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Self-rated health: patterns in the journeys of patients with multi-morbidity and frailty

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Abstract

Rationale, aims and objectives Self-rated health (SRH) is a single measure predictor of hospital utilization and health outcomes in epidemiological studies. There have been few studies of SRH in patient journeys in clinical settings.
Reduced resilience to stressors, reflected by SRH, exposes older people (complex systems) to the risk of hospitalization. It is proposed that SRH reflects rather than predicts deteriorations and hospital use; with low SRH autocorrelation in time series.
The aim was to investigate SRH fluctuations in regular outbound telephone calls (average biweekly) to patients by Care Guides.
Methods Descriptive case study using quantitative autoregressive techniques and qualitative case analysis on SRH time series. Fourteen participants were randomly selected from the Patient Journey Record System (PaJR) database. The PaJR database recorded 198 consecutively sampled older multi-morbid patients journeys in three primary care settings. Analysis consisted of triangulation of SRH (0 very poor – 6 excellent) patterns from three analyses: SRH graduations associations with service utilization; time series modelling (autocorrelation, and step ahead forecast); and qualitative categorization of deteriorations.
Results Fourteen patients reported mean SRH 2.84 (poor-fair) in 818 calls over 13 ± 6.4 months of follow-up. In 24% calls, SRH was poor-fair and significantly associated with hospital use. SRH autocorrelation was low in 14 time series (–0.11 to 0.26) with little difference ($\chi^2 = 6.46$, $P = 0.91$) among them. Fluctuations between better and worse health were very common and poor health was associated with hospital use. It is not clear why some patients continued on a downward trajectory, whereas others who destabilized appeared to completely recover, and even improved over time.
Conclusion SRH reflects an individual's complex health trajectory, but as a single measure does not predict when and how deteriorations will occur in this study. Individual patients appear to behave as complex adaptive systems. The dynamics of SRH and its influences in destabilizations warrant further research.

Introduction

Self-rated health (SRH) is well documented as a valid measure of personal health states. It is arguably the best *single measure* predictor of death, service use, institutionalization and hospitalization in older cohorts [1,2]. Epidemiological cross-sectional and time series studies confirm the utility of SRH as a single measure, but very few studies of SRH at clinically relevant time intervals have been published. According to Jylhä and others, SRH represents an individual's unique access to their own bodily sensations and their meanings [3]. There is emerging evidence that SRH reflects important internal functioning such as inflammatory processes [3]. SRH correlates with changes in inflammatory markers in aging cohorts [4]. Aging and chronic illness is associated with a decline of adaptive immunity to address chronic internal and external stresses [5]. Personal experience narratives developed through conversation have also been recognized as providing explanatory understandings of patient journeys [6,7].

Health services' performance assessment and financial penalties are being driven by the need to reduce expensive hospital utilization and institutionalization internationally. Thus, there is considerable impetus to better predict deteriorations in high-risk patient journeys in order to intervene in a timely but minimally expensive manner. Current models of post-acute care and care management to address these unpredictable journeys have been major drivers of health services costs. For example, recent analysis identified that post-acute care costs led Medicare spending growth from 1994 to 2009 in the US [8].

Internationally, SRH is a significant predictor of admissions and costs [9–11]. Admission prediction interventions [9,12] aim to identify who is at risk of avoidable (re)admissions and the level of care needed to prevent these occurrences.

Aims

The purpose of this case study was to explore the patterns of SRH in outbound phone calls from Care Guides to older patients with multi-morbidity and frailty and their variable hospital utilization events over 6 months or longer [13]. It aims to test the theory that SRH is unpredictable in a cohort of patients identified as being at high risk of (re)hospitalization, but is a useful barometer of illness severity.

Complex adaptive systems theory

With aging and chronic illness, individual and their support network's difficulty in adapting to internal physiological and external health challenges results in vulnerability and destabilizations [14]. Internally, people are subject to diverse set of internal fluctuations including deteriorating organ function, declining immune competence with less ability to adapt to exposure to external agents such as viral infections and treatment side effects or polypharmacy [5,15]. Externally, they live in human systems involving a diverse set of actors (such as caregivers, families and care providers), providing support at many different levels of scale, with differing individual priorities. Social isolation as networks shrink with aging can add to stress, which undermines adaptive capacity [16]. The expanding problem with the aging population and variation in outcomes in different settings cannot be reduced to a single mechanism. Each individual journey is thus said to represent a *complex adaptive system* (CAS) – one composed of many heterogeneous pieces, interacting with each other in subtle or non-linear ways.

Multi-morbid older community-dwelling patients are likely to be in a phase of reduced resilience. Their SRH may reflect the level of inflammatory biomarkers that are generated in the body's attempts to compensate for reduced resilience [17]. Despite differences in disease, treatment and social-emotional-environmental profile, common patterns emerge [18].

These patterns include relatively unpredictable journeys post hospital discharge with heterogeneous deterioration patterns [19], and sometimes inappropriate, high levels of hospital care [19]. In the last 2 years of life, they experience functional decline in multiple bodily systems. SRH has been reported to be an excellent marker of their health trajectory [20] in preference-sensitive care [18,21], where care is oriented to their health experiences rather than to treating disease to externally generated norms.

Theory: Older people at risk of repeat hospitalizations destabilize at times unpredictable from an initial SRH or average SRH, although SRH reflects deterioration as it occurs. Based on CAS theory, this reflects reduced resilience to internal and external stressors. Low SRH autocorrelation from one time point or from a projected average would support this theory. Typical cases with unpredicted timing and level of SRH deteriorations would provide qualitative supportive evidence.

Objectives

To explore patient trajectories at a micro-level to: (i) investigate the relations between SRH level (deterioration) and urgency of medical services; (ii) to look at the patterns and predictability of trajectories of 14 individual SRH as a time series; and finally to identify contrasting patterns of SRH deterioration. This is to test the theoretical prediction of unpredictable SRH fluctuations and urgent care.

Patient population

Patients were consecutively selected from a pragmatic cohort study between 2011 and 2013 set in ambulatory care in Ireland They were adults aged 50 years and older with high probability of repeated admission in accordance with a validated screening tool [9,22] and high risk of destabilization. They had one or more hospitalization and more than seven doctor visits in the past 12 months [23]; a frailty score of 4 or more [24]; and at least one of the major chronic diseases – heart failure, chronic obstructive pulmonary disease (COPD), asthma and/or diabetes [13]. Recruitment was from three care settings: out of hours, post-hospital discharge and general practitioner (GP) practices. Exclusion criteria were nursing home residence; dementia living unless with caregiver; and non-English speaking. Patients were recruited in the autumn months of 2010 or 2011 or 2012 so that all were monitored over at least one winter. The methodology has been described in more detail as the intervention arm of a pragmatic community trial [25].

Care Guides made regular outbound calls (1–5/week) with an average of two calls during the working week and information on SRH, service use and brief narratives was recorded and entered into the electronic Patient Journey Record System (PaJR) during or immediately after the conversation. For 90% calls, the same Care Guide called the same patient each time.

Data

In each call, the patient was asked to report their SRH (0 very poor – 6 excellent); and if they had any planned or unplanned: GP visits, emergency department (ED) visits or hospital admissions since their previous call. Brief explanatory narratives about how the patient felt, possibly why they felt as they did and any obvious consequences were also recorded.

Methods

A random sample of 14 cases, judged as a suitable number for a case study, was randomly selected to provide a micro-level analysis of the original 198 individual patient journeys.

A descriptive case study triangulating quantitative auto-regressive techniques and qualitative case analysis was conducted.

1 Frequencies and comparisons of proportions were used to describe SRH associations with health services use.

2 Autocorrelation regressive modelling investigated how the predictability of SRH fluctuations in individual time series (Box 1).

Box 1 Autocorrelation of SRH time series explanation

Autocorrelation – an explanation

- A mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals, that
- Calculates the correlation between two different time series, except that the same time series is used twice once in its original form and once lagged by one or more time periods.
- The resulting number can range from +1 to –1.
- An autocorrelation of +1 represents perfect positive correlation (i.e. an increase seen in one time series will lead to a proportionate increase in the other time series), while a value of –1 represents a perfect negative correlation (i.e. an increase seen in one time series results in a proportionate decrease in the other time series) [1].
- A predictable journey is stable, non-random, non-cyclic and with a high degree of autocorrelation close to 1 or –1 [1]. For example, if the patient's SRH pattern historically has a high positive autocorrelation value and the patient's pattern was stable over the past several days, you might reasonably expect the patterns over the upcoming several days (the leading time series) to match those of the lagging time series and to remain stable.
- Accounting for seasonality is important [1]; however, it is not necessary if SRH_{n+1} is separated from SRH_n by a matter of days.

3 Following review of all 14 cases, four cases were purposively selected to typify patterns of SRH patterns where people did or did not restabilize from deterioration in SRH. Brief narratives provided context to the deteriorations.

4 An iterative process of qualitative synthesis of materials was conducted to synthesize triangulated descriptors of SRH from three data levels.

Results

The 14 randomly selected patients had an average age of 78 ± 6.3. They had participated in 818 calls over an average of 13 ± 6.4 months per person. Two patients were admitted to nursing homes at around 6 months and one died at 13 months.

Table 1 describes the frequencies of SRH with good to excellent, fair, poor and very poor health associated with service use. Fair, poor and very poor are reported separately as qualitative analysis (below) identified the significance of gradations in 'worse' health patterns. Reporting 'worse' health (fair, poor and very poor) compared with 'better' (good to excellent) health in calls was statistically associated with admissions and ED visits. [continuous maximum likelihood estimate (CMLE) of odds ratio 0.08 (0.02, 0.25), mid-*P* exact 0000072] and GP visits [CMLE odds ratio 0.19 (0.13, 0.30), mid-*P* exact < 0.0000001].

Table 2 describes autocorrelations within each of the 14 trajectories. Autocorrelation was low from – 0.11 to 0.26 significantly < ± 1 in all the cases. There were no significant differences in the autocorrelation ($\chi^2 = 6.46$, $P = 0.93$) among the 14 time series. Statistics not reported in Table 2, including Durbin–Watson statistic >3 and others, demonstrated non-stationary, non-normal, non-random and low predictability in all cases [26]. The prediction of the next successive (next step ahead forecast) values of SRH measures was close to the average of each trajectory, providing a linear trend.

In order to demonstrate typical patterns of short-term fluctuations of SRH to 'worse', sections of individual trajectories were purposively selected from the 14.

1 Type 1. Cases (time series) with fluctuations between good and fair or poor episode that (1) did not lead and (2) did lead to admission with a downward trend in SRH over ≥12 months.

Mrs O'B (born 1925) has multiple conditions of cardiac failure ischaemic heart disease, diabetes, osteoarthritis and anaemia. She lives alone. She was recruited from her GP practice, following a visit to the ED. Her SRH on entry to study was 4 (good) and frailty was 5. During the time series of 14 months, her average SRH was 3.28 with no admissions. Mrs O'B's SRH fluctuated between good and fair, and in the calls she did not report poor health or any admissions or visits to the ED. While Mrs O'B is recovering from

Table 1 Rates of admissions, emergency department (ED) visits and general practice (GP) visits by self-rated health (SRH) in 14 cases monitored with outbound phone calls. Care Guides called patients on a regular basis one to five times per week according to their profile on the previous call [2]

SRH level reported in each call	No. of calls reporting SRH level Total = 818	Admissions and ED reported (rate per call with SRH level)	Circumstances of admissions	GP consultations (rate per call with SRH level)
3. Good – Excellent health	670	Three admissions (0.004)	One planned, two unplanned admissions	60 visits per 670 calls (0.09)
2. Fair health	141	Six admissions (0.04) Two ED visits (0.014)	Four unplanned, two planned, two ED visits – not admitted	23 visits per 121 calls (0.16)
1. Poor health	53	Four admissions (0.75)	Four unplanned	15 visits per 53 calls (0.23)
0. Very poor	8	No admission	Severe pain in three calls Dying at home × 6 calls – palliative care	1 visit per 8 calls (0.13)

Table 2 Time series of self-rated health (SRH) of patients with multiple morbidity and frailty

Case details Frailty score*	Number of calls	Time followed (months)	Admission	A&E visit only	Self-rated health† ith step ahead forecast (SRH prediction) Autocorrelation
Mrs Ob 1925	26	14	2	0	Mean X(t) 3.28 Var. X(t) 0.76
Lives alone					Next step ahead forecast (1)3.46, (2)3.35
Frailty 5					Autocorrelation 0.19 SE 0.20
Mrs Mc 1931	27	8	0	0	Mean X(t) 2.86 Var. X(t) 0.22
Lives alone					Next step ahead forecast (1)2.92, (2)2.80
Frailty 4					Autocorrelation –0.12 SE 0.22
Mr P Q 1929	75	18	4	0	Mean X(t) 3.42 Var. X(t) 0.35
Residential					Next step ahead forecast (1)3.46, (2)3.36
Frailty 5					Autocorrelation –0.02 SE 0.12
Mr K 1927	57	13	0	0	Mean X(t) 2.85 Var. X(t) 0.91
Lives Alone					Next step ahead forecast (1)2.92, (2)2.91
Frailty 6					Autocorrelation 0.01 SE 0.13
Mr A K 1944	74	13	1	1	Mean X(t) 2.89 Var. X(t) 0.37
Lives alone					ith step ahead forecast (1)2.91, (2)2.90
Frailty 4					Autocorrelation 0.01 SE 0.12
Mrs P K 1938	12	7	1	0	Mean X(t) 3.00 Var. X(t) 0.18
Lives alone					Next step ahead forecast (1)3.41, (2)2.70
Frailty 5					Autocorrelation –0.41 SE 0.28
Mr B 1929	84	17	0	0	Mean X(t) 2.84 Var. X(t) 0.58
Lives alone					Next step ahead forecast (1)2.72, (2)2.81
Frailty 5					Autocorrelation 0.122 SE 0.11
Mrs F 1928	60	12	0	0	Mean X(t) 3.14 Var. X(t) 0.56
Lives with son					Next step ahead forecast (1)3.14, (2)3.13
Frailty 6					Autocorrelation –0.09 SE 0.13
Miss P 1928	65	17	2	0	Mean X(t) 2.58 Var. X(t) 0.40
Lives alone					Next step ahead forecast (1)2.72, (2)2.64
Frailty 6					Autocorrelation 0.26 SE 0.12
Mr G 1929	63	14	1	0	Mean X(t) 2.98 Var. X(t) 0.31
Lives alone					Next step ahead forecast (1)2.92, (2)2.96
Frailty 4					Autocorrelation 0.05 SE 0.13
Mrs J 1929	20	6	1	0	Mean X(t) 2.84 Var. X(t) 0.34
Lives with daughter					Next step ahead forecast (1)2.82, (2)2.79
Frailty 6					Autocorrelation 0.25 SE 0.25
Mr P D 1940	65	18	0	0	Mean X(t) 2.69 Var. X(t) 0.22
Lives alone					Next step ahead forecast (1)2.69, (2)2.69
Frailty 7					Autocorrelation 0.24 SE 0.23
Mrs C 1936	84	16	2	0	Mean X(t) 2.80 Var. X(t) 0.66
Lives with daughter					Next step ahead forecast (1)2.82, (2)2.79
Frailty 5					Autocorrelation 0.14 SE 0.11
Mrs F 1950	57	13	0	0	Mean X(t) 2.70 Var. X(t) 0.43
With husband		Died			Next step ahead forecast (1)2.69, (2)2.69
Frailty 8					Autocorrelation –0.01 SE 0.13

*Clinical frailty scale [27]: 1 *Very fit* – robust, active, energetic and motivated; 2 *Well* – no active symptoms; 3 *Managing well* – medical problems are well controlled, but not active beyond routine walking. 4 *Vulnerable* – not dependent on others, but symptoms limit activities; 'slowed up' and/or tired. 5 *Mildly frail* – more slowing and needing help with IADLs (finance, transport, heavy housework, medications). 6 *Moderately frail* – need help with all outside activities, housework and maybe with bathing and dressing. 7 *Severely frail* – completely dependent for personal care, stable not at high risk of dying (≥6 months). 8 *Very severely frail* – completely dependent, approaching the end of life/not able to recover from minor illness. 9. *Terminally ill* – life expectancy <6 months.

†SRH (1 = very poor, 2 = poor; 3 = fair, 4 = good, 5 = very good, 6 = excellent).

A&E, Accident and Emergency Department.

her deteriorations, the trend in her SRH is downwards. She visited her GP after 5 days of fair SRH, as indicated by the arrow in Fig. 1a. Mr S lives alone (born 1931). He is suffering from COPD, hemochromatosis, osteoarthritis and hypertension. His SRH on entry to the PaJR study was 2 and frailty level was 4. Over the 14 months, his SRH average was 2.58, but fluctuated between good and fair for most of the trajectory and her trend was downwards. He was admitted on the day that SRH was reported to be fair, following a chest infection, see the arrow on graph, later in the evening when he felt more 'poorly', Fig. 1b.

2 Type 2. Cases (time series) with SRH fluctuations that drop to fair or poor with an episode that (1) did not lead to admission or (2) lead to an admission with stable or improved trend in SRH over ≥12 months.

Mr R has COPD and ischaemic heart disease. His trajectory fluctuates between SRH (very good) and SRH (fair) in the period monitored, and had no admissions. His SRH trend is stable and he does not report any poor SRH. Mr R has a stable or even slightly upward trend in his SRH, but appears to recover from deteriorations. He attends his GP after a fair SRH, Fig. 2a.

Mrs C lives near her niece. Her mean SRH is 2.84 and SRH was 4 on discharge from hospital. She has asthma. She was admitted with an acute flare-up (see arrow) when her niece went to visit her mother (Mrs C's sister). Despite an admission, she stabilized and her SRH gradually trended upwards, Fig. 2b.

Sections of patients' trajectories demonstrate deterioration with or without hospitalization. Changes in SRH around each low point ranged from gradual over two to three calls to very rapid between calls and more unexpectedly. Not recovering from a fair/poor fluctuation within about three calls was associated with deterioration further. Fluctuations to 'worse' occurred in periods of stable health for some with long periods of better health stability in between, or in periods of relatively fair or poor SRH when some factor, obvious or not, appears to boost health perceptions. In others, there is a rapid decline brought about by a fall, an infection or some social change rapidly taking over or more gradually tipping into worsening functioning of the lungs or heart. Very poor SRH was rarely reported, and together with poor SRH signified very serious concerns about the individual's health in these cases. Not unexpectedly, brief narratives aided interpretation of the SRH metric.

Synthesis

SRH patterns, when poor to fair, were highly correlated with adverse patient outcomes including severe pain, death and hospital

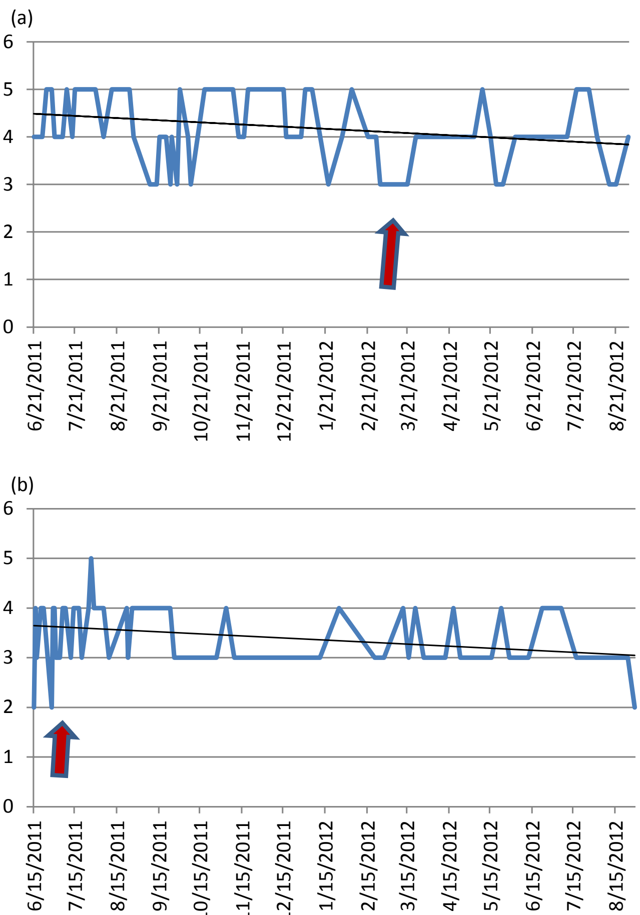

Figure 1 (a) Patterns of fluctuations which stabilize but slowly deteriorate in a linear trend. The arrow identifies deterioration which does not lead to admission. (b) Pattern of fluctuations which led to admission, stabilized and slowly deteriorated. The arrow identifies deterioration which leads to admission.

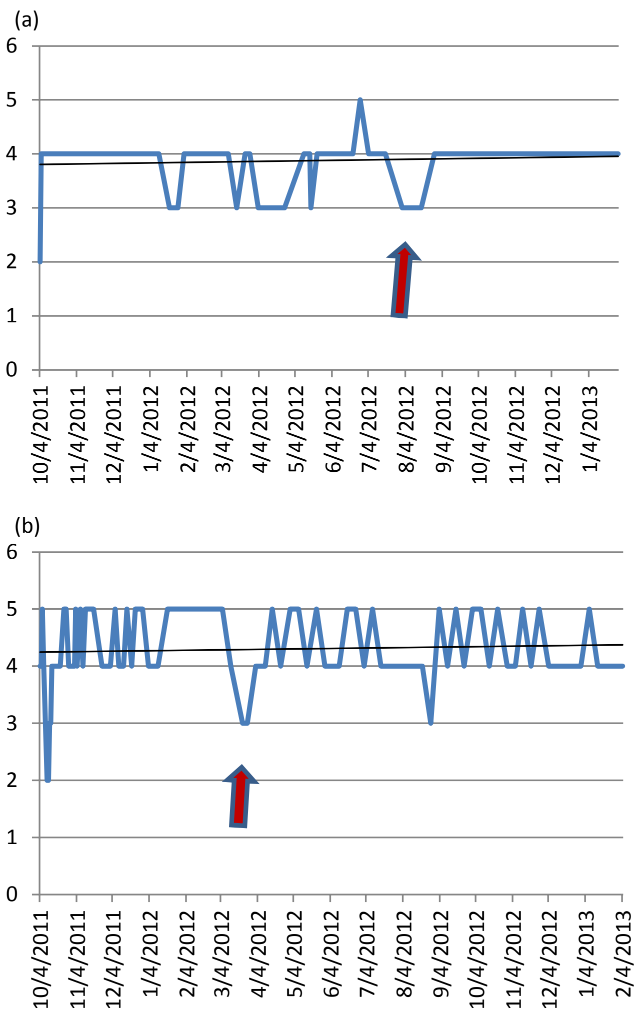

Figure 2 (a) Patterns of fluctuations which stabilize but trend is stable over month despite an admission. The arrow identifies deterioration which does lead to admission. (b) Patterns of fluctuations which stabilize but are stable over months without admission. The arrow identifies deterioration which does not lead to admission.

utilization. Long-term patient SRH trajectories over 6–27 months had low autocorrelations (–0.1 to 0.26). Patterns of deteriorations were not predictable from one segment to the next.

While there is a moderate trend towards a mean SRH value, the ability to forecast from one SRH to the next is not reliable. Clearly, the acute deteriorations were expected but their timing and severity was not. The deteriorations were constrained and non-random, being associated with exacerbations in chronic conditions, infections, falls and demoralization as common 'tipping points'. The consequences of these destabilizations were apparently influenced by the availability of personal support, carer issues and timely medical care, which often was at primary care level, as predicted in the literature [28–30]. Linear trends were interesting. It is not clear why some patients continued on a downward trajectory, whereas others who destabilized appeared to completely recover, and even improved over time.

Understanding patients as a CAS provides a theoretical perspective on resilience in any or all of physical, psychological, social and environmental domains of later life. Tipping points in these domains appear at the root of the personal health crisis that leads to emergency admissions or visits. SRH reflects personal perceptions of different inflammatory patterns in older cohorts [31].

This case study findings support CAS theory that individual's at-risk health journeys due to frailty and multi-morbidity are volatile and non-linear in parallel with decline in internal resilience.

Other observational studies have also identified that unpredictable instabilities may arise following intense assessment such as geriatric assessment [30,32] and post-discharge [19,33]. There is a need to keep in touch with people in these potentially unstable dynamic trajectories on a regular basis. Indeed, this is the basis for the whole tele-health home monitoring movement. However, less is known about how best to support and monitor which patients.

Discussion

In a clinical as well as in epidemiological studies, SRH is an important vehicle for understanding how an individual is faring at a point in time. Clinically, it appears to have low predictive capacity as a single measure at a time point compared with epidemiological studies. The bulk of SRH literature demonstrates that older at-risk people's trajectory is more likely related to the level of maladaptive inflammatory markers than any specific diagnosis [17], but requiring more research. Disease-specific monitoring may help in clinical care, but generic and single item health monitoring is likely to adequately reflect the health journey across multiple diseases [34]. However, if a patient's SRH deteriorates between doctor visits and detected by the Care Guide call, and the patient is referred to the doctor to address the medical issues arising in a timely manner, containment of the deterioration is possible [13]. Moreover, previous work [13] has demonstrated the added predictive value of SRH with the use of multiple data points, recorded by Care Guides, including symptoms, self-care activities and brief narratives analysed with machine learning. Using machine learning on as much information is possible, and including material from medical records, sensors in the home or on the person may enhance such predictions [13]. Other metrics such as biomarkers might add value after further research.

Nevertheless, SRH appears to be a very potent metric of an 'individual's unique access' to the severity of problems in their own bodily sensations [35], their closeness to death and their ability to survive in their current environment [31]. Further research is needed to untangle complicated dynamics of SRH, stress, resilience and internal biomarkers in the patient journey further.

Conclusion

This case study of 14 patient journeys demonstrates that SRH reflects an individual's health trajectory, but predicting when and how deteriorations will occur is challenging. Poorer SRH while highly correlated with more urgent service use and hospitalization was not predictable from repeated measures. The findings support the theory that multi-morbid frail patients intermittently experience reduced adaptability, with difficulty maintaining physiological, psychological and social stability within an overall trend in their health.

SRH appears to be very worthwhile as a single measure in monitoring people's daily status. Fluctuations in everyday SRH appear to require close attention in high-risk individuals in clinical settings if prompt intervention is to be delivered in response to deteriorations.

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