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Instability and Plasticity in High Need High-Cost Multimorbidity Care Trajectories

Complex Systems Theory Framework for Detecting and Nudging Critical Transitions Grounded in Relational Monitoring

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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 empirical evidence linking these ideas to longitudinal patient monitoring remains limited. The PaJR (Patient Journey Record) monitoring 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 complex adaptive system–informed theory of instability phases within patient trajectories using longitudinal monitoring data generated by the PaJR system. **Methods:** Analyses draw on two PaJR monitoring datasets used for complementary purposes: a MonashWatch cohort dataset comprising 100 patients and 1,137 monitoring calls used to illustrate trajectory dynamics, and an Irish monitoring dataset comprising 286 patients and 11,108 monitoring calls over 18 months used to examine signal distributions and instability patterns. Monitoring calls capture structured signals across multiple domains including illness, medication, healthcare utilisation, social support, environmental factors, and self-care. **Results:** Instability signals were concentrated within a minority of monitoring observations, producing a long-tail distribution of alert intensity. Alerts frequently occurred in clusters across consecutive monitoring calls, with approximately 63% of alert calls occurring immediately after a previous alert. Alerts were also commonly multi-domain, with approximately 42% involving disturbances across more than one domain simultaneously. These observations support an instability–plasticity framework that integrates empirical monitoring data with concepts from complex adaptive systems and resilience theory, interpreting clusters of patient-reported signals preceding hospital admission as indicators of declining resilience and increasing trajectory plasticity. **Conclusions:** Longitudinal relational monitoring can reveal instability patterns within patient journeys that are not visible through episodic health system data. These findings help empirically ground emerging theories of complex healthcare trajectories and suggest that recognising instability phases may support earlier and more adaptive responses for patients with complex healthcare needs.

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

1. Introduction

This paper proposes an **instability–plasticity framework** that integrates empirical observations from longitudinal relational monitoring with concepts from complex adaptive systems and resilience theory. Within this framework, clusters of patient-reported signals preceding hospital admission are

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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.

Healthcare utilisation and costs are highly concentrated among a relatively small proportion of patients with complex health and social needs. Across many health systems internationally, the highest-need patients account for a disproportionate share of healthcare expenditure and service use [1]. These individuals are often described as **high-need, high-cost patients**, typically characterised by multimorbidity, functional limitations, complex care requirements, and frequent interactions with emergency departments and hospitals[2]. Multiple interventions have focused on such patients as Superutilizers who consume 'excessive health care costs' with little attention to improving their experiences of care,[3]nor the complex systems of personal trajectories and health and social from which they emerge[4].

For this population, healthcare journeys rarely follow stable or predictable pathways. Instead, they often involve recurrent cycles of deterioration, acute care utilisation, partial recovery, and renewed instability. These trajectories emerge through interactions among biological illness processes, psychological coping capacity, social circumstances, and the organisation of healthcare services[5]. Multimorbidity in **high-need, high-cost patients**, therefore, represents not simply the coexistence of multiple diseases, but the emergence of **complex longitudinal care trajectories shaped by interacting systems[6,7]**.

Traditional healthcare data systems observe patient journeys primarily through episodic encounters such as hospital admissions, clinic appointments attendances diagnoses, or procedures[3]. While these records provide valuable clinical and administrative information, they offer limited visibility into the evolving lived experience of illness between events[8]. Consequently, deterioration may remain largely invisible until it culminates in an acute care episode[9].

Increasing attention has therefore turned toward approaches capable of observing healthcare trajectories longitudinally. Relational telehealth monitoring represents one approach[10]. Through repeated interactions with patients, these systems capture evolving signals related to symptoms, coping capacity, functional activity, and social circumstances[11].

This shift reflects a broader movement within health research toward understanding healthcare systems as **complex adaptive systems[12]**. Complex systems consist of interacting agents whose behaviours influence one another and whose collective dynamics produce nonlinear and emergent outcomes. In such systems, outcomes arise through interactions rather than through linear cause-and-effect relationships[13].

Research across fields including ecology, climate science, and social interactions demonstrates that systems approaching critical transitions often exhibit **early warning signals**, such as increasing variability or clustering of fluctuations in the conceptualisation of systemic resilience[14]. These signals reflect declining resilience within the system as it approaches a tipping point[15]. Connected health approaches from telehealth to wearables may contribute to early warning systems such as activity decline[16].

These concepts may also apply to healthcare trajectories among individuals with multimorbidity (multiple long term conditions)[17]. Underlying biological processes, psychological coping capacity, social support networks, and health-system responses interact continuously to shape patient journeys. 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[18,19]. Work on multimorbidity resilience offers a useful frame for thinking about plasticity in patient trajectories beyond disease counts[20]. Wister and colleagues' complement this by conceptualising resilience as a biopsychosocial and environmental process in which adversity triggers the mobilisation of individual resources leading to adaptation, recovery or growth despite accumulating conditions, significant decline[21]. Longitudinal studies of older adults with multimorbidity suggesting that trajectories are plastic—capable of bending toward better or worse outcomes—depending on how these biopsychosocial and environmental resources are engaged over time[22].

The PaJR monitoring system was originally designed using concepts from complex adaptive systems theory, including the recognition that patient journeys evolve as dynamic trajectories shaped by interacting clinical, social, and organisational factors. By enabling longitudinal relational monitoring of patients' lived experience, PaJR generates structured signals across multiple domains of health and care. These real-world data provide an opportunity to empirically examine instability patterns within complex patient trajectories and to refine emerging theories of healthcare journeys within complex adaptive health systems.

The empirical observations discussed in this paper arise from implementation of the **Patient Journey Record (PaJR)** relational monitoring system within the MonashWatch telehealth program. PaJR supports structured longitudinal monitoring through repeated telephone conversations between patients and trained peer health navigators supported by multidisciplinary clinicians[23,24]. The PaJR system operates through relational monitoring of patient trajectories. Weekly telephone conversations between patients and trained peer health navigators capture patient-reported signals across symptoms, coping capacity, functional activity, and social circumstances. Emerging clusters of deterioration signals trigger increased monitoring and escalation to primary care or community services. By enabling small, timely responses during instability phases, PaJR may redirect patient trajectories before deterioration culminates in hospital admission. In this way, PaJR functions as a trajectory-sensing system or early warning system within complex care environments.

Within this milieu, patient journeys are observed through longitudinal conversational monitoring rather than episodic clinical measurement. Analysis of these trajectory signals reveals patterns in which clusters of deterioration signals frequently precede hospital admission[25]. Such longitudinal relational monitoring datasets are uncommon in health services research, where most analyses rely on episodic administrative data such as hospital admissions or claims records.

This study therefore seeks to develop a middle-range theory explaining instability phases within multimorbidity care trajectories. Middle-range theories bridge the gap between highly abstract grand theory and context-specific empirical observation, providing explanatory frameworks grounded in observable phenomena while retaining broader conceptual relevance[26]. The instability–plasticity framework developed in this paper emerges from empirical observations generated through the PaJR monitoring system, which provides unusually dense longitudinal data on patient-reported signals across multiple domains of health and care. These datasets provide a rare opportunity to observe healthcare trajectories as evolving processes rather than isolated clinical encounters.

1.1. The 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:

- 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

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from other system components. Such systems exhibit non-linear dynamics, emergent patterns, and evolving trajectories over time.

See Figure 1 for theoretical framework

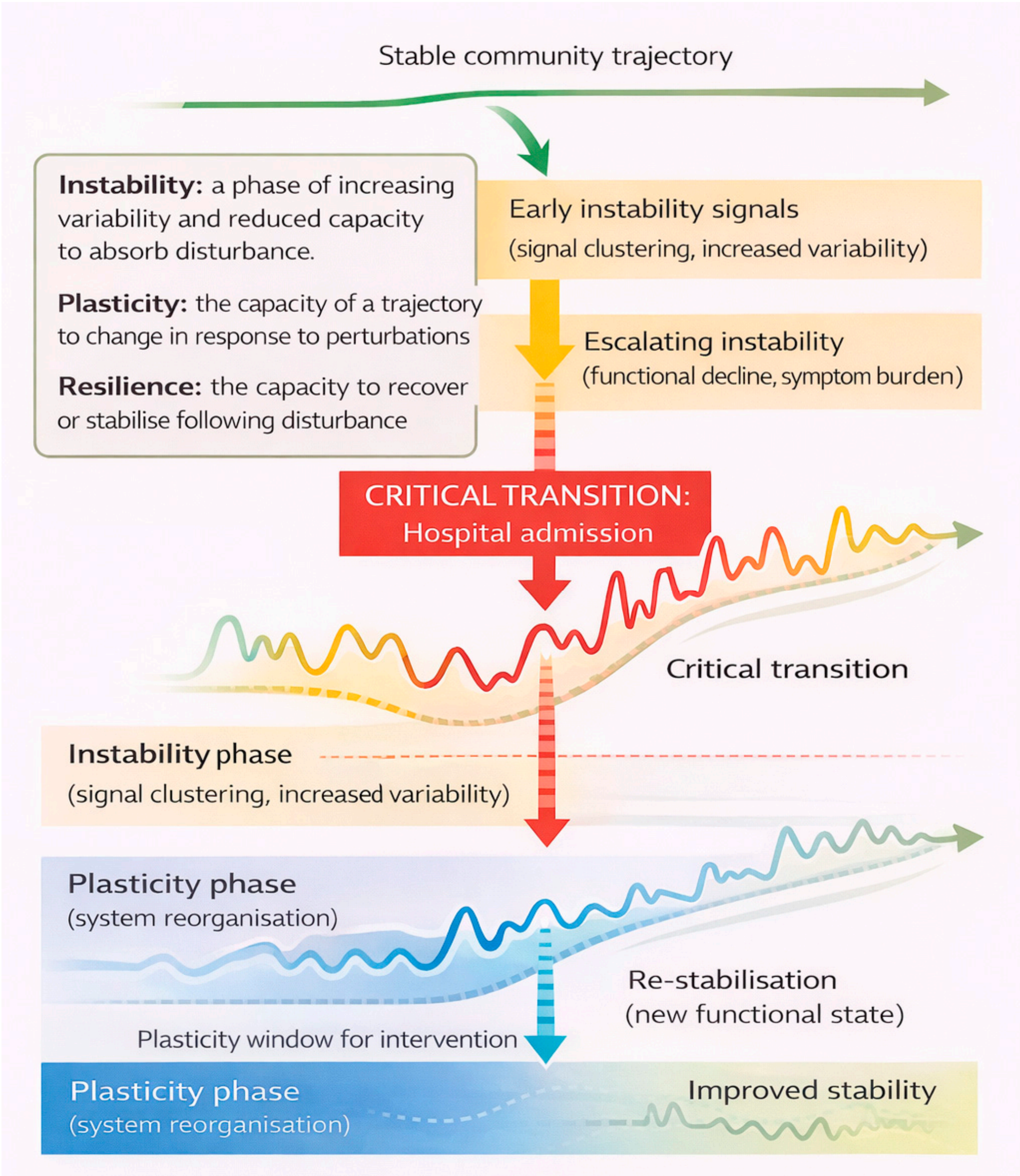

Figure 1. Theoretical concepts for heterogeneous instability, stability and resiliences patterns across individual patient trajectories in complex (adaptive) systems.

2. Materials and Methods

2.1. Study Design

This study presents a conceptual systems analysis informed by previously published empirical observations derived from the Patient Journey Record (PaJR) telehealth monitoring system. The aim is not to conduct new statistical analysis but to interpret previously reported trajectory patterns through the lens of complex adaptive systems and resilience theory.

The analytical approach combines implementation observation, longitudinal trajectory interpretation, and conceptual theory development. Data derived from the PaJR monitoring 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 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

The empirical observations discussed in this paper originate from the telehealth outreach service implemented initially in Ireland as an initiative from the National Digital Research Centre. It was then implemented within Monash Health – an inner city area as part of the HealthLinks: Chronic Care initiative[27]. The initiatives were designed to support patients identified as being at high risk of recurrent hospitalisation through proactive monitoring and care coordination, which meet international concepts of High Need, High Cost multimorbidity patients.

Central to the program is the Patient Journey Record (PaJR) system, a web-based monitoring platform designed to track the evolving healthcare journeys of patients with complex chronic conditions. Telecare guides—trained peer health workers (also known as community health wortkers)—conduct regular telephone conversations with patients using the PaJR system to identify potential deterioration[28]. Alerts generated through these calls are reviewed by supervising clinicians ("health coaches"), typically nurses or allied health professionals, who coordinate responses when risk signals emerge[29].

Each Australian telehealth program maintained a rolling cohort of approximately 250–300 actively monitored patients, recruited from a population identified through predictive modelling of hospital utilisation[30]. For example, over the initial Monash Health program evaluation period, 1373 eligible patients were recruited, allowing analysis of healthcare utilisation outcomes including hospital bed-days[27], similar findings were reported in another deployment of the PaJR system in a different health service[31]

Unlike many remote monitoring systems that rely primarily on physiological sensors, PaJR captures longitudinal patient-reported signals through relational conversations, generating insights into symptoms, coping capacity, daily functioning, and emerging concerns[12].

Data Sources

Two PaJR monitoring datasets were used for illustrative and analytic purposes. First, a cohort dataset from the **MonashWatch program in Australia**, comprising **100 monitored patients and 1,137 monitoring calls**, was used to illustrate longitudinal instability trajectories and escalation patterns. Second, population-level signal dynamics were analysed using an **Irish PaJR monitoring dataset containing 286 patients and 11,108 monitoring calls over 18 months**, enabling examination of alert distribution, clustering, and multi-domain signal synchrony across monitoring observations.

Together, these datasets provide complementary perspectives on patient trajectory dynamics within longitudinal monitoring systems. The datasets represent **independent PaJR monitoring cohorts collected in different health system contexts and time periods**, but share a common monitoring framework that enables comparison of trajectory patterns and signal distributions across cohorts.

De-identified call data were obtained with ethical approval from the participating services. Datasets analysed in this study 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	100	1,137	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. Longitudinal Relational Monitoring

Within the PaJR model, telecare guides maintain repeated contact with the same patients over extended periods. During each conversation, participants describe aspects of their current health experience, including illness and disease burden, biopsychosocial and healthcare experiences with structured and semi structured narratives.

These conversations generate structured indicators within the PaJR system that reflect changes in patient experience over time. Alerts derived from these signals indicate varying levels of concern and may trigger review by supervising clinicians.

Because interactions occur repeatedly across time, the monitoring system produces longitudinal trajectory data, enabling observation of patient journeys as evolving processes rather than isolated clinical events.

2.4. Trajectory Observation and Alignment

Previous analyses of the PaJR dataset examined temporal relationships between patient-reported signals and acute care events such as hospital admission. 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 those previously published analyses. In the present study, these observations are used as empirical illustrations supporting the conceptual development of the instability–plasticity framework.

2.5. Conceptual Systems 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 organisational 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.

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Methodologically, this approach aligns with the development of middle-range theory, which seeks to generate explanatory frameworks grounded in empirical observation while remaining sufficiently abstract to inform broader system understanding. Middle-range theories bridge the gap between grand theories (broad, abstract frameworks) and narrow, situation-specific hypotheses[26].

2.6. 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, the Irish College of General Practitioners and Deaken University respectively.

The present manuscript does not involve access to identifiable patient-level data or new data collection. 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

3.1. Population Context: High-Risk Multimorbidity Trajectories

The instability–plasticity framework proposed in this paper does not attempt to describe healthcare journeys across the general population. Most individuals experience relatively stable health trajectories with relatively infrequent interactions with emergency departments or hospitals. Instead, the framework focuses on a specific subset of patient journeys characterised by multimorbidity, functional vulnerability, and recurrent acute care utilisation.

Across health systems internationally, healthcare utilisation and expenditure are highly concentrated within a small proportion of patients. Numerous studies have shown that approximately five percent of patients account for around half of total healthcare spending, reflecting the intensive service use associated with complex chronic illness and social vulnerability. These individuals are commonly described as high-need, high-cost (HNHC) patients and typically experience multiple chronic conditions, recurrent hospital admissions, emergency department visits, polypharmacy, and substantial social care needs.

The healthcare journeys experienced by this population differ substantially from those of most patients. Rather than following stable or linear trajectories, these journeys often involve recurrent cycles of deterioration, acute care utilisation, partial recovery, and renewed instability. Interactions among biological disease processes, psychological coping capacity, social context, and the organisation of healthcare services produce trajectories that evolve dynamically over time. For many individuals within this population, hospital admission represents not an isolated event but a transition within a longer unstable care trajectory.

The empirical material presented in this paper arises from a real-world implementation designed specifically to support this high-risk population. The Patient Journey Record (PaJR) system, developed within the MonashWatch program, provides longitudinal telehealth support for patients identified as being at risk of recurrent hospitalisation.

The trajectories analysed in this paper therefore represent relationally observed multimorbidity journeys within a population already identified as being at high risk of acute care utilisation. The instability patterns identified in these trajectories should therefore be interpreted within this context. These patterns support the theories that patient trajectories often enter detectable instability phases prior to transitions to acute care.

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3.2. *Observing Healthcare Trajectories Through Relational Sensing*

Traditional health system data capture patient care, primarily through episodic events such as clinic visits, hospital admissions, and diagnostic procedures. While these records provide important information about service utilisation, they offer limited insight into the evolving lived experience of illness between encounters. For patients with multimorbidity and recurrent hospital use, deterioration often develops gradually through interactions between symptoms, functional capacity, psychological coping, and social circumstances.

The PaJR system differs from many remote monitoring approaches in that it relies primarily on relational sensing rather than physiological devices or automated measurements. 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:

Acute red alerts

- perceived symptom burden triggering an acute red alert when the intensity is high

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 generates **longitudinal time-series data describing evolving patient trajectories[25,32]**.

Rather than representing isolated clinical measurements, these data provide a continuous observational record of the patient's lived healthcare journey as it unfolds over time. This relational monitoring approach captures fluctuations in illness burden, coping capacity, and social context that may precede clinical deterioration and acute care utilisation.

3.3. *Empirical Observations of Trajectory Instability*

Analysis of these longitudinal trajectories reveals recurring patterns in which clusters of deterioration signals precede acute care events such as hospital admission or emergency department attendance. These patterns can be observed both within individual patient trajectories and when signals are aggregated across populations.

3.3.1. Individual Patient Trajectories

Figures 2A and 2B illustrate an example of an individual healthcare trajectory derived from the PaJR monitoring system. The figure presents multiple longitudinal signals—including illness burden, functional activity, and self-rated health—plotted over time alongside hospital admission events. Several features of the trajectory are notable. First, signals fluctuate continuously rather than remaining stable, reflecting the dynamic nature of multimorbidity care journeys. Second, clusters of signal volatility often emerge in the days or weeks preceding hospital admissions. These clusters are characterised by increasing symptom burden, reductions in activity, and deterioration in self-rated health. Third, following hospital admission, signals frequently stabilise temporarily before new fluctuations emerge as the patient returns to community care. These observations suggest that hospital admissions may represent transitions within evolving trajectories rather than isolated events, with instability accumulating prior to escalation into acute care. The trajectory in Figure 2 illustrates how clusters of deterioration signals can precede hospital admissions within an individual patient journey. Figure 3 demonstrates that similar instability windows occur across multiple

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trajectories, although their timing and duration vary considerably between patients. Not all instabilities are predicted by weekly call monitoring, they may represent a rapid decline such as a fall which is a 'tripping' event or events related to social or environmental condition rather that the individual's trajectory. See Call 35.Conversely, the health system structures and patient and family capacity limits the execution of necessary actions including timeliness.

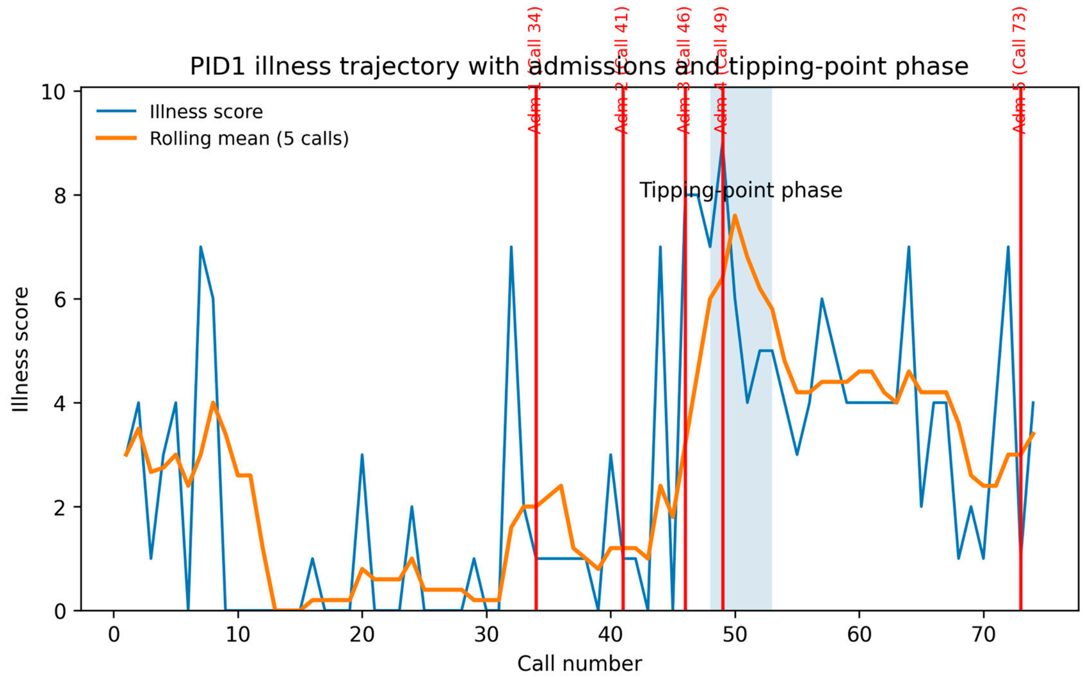

Figure 2A. Raw multi-domain monitoring signals for an individual patient trajectory (Monash data).Sequential PaJR monitoring calls for a single patient illustrate the raw alert signals recorded across domains including illness, medication, medical/healthcare services, social support, environmental factors and health promotion. Vertical dashed lines indicate hospital admissions. Fluctuations and clustering of deterioration signals occur prior to several admissions, illustrating periods of trajectory instability within the patient journey.Each monitoring call captures structured information derived from relational telephone conversations with the patient. The signals represent domain-specific concerns detected during each interaction.

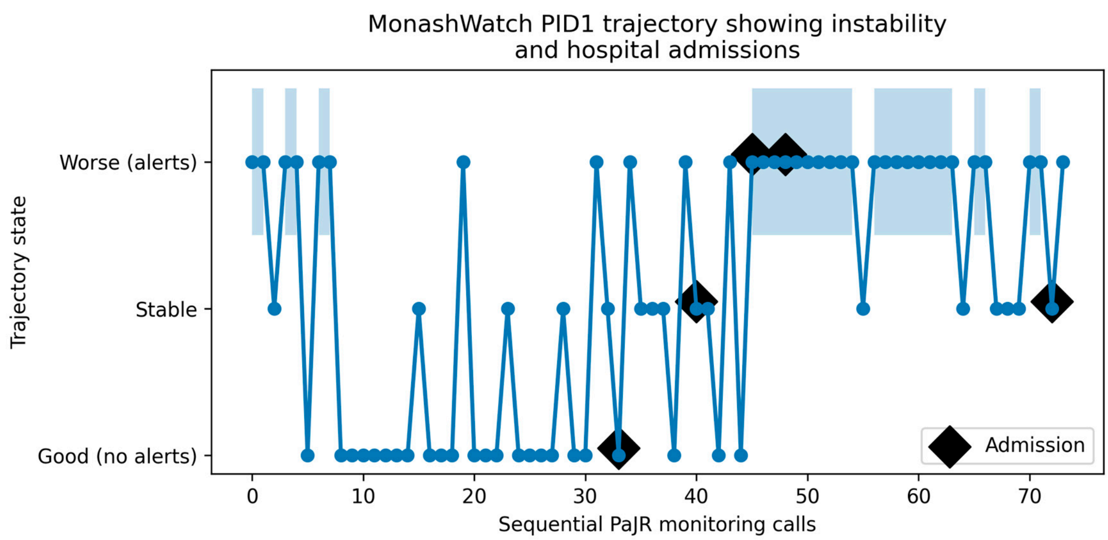

Figure 2B. Derived patient trajectory and admission events from longitudinal monitoring (Monash data). The same patient trajectory derived from the raw signals in Figure 1A is shown as a simplified health trajectory

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across sequential monitoring calls. States are categorised as good (no alerts), stable, or worse (alerts). Acute care admissions are marked along the trajectory. Periods of instability can be observed preceding admission events, illustrating how longitudinal monitoring may reveal emerging deterioration before acute escalation. However, the prefigured instability, did not always lead to an event, and some events appeared to be acute precipitations with little warning in the monitoring system.

3.3.2. Population-Level Signal Patterns Around Admission

To examine whether similar patterns occur across the broader monitored population, trajectory signals were aligned relative to the timing of hospital admission. This alignment allows observation of signal behaviour during the days preceding and following admission events retrospectively. The heterogeneous trajectory patterns illustrated in Figure X2 and 3 are consistent with earlier observations that patient-reported monitoring signals exhibit temporal dependence within individual journeys rather than random variation. Previous analysis using autocorrelation methods demonstrated that deterioration signals tend to cluster in time within individual patient trajectories, reflecting periods of instability followed by partial recovery[32]. These dynamics suggest that instability is an emergent property of individual healthcare journeys rather than a population-level phenomenon. Longitudinal relational monitoring therefore provides a means of detecting these instability phases as they develop, potentially allowing earlier responses during periods when trajectories remain modifiable.

Figure 3 presents aggregated signals across the monitored population for the ten days before and after hospital admission. Several consistent patterns emerge. Alert density increases progressively in the days preceding admission, with a marked rise in severe alerts and patient-reported difficulty coping. These signals typically peak around the time of admission and decline during the post-admission period as the system stabilises.

The alignment of signals relative to admission therefore retrospectively reveals a **population-level pattern of escalating instability preceding hospitalisation**.

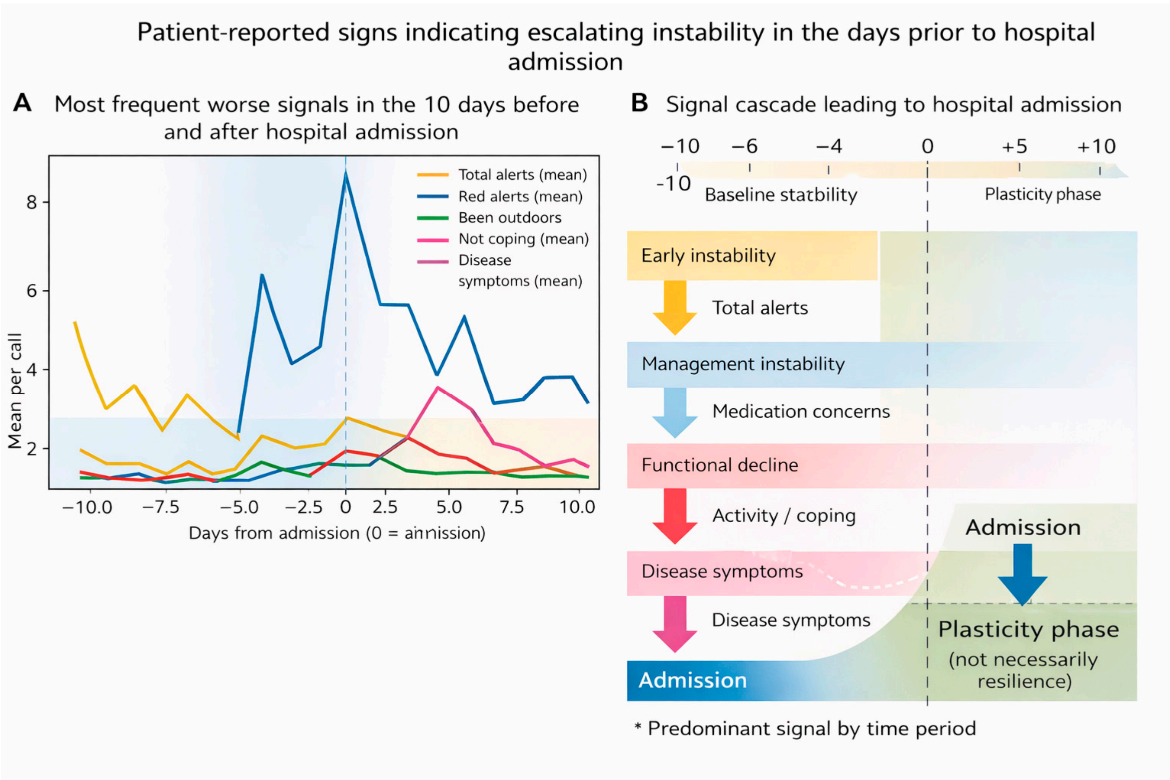

Figure 3. Temporal cascade of patient-reported instability signals preceding hospital admission (**(Monash data)**. (A) Mean trajectories of selected patient-reported signals during the 10 days before and after admission (day 0). Increasing signal intensity in the pre-admission period reflects escalating system instability across behavioural,

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functional, and disease domains. (B) Conceptual model of the signal cascade leading to admission. Signals emerge sequentially across subsystems—early alert signals, management concerns, functional decline, and disease symptoms—culminating in a critical transition represented by hospital admission. The post-admission period reflects a plastic phase during which the system reorganises and stabilises, though not necessarily at the previous level of resilience. Monash data set.

Together, these panels illustrate how patient journeys in complex health systems may progress through phases of instability and plasticity, with hospital admission representing a system perturbation rather than a discrete event, and subsequent re-stabilisation reflecting adaptation rather than restoration of the prior state, in keeping with the resilience literature. These empirical observations suggest that multimorbidity care trajectories may periodically enter phases of increasing instability prior to escalation into acute care[33,34]. The following section builds on these observations to develop a conceptual explanation of these dynamics, drawing on concepts from complex adaptive systems and resilience theory. Early deterioration signals often appear in domains such as activity and participation before progressing to more fundamental functional limitations, consistent with the hierarchy of disability described in gerontological research[35].

3.4. Conceptual Framework: Instability, Plasticity, and Trajectory Stewardship in Multimorbidity Care

The Results show that, within a high-risk multimorbidity cohort monitored through PaJR, patient-reported signals often cluster and intensify in the days/weeks preceding hospital admission, both at the individual level and when aligned across admissions at the population level (Figure 3). The conceptual task is therefore to explain (i) why instability emerges in these journeys, (ii) why it clusters before transitions to acute care, and (iii) how a relational telehealth system could plausibly influence these dynamics.

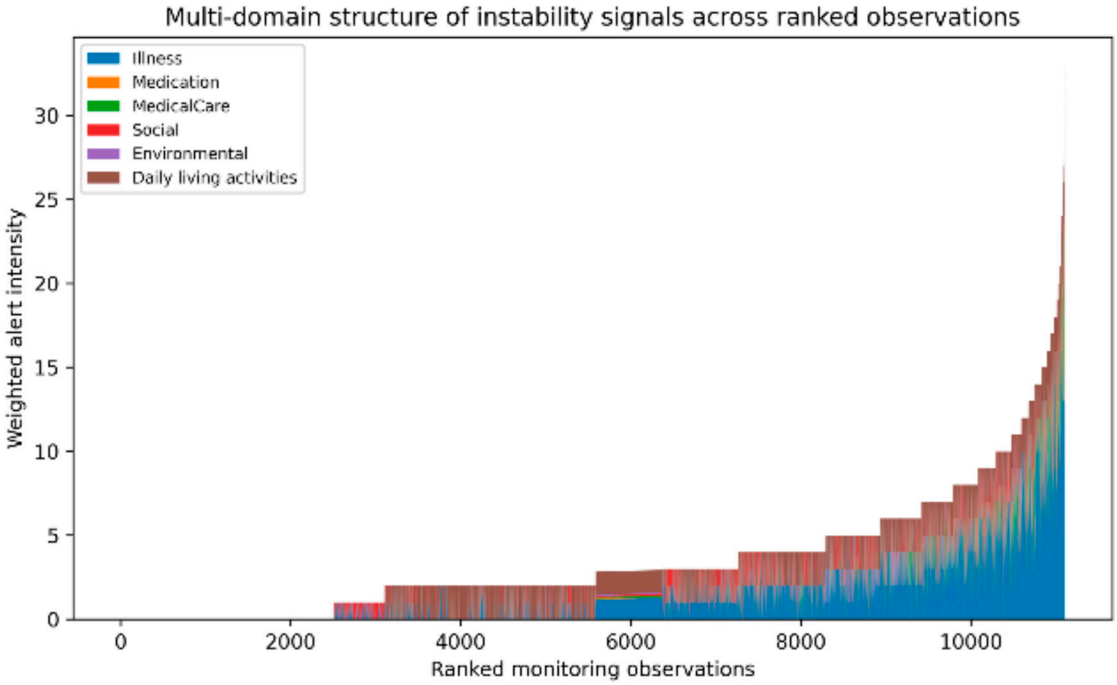
Multimorbidity journeys unfold within a complex adaptive system comprising interacting biological illness processes, psychological coping capacity, social supports, and the organisation and responsiveness of health and social care. In complex systems, outcomes emerge from interactions rather than linear cause–effect chains, and trajectories may shift abruptly between states (e.g., from "managing at home" to "hospital admission") when system conditions change.

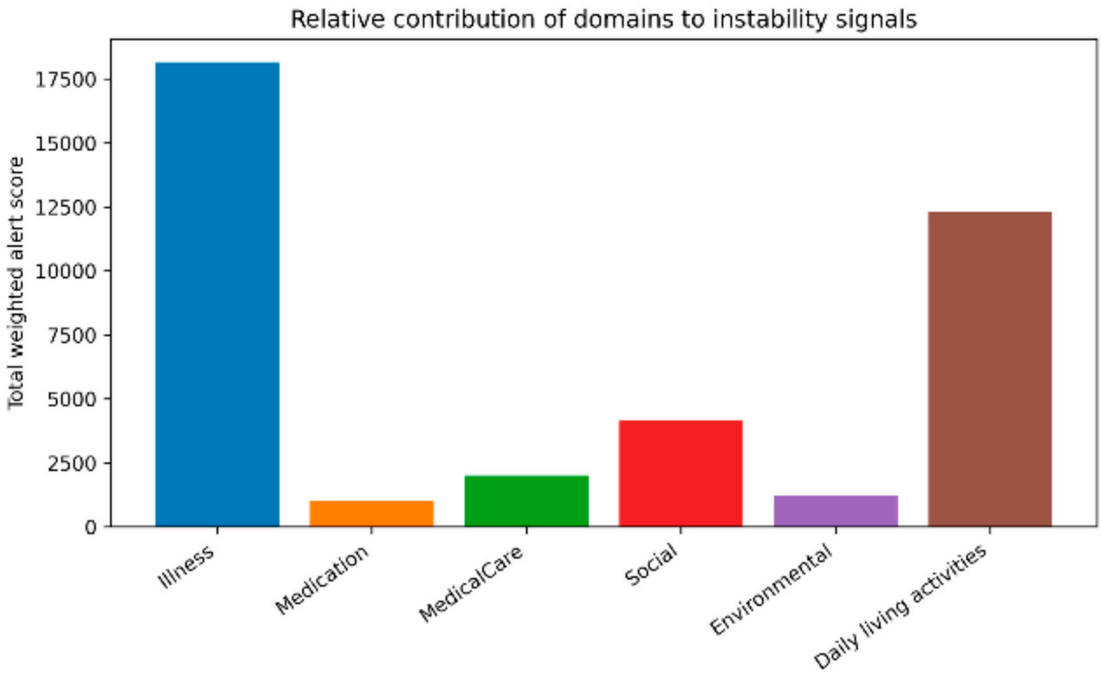
In many complex systems, approaching a transition is associated with increasing variance, clustering, and amplification of fluctuations. In the PaJR trajectories, analogous pre-transition signatures appear as escalating alert density, worsening coping, and accumulating "not coping" or distress signals before admission and as increased volatility across multiple patient-reported dimensions in individual trajectories (Figures 2& 3).

Within this framework, hospital admission is interpreted as a critical transition in the trajectory—often preceded by a detectable instability phase rather than occurring as a purely sudden event.

A central claim of the framework is that instability phases may also represent plasticity windows: periods when the trajectory becomes more responsive to intervention because interacting subsystems are strained but not yet overwhelmed. During plasticity windows, modest changes—timely clinical review, rapid mobilisation of social supports, removal of practical barriers, or targeted behaviour support—may shift the trajectory back toward stabilisation.

This reframes "instability" from being only a risk marker to being a time-sensitive opportunity structure for trajectory redirection. The empirical structure of instability signals observed across the Irish PaJR monitoring dataset is shown in Figure 4.The distribution of signals demonstrates a pronounced long-tail pattern, with most monitoring observations showing no alerts while a small fraction contain clustered multi-domain signals.


Multi-domain structure of instability signals across ranked observations
Illness
Medication
MedicalCare
Social
Environmental
Daily living activities
Weighted alert intensity
0
5
10
15
20
25
30
0
2000
4000
6000
8000
10000
Ranked monitoring observations


Relative contribution of domains to instability signals
Total weighted alert score
0
2500
5000
7500
10000
12500
15000
17500
Illness
Medication
MedicalCare
Social
Environmental
Daily living activities

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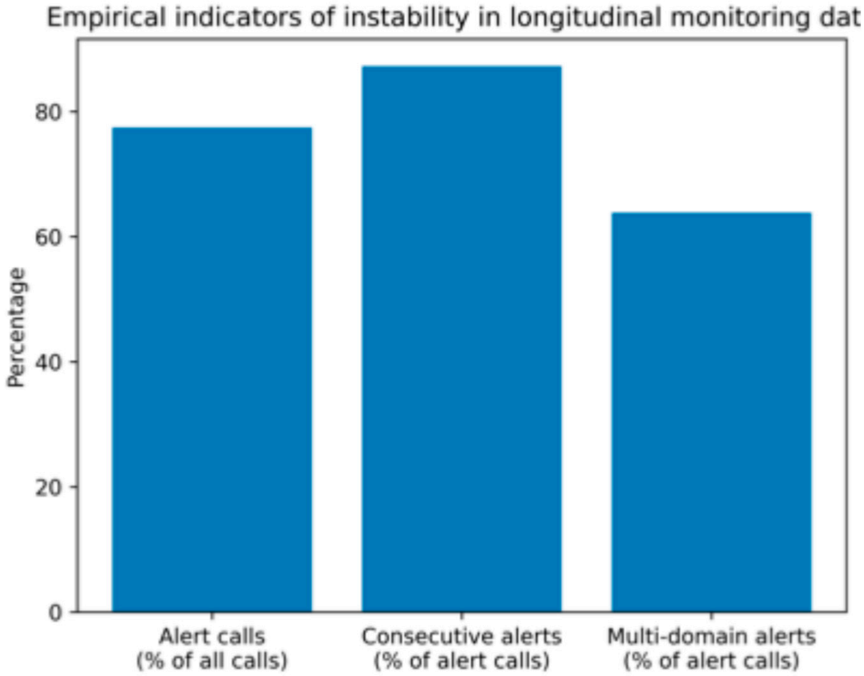

Figure 4. Empirical structure of instability signals in PaJR Irish longitudinal monitoring data. (A) Ranked monitoring observations showing the long-tail distribution of weighted instability signals across domains. Most observations show no alerts, while a small fraction contain high-intensity signals. (B) Relative contribution of each domain to the overall instability signal profile. Together these panels demonstrate that instability signals are rare but cluster across multiple domains, supporting the concept of multi-domain instability phases within patient trajectories. [C]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.

Transition from Empirical Signal Structure to Instability Theory

The empirical patterns observed in the Irish PaJR monitoring dataset provide insight into the structural characteristics of instability signals within patient trajectories. As illustrated in Figure 4, most monitoring observations contain no alert signals, while a relatively small proportion exhibit clusters of alerts across one or more domains. This pronounced long-tail distribution suggests that instability is not continuously present but emerges episodically within trajectories. Moreover, the presence of multi-domain alerts indicates that deterioration often occurs simultaneously across several aspects of a patient's lived health experience, including illness symptoms, medication issues, healthcare interactions, social circumstances, and daily living activities.

These patterns are consistent with expectations from complex adaptive systems, where state transitions are often preceded by periods of increasing variability or signal clustering. In this context, clusters of alerts may represent early manifestations of trajectory instability, reflecting moments when the system becomes more sensitive to perturbation. Such periods can be conceptualised as **instability phases**, during which patient trajectories may become more susceptible to escalation events such as hospital admission.

Importantly, instability phases may also correspond to periods of **increased trajectory plasticity**. When signals accumulate across domains, the trajectory may temporarily become more modifiable, creating a window in which relational intervention, care coordination, or clinical response can redirect the trajectory toward stabilisation. The empirical signal structures observed in the monitoring data therefore provide a basis for conceptualising instability not simply as deterioration, but as a dynamic phase within trajectories in which both risk and opportunity for intervention are heightened.

3.5. Trajectory Stewardship System: Sensing → Interpretation → Relational Action

The relational telehealth system is not only a data collection tool. Conceptually, it functions as a trajectory stewardship system with three linked capabilities:

1. Trajectory sensing (relational sensing)
   Repeated structured conversations capture dynamic biopsychosocial signals (symptoms, function/activity, coping, and contextual stressors) that are not visible in episodic administrative datasets.
2. Interpretation (instability detection)
   Signals are translated into alerts and patterns that enable recognition of *when* trajectories are destabilising (not only *who* is high risk).
3. Relational action (nudges within the same system)
   Because sensing occurs in an ongoing relationship, the same system can deliver corrective inputs quickly—"relational nudges"—supported by clinician health coaches and connections to primary care/community services.

Relational nudges are defined here as small, timely, relationship-mediated actions introduced during instability phases to influence trajectory direction. Examples include: encouraging earlier help-seeking, organising GP review, coordinating home supports, addressing medication or appointment barriers, mobilising family/community assistance, or supporting coping and sensemaking. Examples from previous work demonstrate the utilization of unplanned visits to the GP one of the consequences of nudging[36]. In other situations, urgent escalation to emergency care may also be the right decision.

Experiences of care were significantly improved when measured[37]. In complex systems terms, these are *micro-perturbations* intentionally introduced when the trajectory may be especially sensitive. Resilience in this framework is not treated as a fixed patient trait. It is an emergent property of repeated interactions among patient capacities, social supports, and service responsiveness. Over time, repeated cycles of sensing–nudging–stabilising may build "trajectory skill" and supportive scaffolding that reduces the depth/duration of decompensation—even if acute care is not always avoidable. A distinctive feature of this work is the learning cycle: theory informed implementation; implementation generated longitudinal observations; observations refined theory; and the refined theory implies new analytic and service design directions. This feedback loop aligns with the logic of learning health systems, but with a specific focus: learning is organised around trajectory dynamics and instability detection, rather than solely around retrospective utilisation. If instability phases are detectable and plasticity windows are real, then the logical next step is to develop trajectory instability metrics, operationalise early-warning patterns, and design services that can reliably deliver timely relational action. These implications are described in the next Figure b describing Relational monitoring, Trajectory Analytics and Journey Stabilisation, which translates into measurable and actionable component.

Insert figure 5

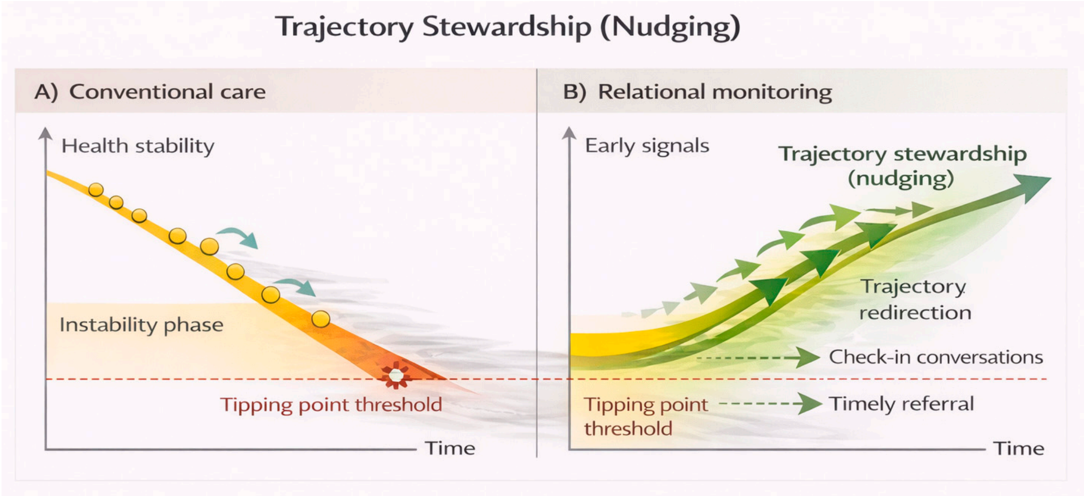

Figure 5. Trajectory stewardship and tipping dynamics in healthcare journeys. Conceptual representation of patient trajectories under conventional care compared with trajectories supported by relational monitoring. In conventional care, accumulating signals of instability may go unrecognised until the trajectory approaches a tipping point threshold, beyond which deterioration accelerates and hospital admission becomes more likely. Relational monitoring systems such as PaJR enable the early detection of multidomain signals through regular check-in conversations, revealing periods of increased trajectory plasticity. During these phases, relatively small relational interventions and timely referrals can act as nudges that redirect the trajectory toward stabilisation or recovery. The tipping point threshold represents a dynamic boundary in the system: crossing it may lead to escalating illness, although in some circumstances timely admission can also interrupt deterioration and support recovery.

4. Discussion

This study proposes a systems-based instability–plasticity framework to explain how unstable multimorbidity trajectories may be detected and potentially redirected through longitudinal relational monitoring. Drawing on empirical observations from the PaJR telehealth system, we identified recurring patterns in which clusters of patient-reported signals precede hospital admissions and emergency department presentations. These observations suggest that healthcare journeys among high-risk multimorbidity populations may periodically enter phases of increasing instability prior to escalation to acute care.

The instability–plasticity framework interprets these patterns through the lens of complex adaptive systems and resilience theory. Within this perspective, healthcare trajectories are understood as dynamic systems shaped by interactions among biological illness processes, psychological coping capacity, social environments, and healthcare services. Instability phases observed in longitudinal monitoring data may therefore reflect periods of declining system resilience in which fluctuations in symptoms, coping capacity, and functional activity intensify.

Importantly, instability does not necessarily imply inevitable deterioration. In many nonlinear systems, periods of instability correspond to phases in which the system becomes particularly responsive to perturbations. Within healthcare trajectories, such phases may represent plasticity windows during which relatively small relational interventions can influence the direction of the patient journey. The PaJR model provides a mechanism through which such interventions may occur, as ongoing conversations between peer health navigators and patients allow emerging instability signals to be recognised and addressed before escalation to acute care.

4.1. Theoretical Contribution

This study contributes to complexity-informed health services research by proposing a middle-range systems theory of unstable multimorbidity trajectories. While complexity science has

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increasingly been used to conceptualise healthcare systems as dynamic networks of interacting agents, much of this literature remains conceptual or descriptive rather than empirically grounded.

The instability–plasticity framework links empirical observations from longitudinal relational monitoring with concepts from complex adaptive systems and resilience theory. By interpreting clusters of patient-reported signals preceding hospital admission as indicators of declining resilience and increasing trajectory plasticity, the framework provides a systems-based explanation for how healthcare journeys may transition between stability, instability, and acute care states.

Importantly, the framework also proposes a mechanism through which these transitions may be modulated. In complex systems, relatively small perturbations can influence system behaviour when resilience is reduced. Within the PaJR model, relational telehealth interactions enable such perturbations—conceptualised here as relational nudges—to be introduced during periods of trajectory instability.

Taken together, these insights extend existing complexity perspectives in healthcare by proposing a trajectory-oriented conceptual model that integrates trajectory sensing, instability detection, and relational intervention within multimorbidity care.

4.2. Healthcare Trajectories as Dynamic Systems

The trajectory patterns observed in the PaJR monitoring data reinforce the view that healthcare journeys for patients with multimorbidity behave as dynamic systems rather than linear care pathways. In complex adaptive systems, behaviour emerges from interactions among many components, and outcomes cannot be predicted solely from the properties of individual elements.

Healthcare systems exhibit these characteristics through interactions among patients, clinicians, families, and organisational structures operating within institutional and social environments. In multimorbidity populations, biological illness processes interact with psychological coping capacity, social circumstances, and access to care, producing trajectories that may fluctuate significantly before reaching critical transitions such as hospital admission.

The clustering of alerts and distress signals observed prior to acute care events suggests that hospital admissions may often represent transitions within evolving trajectories rather than isolated clinical events.

4.3. Relational Telehealth as a Trajectory Stabilisation Mechanism

The relational telehealth model examined in this study provides a mechanism through which trajectory instability may be both detected and addressed. The PaJR system combines longitudinal conversational monitoring with peer health navigators supported by clinician health coaches. This structure enables emerging instability signals to be recognised and acted upon through relational engagement with patients.

Relational nudges introduced during instability phases may include encouraging earlier help-seeking, coordinating primary care review, mobilising social support, or addressing practical barriers to care. Although modest individually, such interventions may influence trajectory dynamics by acting across multiple interacting domains within the system.

Within complex adaptive systems, small perturbations introduced at sensitive moments can propagate through networks of interaction and alter system behaviour. Relational telehealth systems therefore represent a practical mechanism for introducing timely interventions during instability phases within multimorbidity trajectories.

4.4. Implications for Health System Design

Viewing healthcare journeys through the instability–plasticity lens suggests that health systems may benefit from shifting attention from reactive responses to acute events toward proactive trajectory stewardship for high-risk populations. Conversely, more timely escalation to acute care,

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when appropriate may reduce the acuity and decompensation presentation allowing for shorter hospital stays.

Trajectory-oriented care models seek to stabilise patient journeys earlier through longitudinal monitoring, relational engagement, and coordinated support. Telehealth-supported navigation systems represent one operational approach to this strategy.

Programs such as MonashWatch demonstrate how longitudinal telehealth coaching and navigation can support patients at risk of hospitalisation while reducing hospital bed-day utilisation in real-world settings. From a systems perspective, these models function not only as monitoring tools but also as trajectory stabilisation systems combining sensing, interpretation, and relational intervention. Nevertheless health care services may and family dynamics may not have the capacity to adapt to dynamic care needs.

The instability–plasticity framework also suggests new directions for healthcare analytics. Traditional predictive models typically estimate long-term risk using static variables such as diagnoses or past utilisation patterns. While such models may identify high-risk populations, they often fail to capture dynamic changes occurring within patient trajectories.

A trajectory-oriented analytic approach would instead focus on detecting instability patterns emerging in real time, such as clustering of alerts, rapid shifts in coping capacity, or changes in activity levels. Such signals may provide early indicators that a trajectory is approaching a transition point and may therefore represent opportunities for timely intervention.

Developing reliable instability metrics and integrating them into learning health systems represents an important area for future research. Implementation–Theory Feedback

Finally, this work illustrates the value of iterative interaction between implementation and theory in systems research. The instability–plasticity framework emerged from empirical observations generated through real-world deployment of the PaJR system. These observations informed conceptual interpretation using complex systems theory, which in turn suggests new directions for analytic development and service design.

Such feedback between practice and theory is characteristic of complexity-informed health systems research. Longitudinal relational monitoring systems therefore provide not only a mechanism for patient support but also a platform for advancing theoretical understanding of healthcare system dynamics.

However, trajectory plasticity alone is insufficient to ensure redirection. Effective intervention requires alignment between the emergence of instability signals, the operational responsiveness of the health system, and the patient's capacity to engage with recommended actions. When these elements are misaligned—due to service constraints, delayed access, or patient-level barriers—windows of plasticity may close before effective action can occur.

Future research should extend the instability–plasticity framework in several directions. First, empirical testing is needed to determine whether interventions delivered during instability–plasticity windows are more effective in redirecting patient trajectories than interventions delivered outside these periods. Second, the temporal dynamics of instability require further investigation, including how monitoring frequency and the timing of relational contact influence the ability to detect emerging instability before escalation to acute care. Third, advances in data science and artificial intelligence may enable improved detection of signal clustering, trajectory inflection points, and early indicators of instability, potentially enhancing the responsiveness of longitudinal relational monitoring systems.

4.5. Limitations

This study has several limitations. The empirical material draws on observational datasets from three PaJR monitoring programs implemented in different health system contexts. Although these datasets provide valuable insight into longitudinal signal patterns preceding hospitalisation, the analyses are exploratory and should be interpreted as hypothesis-generating rather than causal. The cohorts analysed are relatively modest in size and derived from specific implementation sites, which may limit generalisability to other populations or health system settings. In addition, the signals analysed are derived from patient-reported experiences collected through relational telephone monitoring rather than physiological or administrative data alone, and may therefore reflect conversational or contextual influences. Some acute events may unfold over timeframes shorter than the interval between monitoring contacts, meaning that deterioration can progress from sensing to hospitalisation before intervention is possible. This temporal limitation highlights the importance of optimising monitoring frequency and developing enhanced analytic approaches. Future research may explore whether predictive modelling, adaptive monitoring intervals, or AI-assisted signal detection could improve the identification of rapidly evolving instability.

Finally, the instability–plasticity framework proposed in this paper is informed partly by clinical and implementation experience and requires further quantitative testing and prospective evaluation.

5. Conclusion

Healthcare journeys for patients with HNHC patients with multimorbidity often evolve through dynamic trajectories rather than isolated clinical events. The instability–plasticity framework proposed in this paper suggests that clusters of patient-reported signals observed through longitudinal relational monitoring may indicate periods during which trajectories become both vulnerable to escalation and potentially modifiable. Interpreting these signals through a complex adaptive systems lens shifts attention from single acute episodes toward the evolving patterns that precede them. Telehealth-supported relational monitoring systems such as PaJR may therefore help identify emerging instability and enable earlier relational interventions aimed at redirecting patient trajectories. Further research is needed to test the predictive validity of instability signals and to determine how trajectory-oriented monitoring and analytics can support more responsive health systems.

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