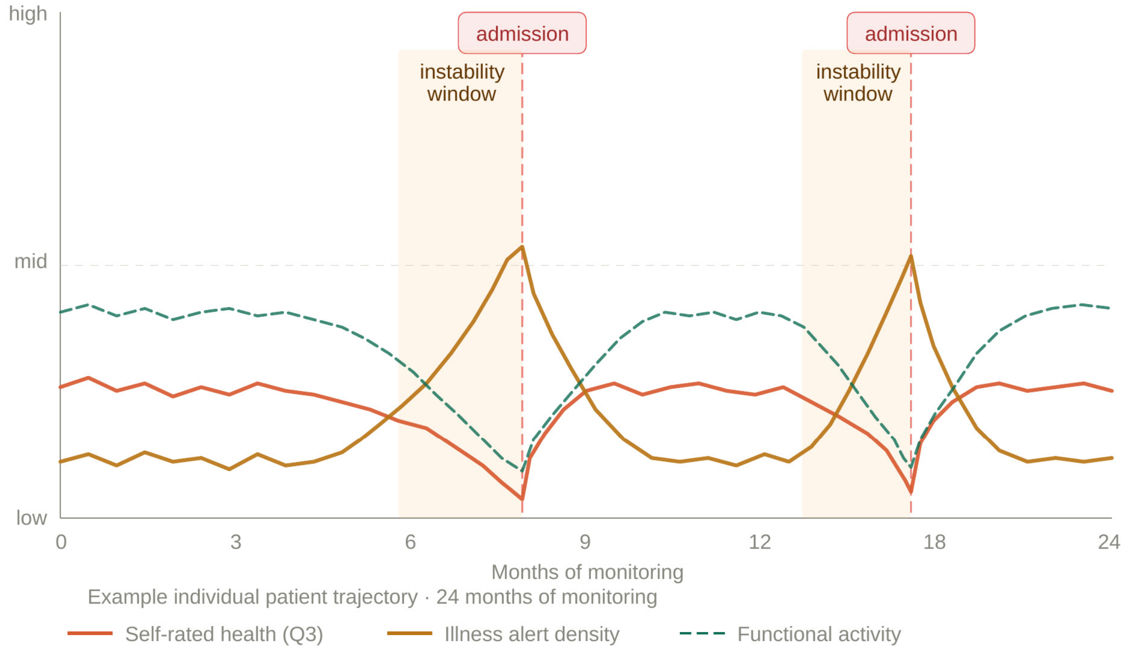

Figure 2. Example of an individual multimorbidity trajectory showing multi-domain signal dynamics.

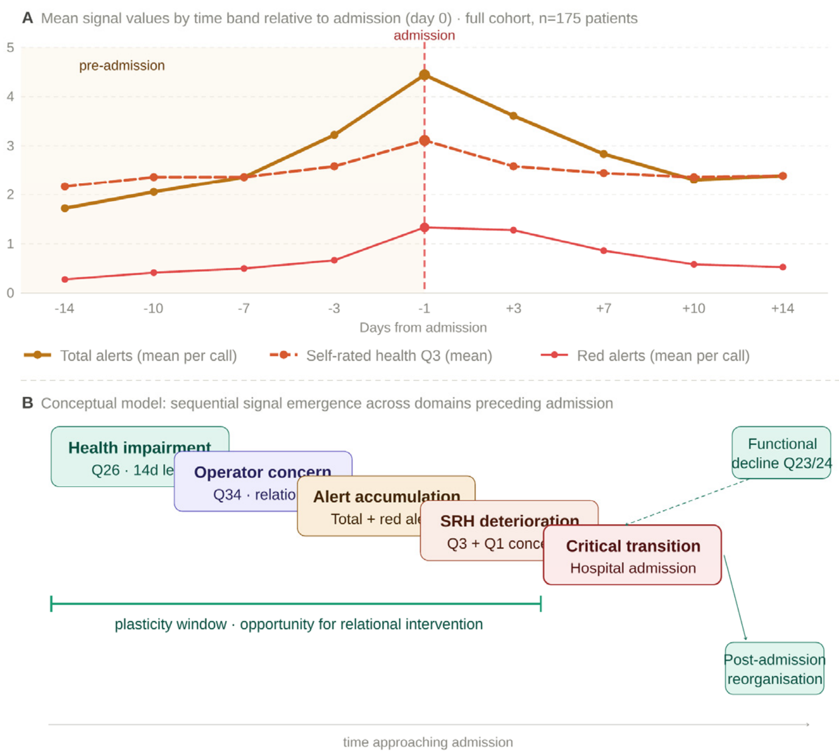

Figure 3. Population-level temporal patterns of instability signals around hospital admission. (**A**) Mean trajectories of patient-reported signals aligned relative to admission (day 0), showing increasing signal intensity in the pre-admission period and partial stabilisation post-admission. (**B**) Conceptual representation of a multi-domain signal cascade, in which interacting changes across functional, behavioural, and illness domains accumulate prior to transition. These patterns illustrate that hospital admission is typically preceded by a period of escalating, multi-domain instability within patient trajectories.

3.2.2. Population-Level Signal Patterns Around Admission

Most detected instability phases resolved without hospital admission. Across 621 instability windows identified in 157 patients (64% of the monitored cohort), 67.3% resolved without hospital admission or emergency department attendance. This proportion was stable across alert detection thresholds from 1 to 5.

Among the 70 patients who experienced both admitted and resolved instability windows, admitted windows were characterised by greater multi-domain breadth—defined as the number of clinical domains simultaneously active at high severity—rather than by greater alert intensity within the same patient (median difference +0.18, $p < 0.001$; alert intensity $p = 0.12$).

To examine whether similar patterns were present at the population level, trajectory signals were aligned relative to the timing of hospital admission, with day 0 representing the admission event. This alignment enabled retrospective analysis of signal behaviour in the 14 days preceding and following admission.

Figure 3 presents aggregated signals across the MonashWatch cohort for the 14-day period before and after hospital admission. A consistent pattern of increasing signal activity was observed in the pre-admission period, followed by partial stabilisation after admission. Health impairment demonstrated the highest individual predictive performance (AUC 0.61) and was the only signal whose predictive strength increased with a wider pre-admission window, suggesting elevation up to 14 days before admission.

Overall, alignment of signals relative to admission revealed a population-level pattern of escalating instability preceding hospitalisation, despite substantial heterogeneity in individual trajectories.

To further characterise these patterns, the structural properties of instability signals were examined (Figure 4). The distribution of signal intensity across monitoring observations was strongly long-tailed, with most observations showing minimal disturbance and a minority exhibiting high-intensity clustering. Signal patterns were non-linear over time, with irregular fluctuations and episodic clustering rather than steady progression. In addition, instability signals frequently involved concurrent activity across multiple domains, with different domains contributing variably to overall signal burden.

Together, these findings show that instability is episodic, temporally clustered, and multi-domain in nature across patient trajectories.

3.3. Conceptual Synthesis: Instability and Plasticity in Patient Trajectories

Across the analyses presented, several consistent empirical patterns are observed. Instability signals are episodic rather than continuous, cluster temporally once initiated, and frequently involve concurrent changes across multiple domains of patient experience. These patterns are evident both within individual trajectories (Figure 2) and when signals are aligned relative to hospital admission at the population level (Figure 3), and are further reflected in the structural properties of signal distributions (Figure 4).

Taken together, these observations suggest that patient trajectories in complex multimorbidity periodically enter phases of increased instability prior to transitions to acute care. These phases vary in duration and intensity and do not uniformly lead to hospital admission, indicating heterogeneity in how trajectories evolve.

These findings also indicate that periods of instability may represent phases in which trajectories are more dynamic and potentially modifiable. This provides an empirical basis for considering instability not only as a marker of deterioration, but as a state within trajectories that may precede different outcomes, including both escalation and stabilisation (see Figure 5).

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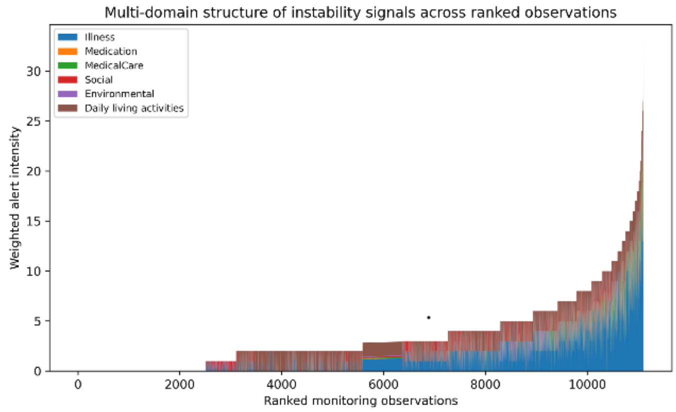

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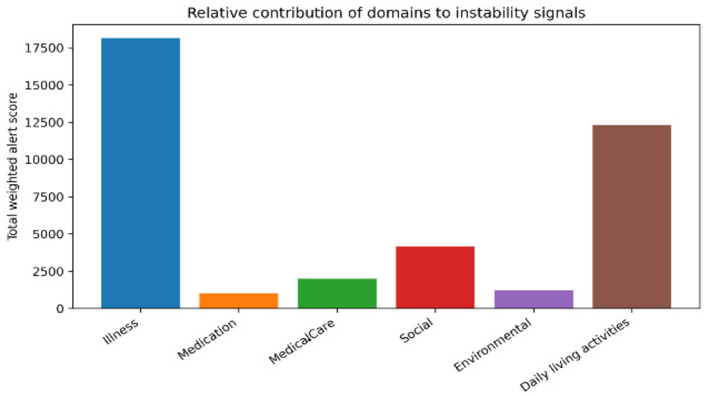

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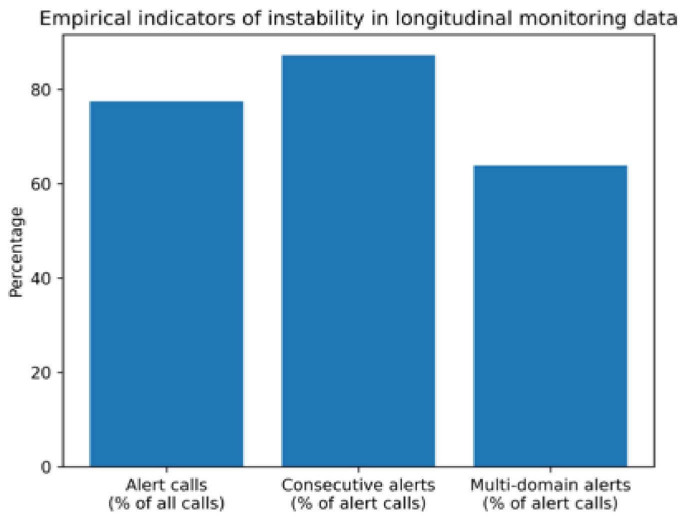

(**C**)

Figure 4. Frequency of instability indicators across 16,383 monitoring calls in the MonashWatch PaJR cohort (n = 244 patients, 2016–2019). Recognising instability and plasticity within multimorbidity trajectories may enable health systems to shift from reactive management of acute events toward proactive trajectory stewardship, supporting more adaptive responses within complex healthcare systems. (**A**) Distribution of signal intensity across monitoring observations, demonstrating a long-tail pattern in which most observations show minimal disturbance and a minority exhibit high-intensity clustering; (**B**) Relative contribution of different domains to overall signal burden, highlighting the multi-domain nature of instability. Together, these patterns indicate that instability emerges episodically and involves concurrent disruption across multiple domains of patient experience;

(**C**) Empirical indicators of instability in longitudinal monitoring data. Among all monitoring calls, 77% generated at least one alert. Of alert calls, 88% were part of a consecutive alert sequence and 64% involved alerts across multiple domains.

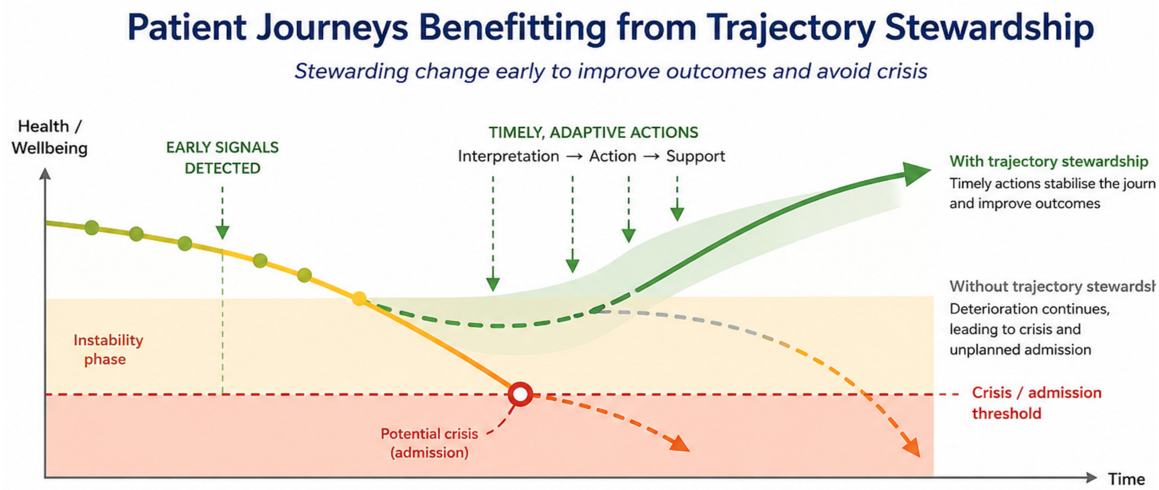

Figure 5. Trajectory stewardship model: sensing, interpretation, and response. Schematic representation of a trajectory-oriented care model in which longitudinal monitoring supports detection of emerging instability, enabling interpretation of trajectory dynamics and timely response. Interventions delivered during instability phases may influence trajectory direction, supporting stabilisation or appropriate escalation. The model integrates sensing, interpretation, and action within a continuous care framework.

4. Discussion

This study develops an instability–plasticity framework to explain how healthcare trajectories in high-need, high-cost multimorbidity evolve through detectable phases of instability, some of which represent windows of potential trajectory modification. Drawing on longitudinal monitoring data, we identified consistent empirical patterns in which patient-reported signals cluster, spread across domains, and intensify prior to transitions to acute care. Rather than viewing hospital admission as an isolated event, these findings support an interpretation of admission as a transition within an evolving trajectory. Instability emerges as a dynamic state characterised by increasing variability, temporal clustering, and multi-domain disruption. Importantly, a substantial proportion of instability phases resolve without escalation, indicating that instability does not represent inevitable deterioration.

4.1. Instability as a Dynamic State in Multimorbidity Trajectories

The empirical patterns observed in this study align with established concepts from complex adaptive systems and resilience theory [23,24]. In such systems, transitions are often preceded by increasing fluctuations, clustering of signals, and reduced capacity to absorb perturbation. Within multimorbidity care, these dynamics manifest as interacting changes in symptoms, functional capacity, coping, and social context. The finding that escalation is associated more strongly with multi-domain breadth than with signal intensity suggests that instability reflects system-wide disruption rather than isolated deterioration. This reinforces the view that healthcare trajectories are shaped by interactions across biological, psychological, and social domains, rather than by single disease processes. Instability, in this framework, is therefore best understood as a phase within the trajectory rather than a fixed patient characteristic.

4.2. Instability and Plasticity: From Risk to Opportunity

A central contribution of this study is the interpretation of instability not only as a marker of risk but also as a potential indicator of trajectory plasticity. In many complex systems, periods of instability coincide with increased responsiveness to perturbation. Applied to healthcare trajectories, this suggests that instability phases may represent periods in which trajectories are more susceptible to both deterioration and stabilisation.

The observation that many instability phases resolve without hospital admission provides empirical support for this interpretation. These findings indicate that instability does not uniformly progress to acute care but may instead represent a branching point in the trajectory.

This reframing shifts the conceptual focus from prediction of adverse events toward identification of time-sensitive windows in which intervention may influence trajectory direction.

4.3. Trajectory Stewardship and Relational Intervention

The instability–plasticity framework implies a model of care oriented toward trajectory stewardship rather than episodic intervention. In this model, the key task is not only to identify high-risk patients, but to detect when trajectories are destabilising and to respond during periods when they remain modifiable.

Longitudinal relational monitoring enables detection of instability as it develops, while ongoing engagement provides a mechanism for timely response. Interventions during instability phases may include clinical review, support for self-management, mobilisation of social resources, or coordination of care. Although modest in isolation, such actions may influence trajectory dynamics by acting across multiple interacting domains.

Within this framework, resilience is not treated as a fixed attribute but as an emergent property of interactions between patient capacity, social context, and system responsiveness over time.

4.4. Positioning Relative to Physiological Monitoring and IoMT Systems

The instability–plasticity framework addresses a different detection problem from physiological early warning systems and IoMT-based monitoring approaches. Systems such as NEWS2 and MEWS are designed to detect acute physiological deterioration [25,26], while IoMT platforms extend physiological and behavioural monitoring into community settings.

The findings of this study suggest that much of the instability preceding hospital admission in complex multimorbidity is not primarily physiological in its early stages. Instead, it involves gradual, multi-domain changes in functional capacity, coping, and social context that are not captured by vital sign monitoring.

A key limitation of many sensing systems is that signal detection is not consistently linked to interpretation, action, and responsibility within a longitudinal care context. Effective monitoring therefore requires not only data capture, but also mechanisms for recognising instability patterns and responding in a timely and coordinated manner [27].

These approaches should be understood as complementary rather than competing. Physiological monitoring is well suited to detecting acute biological deterioration, whereas relational monitoring enables earlier identification of multi-domain instability within patient trajectories. Despite differences in the variables measured and contexts of use, these systems can be understood as detecting different manifestations of the same underlying phenomenon—trajectory instability at different points along the trajectory. The instability–plasticity framework therefore provides a unifying conceptual model across these monitoring modalities, despite differences in the variables measured.

Table 2 summarises these complementary roles across monitoring modalities.

Table 2. Monitoring modalities as complementary observations of trajectory instability within complex care systems. Different approaches capture distinct manifestations of instability across domains and time, which may be interpreted within a common instability–plasticity framework.

Dimension	NEWS2/MEWS	IoMT/Wearables	Relational Monitoring
What is detected	Physiological deterioration	Physiological/ behavioural change	Multi-domain trajectory instability
When detected	Late (acute phase)	Earlier (continuous signals)	Early (emerging instability)
How signals are used	Trigger escalation	Generate alerts	Interpreted and acted upon within care context
Conceptual framing	Event-based	Continuous monitoring	Trajectory-based (instability–plasticity)

4.5. Implications for Health System Design and Analytics

The findings of this study suggest a shift in focus from static risk stratification toward dynamic trajectory monitoring. Traditional predictive models identify patients at elevated risk but do not capture when trajectories are changing in ways that may require intervention.

A trajectory-oriented approach emphasises detection of emerging instability patterns, including clustering of signals, changes in functional capacity, and multi-domain disruption. Such patterns may provide actionable indicators of when a trajectory is approaching a transition point.

From a system perspective, this implies the need for monitoring models that integrate sensing, interpretation, and response within a continuous care framework. It also highlights the importance of workforce structures capable of supporting longitudinal engagement and timely action. Ongoing analyses by the authors to further test and refine the instability–plasticity framework are underway as part of the learning system supporting HNHC care journeys [3].

4.6. Limitations

This study is based on observational data derived from longitudinal monitoring cohorts and should be interpreted as hypothesis-generating rather than causal. The datasets are drawn from specific implementation contexts and may not generalise to all populations or health systems.

The analyses are descriptive and do not establish causal relationships between monitoring, intervention, and outcomes. Some acute events may occur over timeframes shorter than monitoring intervals, limiting the ability to detect rapidly evolving deterioration.

In addition, the signals analysed are derived from patient-reported data and may reflect contextual or relational influences. Further research is required to test the predictive validity of instability signals and to evaluate whether interventions delivered during instability phases influence trajectory outcomes.

4.7. Contribution and Future Directions

The instability–plasticity framework represents a middle-range theoretical contribution grounded in empirical observation. It seeks to explain recurring patterns observed in multimorbidity trajectories, including clustering of deterioration signals, multi-domain instability, and the frequent resolution of instability phases without escalation.

The value of this contribution lies in its explanatory coherence, empirical grounding, and its capacity to generate testable propositions for future research. These include development of instability detection methods, evaluation of interventions delivered during instability phases, and integration with other monitoring approaches.

5. Conclusions

The instability–plasticity framework presented here offers a middle-range theoretical account of how healthcare trajectories in complex multimorbidity evolve through detectable phases of instability. Grounded in longitudinal empirical observation across two independent monitoring cohorts, the framework explains recurring patterns including clustering of deterioration signals prior to admission, the multi-domain nature of instability, and the frequent resolution of instability phases without hospitalisation.

By reframing instability as a dynamic and potentially modifiable state within patient trajectories, the framework shifts attention from identifying who is at risk to recognising when trajectories are changing. This perspective highlights the importance of longitudinal monitoring approaches that integrate sensing, interpretation, and action within ongoing care relationships.

The framework generates testable propositions for future research and has practical implications for monitoring system design, workforce configuration, and models of care. Further work is required to evaluate instability detection methods, examine interventions delivered during instability phases, and explore integration with connected health technologies.

Improving outcomes in complex multimorbidity may depend not only on identifying high-risk patients, but on recognising periods of trajectory change and acting within windows where outcomes remain modifiable.

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Conflicts of Interest: Carmel Martin declares a conflict of interest as a majority shareholder (51%) of PHC Research Pty Ltd., Brisbane, Australia a company that researches, develops and provides software for relational monitoring systems including PaJR. The remaining authors declare no conflicts of interest. The PaJR software originated as an academic spinout from the National Digital Research Centre of Ireland (NDRC), a government-funded initiative established to support innovative technology development in the public interest. The original implementation was an Irish government-funded academic project, not a commercial venture. The corresponding author's ownership stake reflects that founding academic relationship. The model has sustained itself (with ongoing evaluation and implementation) through adoption by Victorian public health services—Monash Health, Northern Health, Grampians Health, and others—who have commissioned its use as part of their care programs. There are no industry sponsorship, no pharmaceutical or device company funding, and no paid consulting arrangements related to PaJR.

Abbreviations

The following abbreviations are used in this manuscript:

HNHC	High-Need, High-Cost
PaJR	Patient Journey Record
IoMT	Internet of Medical Things
AUC	Area Under the Curve

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