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Resilience, health perceptions, (QOL), stressors, and hospital admissions—Observations from the real world of clinical care of unstable health journeys in Monash Watch (MW), Victoria, Australia

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Abstract

Rationale, aims, and objectives: Monash Watch (MW) aims to reduce potentially preventable hospitalisations in a cohort above a risk "threshold" identified by Health Links Chronic Care (HLCC) algorithms using personal, diagnostic, and service data. MW conducted regular patient monitoring through outbound phone calls using the Patient Journey Record System (PaJR). PaJR alerts are intended to act as a self-reported barometer of stressors, resilience, and health perceptions with more alerts per call indicating greater risk.

Aims: To describe predictors of PaJR alerts (self-reported from outbound phone calls) and predictors of acute admissions based upon a *Theoretical Model for Static and Dynamic Indicators of Acute Admissions*.

Methods: Participants: HLCC cohort with predicted 3+ admissions/year in MW service arm for >40 days; $n = 244$. Baseline measures—Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey scores Mental (MSC) and Physical (PSC) and ICECAP-O. Dynamic measures: PaJR alerts/call in 10 869 MW records. Acute (non-surgical) admissions from Victorian Admitted Episode database. Analysis: Logistic regression, correlations, and timeseries homogeneity metrics using XLSTAT.

Findings: Baseline indicators were significantly correlated except SF-12_MCS. SF12-MSC, SF12-PSC and ICECAP-O best predicted PaJR alerts/call (ROC: 0.84). CFI best predicted acute admissions (ROC: 0.66), adding CD-RISC, SF-12_MCS, SF-12_PCS and ICECAP-O with two-way interactions improved model (ROC: 0.70). PaJR alerts were higher ≤10 days preceding acute admissions and significantly correlated

[Correction added on 5 October 2018, after first online publication: Tables 4 and 5 have been updated in this corrected version.]

with admissions. Patterns in PaJR alerts in four case studies demonstrated dynamic variations signifying risk. Overall, all baseline indicators were explanatory supporting the theoretical model. Timing of PaJR alerts and acute admissions reflecting changing stressors, resilience, and health perceptions were not predicted from baseline indicators but provided a trigger for service interventions.

Conclusion: Both static and dynamic indicators representing stressors, resilience, and health perceptions have the potential to inform threshold models of admission risk in ways that could be clinically useful.

KEYWORDS

health perceptions, hospital admissions, potentially preventable hospitalisations, resiliencestressorsunstable health journeys

1 | INTRODUCTION

Avoidable hospitalisations in adults are expensive, often unhelpful or even harmful to patients and generally reflect a poorly coordinated health system. Low resilience in physical, psychological, social, and environmental domains of multimorbidity (multiple chronic diseases in an aging population)[1] is at the root cause of the personal health crisis that leads to many emergency admissions.[2] Predicting who is at risk for avoidable hospitalisations often uses clinical algorithms based on specific chronic diseases, and high service utilization called threshold models,[3] often accompanied by additional case finding activities. However, there is little clarity about how static measures can inform threshold algorithms in the dynamic systems of patient journeys. Dynamic and real-time indicators have little currency yet in clinical programs, outside of biometric monitoring, although there is a growing interest in the topic.

2 | BACKGROUND

The Victorian Department Health and Human Services state-based public hospitals database Health Links Chronic Care (HLCC) utilizes clinical algorithms to predict a cohort at risk of ≥3 potentially avoidable hospitalisations.[3]

The HLCC algorithm identifies an eligible cohort of patients who are at high risk of unplanned readmission to hospital, above a minimum threshold based on the previous 12 months of Victorian Admitted Episode Data/Victorian Emergency Minimum Dataset data, with 30% of eligible patients predicted to be admitted ≥3 times over the next year. The general parameters of the HLCC algorithm involve the following: number of unplanned admissions in past 6/12; number of ED visits in past 3/12; age; residence status, current and past smoking, including selected chronic conditions such as digestive disorders, kidney disease, asthma, COPD, rheumatoid arthritis, diabetes, pancreas conditions, cirrhosis/alcoholic hepatitis and excluding conditions such as cancer, dementia and serious mental illness. The Department supplies health services with a list of patients forming the "HLCC eligible cohort" at the start of the trial and periodically updates lists based on ongoing analytics.

Monash Health is the largest public hospital and community care system in Victoria. Its 15 000 staff work at more than 40 sites, providing over 3 million occasions of service, admitting more than 238 000 hospital patients, and handling more than 206 000 emergency presentations. Analytics from the HLCC state-based public hospitals database indicate that there are over 3000 patients with 4+ admissions, and over 12 000 with 3+ admissions a proportion of which are potentially avoidable per year. Monash Health was an early adopter of readmission prevention programs with a large community service. The Monash Health HLCC program called Monash Watch (MW) commenced its service in the geographically defined area around Dandenong Hospital, one of the lowest socioeconomic status and ethnically diverse areas of Melbourne.[4]

Ethics approval was obtained from the Health Research Ethics Committee, Monash Health for the conduct of the pilot service and its internal evaluation by the MonashWatch team. The Commonwealth Scientific and Industrial Research Organization, an independent Australian federal government agency is conducting an external evaluation of diverse state-wide HLCC initiatives in Victoria which also has Health Research Ethics Committee approval.

The findings in this paper are based on an internal evaluation of the initial MW HLCC cohort in the intervention arm. The PaJR system embedded in MW was developed in Ireland and validated in an Irish primary care cohort. Alerts are based upon conversations[5-7] based on the biopsychosocial model developed to identify change in journeys—based upon stressors and status.

A key question arose—can the HLCC generic risk cohort be further stratified? The US National Academy of Medicine[8] groups patients such as frail elderly, end of life, and major complex conditions further stratified by psychological and social needs. Would such groupings or others help to manage the HLCC cohort from the outset?

Baseline data on the MW intervention cohort included measures which have been validated in the Australian population: Clinical Frailty Index[9]—frailty is a term widely used to denote a multidimensional syndrome of loss of reserves (energy, physical ability, cognition, health) that gives rise to vulnerability; and worse health outcomes; SF-12v2 Health Survey[10,11] which measures health-related quality of life in two domains Physical Component Summary (PCS) and the Mental Component Summary (MCS) scores,[12] and the ICECAP-O (ICEpop CAPability measure for Older people)—a measure of QOL capability in older people that focuses on wellbeing defined in a broader sense (QOL), rather than health.[13,14] At around 6 months into the MW program, as it emerged that some participants appeared to exhibit a lack of psychosocial resilience, the Connor-Davidson Resilience scale (CD-RISC)[15] was administered to the service cohort as a late baseline measure.

3 | THEORETICAL MODEL FOR STATIC AND DYNAMIC INDICATORS OF ACUTE ADMISSIONS

Unstable health journeys represent low resilience in the face of stressors in the physical, psychological, social, and/or environmental domains of life.[1,16] A theoretical framework proposed in 2016[16]—incorporated interoception (self-reported health perceptions) and resilience into clinical care to guide care in the complex nature of multimorbidity in unstable health journeys. This formed the basis for Theoretical Model for Static and Dynamic Indicators of Acute Admissions (Figure 1). *Resilience in an individual's context—systemic and/or psychosocial—in response to predictable and unpredictable stressors, mediated through worse health related QOL, trigger emergency admissions.*[2] Because stressors are may be unpredictable, continual monitoring may be required to identify triggers with dynamic indicators of resilience and self-rating of health status. Dynamic indicators of resilience have been correlated with frailty measures[17] and depression,[18,19] and approaches becoming implementable in clinical practice[9,20]?

The Patient Journey Record system (PaJR) is an outbound call system that is embedded in MW to assesses self-reported dynamic stressor and resilience patterns in people with unstable health journeys to trigger PaJR alerts so that clinicians can seek to identify and intervene in root causes of readmissions where possible.[7,21] Outbound regular calls between 1 and 5 times per week are conducted by trained lay care guides using a semi-structured biopsychosocial monitoring script.

4 | AIMS

To explore the capacity of baseline measures to predict service processes and avoidable hospitalisations in MW. To explore the utility of baseline measures and dynamic measures from PaJR to inform future care delivery.

Participants: 222 MW participants who completed ≥3 months in MW and completed all measures in baseline and follow-up surveys (12 were excluded due to incomplete data and 10 who had not completed 40 days).

5 | DATA

Static Indicators—Baseline data from MW service measures: Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey and ICECAP-O[13,14] (see Table 1).

Dynamic Indicators—10 869 phone call records from the PaJR[7] provided longitudinal data on intervention patients from 23/12/16 to 7/4/18.

Outcome measures—hospital admissions from the Victorian Admitted Episode Data/Victorian Emergency Minimum Dataset 23/12/16 to 7/4/18.

TABLE 1 Static and dynamic indicators and outcome measures

Measure	When Administered
Stressors (proxy)	
*alerts per outbound call (stressors) *while problems and alerts reported are a marker of biopsychosocial stressors, they are also the triggers for service activation	December 2016 - April 2018
Resilience measures	
Clinical Frailty Index (CFI)[22]	Intake in the home
Connor Davis Resilience (CD-RISC)[15,23]	May 2017
Quality of Life	
SF-12v2 Health Survey[10,11] Physical Component Summary (PCS) and the mental component summary (MCS) scores. Australian population.[12]	Intake in the home
ICECAP-O[13,14]	Intake in the home
PaJR calls service triggers	
*alerts per outbound call (stressors) *while problems and alerts reported are a marker of biopsychosocial stressors, they are also the triggers for service activation	December 2016 - April 2018
Service utilization	
Acute hospital admissions categories 2 categories: None vs any per 30 days	December 2016 - April 2018

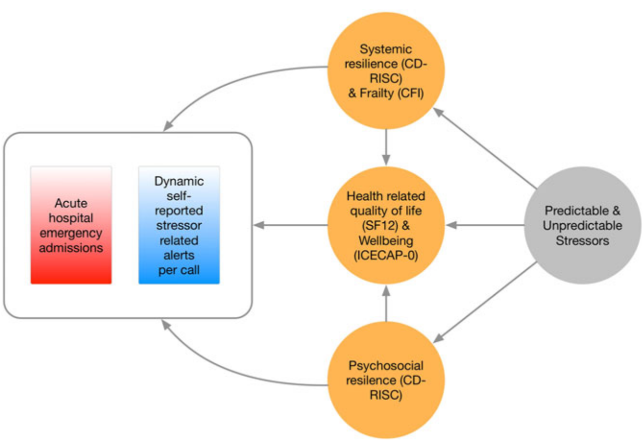


FIGURE 1 Theoretical model for static and dynamic indicators of acute admissions

6 | METHODS

Internal formative evaluation of clinical service pilot. Regression, correlation, and time series homogeneity metrics using XLSTAT data analytics package. Univariate and bivariate analyses were initially conducted with CFI and CD-RISC, then other baseline variables were added. We used *t*-tests to compare continuous variables and chi-square tests to compare categorical variables. Non-normally distributed data are described with medians and interquartile ranges and compared with the Mann-Whitney-Wilcoxon test. All tests were two sided, and alpha was set at 0.05. We used a Kendall's tau-b test to examine the correlations.

Logistic regression[24] was chosen as the major analytic tool for understanding the contribution of baseline factors predicting more than vs less than median PaJR alerts and having any admissions per 30 days vs 0 admissions due to the non-normal distributions of all the variables. Predictive modelling using logistic regression gives a predicted probability of a positive for each individual based on the values of that individual's baseline values. Receiver operating characteristic (ROC) is a method to see how well the predictive model can distinguish between the true positives and negatives. The ROC curve does this by plotting sensitivity, the probability of predicting a real positive will be a positive, against 1-specificity, the probability of predicting a real negative will be a positive. ROC area under the curve: ≥0.7 or 70% was taken as a clinically important level of explanation of the influence of baseline metrics. Descriptive homogeneity tests on a time series aimed to determine if a series is homogeneous over time, or if there is a time at which a change occurs. For all tests, XLSTAT provides *P*-values using Monte Carlo resampling. The Pettit test was selected, as a very powerful tool for detecting the time of changes and suitable for all distributions.[25]

7 | FINDINGS

7.1 | Baseline indicators

A total of 224 MW participants who completed ≥3 months in MW and completed all measures in baseline and follow-up surveys (12 were excluded due to incomplete data). All data were skewed and non-normal (Figure 2 and Table 2).

Frailty (CFI) was associated with psychosocial resilience (CD-RISC) both in bivariate analysis, and in a correlation matrix where both were statistically correlated with quality of life (ICECAP-O) and physical health (PCS). Mental health was not correlated with the other measures. Clinical CFI Index (CFI) and CD-RISC were not independent. (Test of independence: Chi-square (Observed value) 41.316 Chi-square (Critical value) 23.685 DF 14 *P*-value 0.000 alpha 0.05). CFI, ICECAP-O, SF12_PCS, and CD-RISC were all significantly correlated, while SF12_MCS was not correlated (see Table 3).

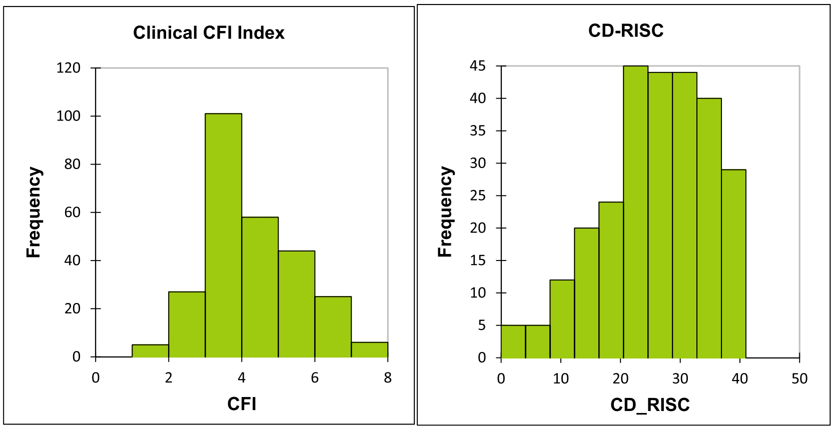


FIGURE 2 Histogram of baseline indicators clinical frailty index (CFI); Connor Davis Resilience (CD-RISC)

TABLE 2 Descriptive statistics—baseline and outcome measures in MonashWatch: Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey Scores Mental (MSC) and Physical (PSC) and ICECAP-O; and Alerts in biopsychosocial and environmental domains as reported in outbound phone calls in the patient journey record system and length of stay per acute admission during Monash Watch deployment December 2016 to April 2018

Statistic	Frailty (CFI)	ICECAP-O	SF12_MSC	SF12_PSC	CD_RISC	Average Alerts/Call	los/Admit/30 Days
No.	224.0	224.0	224.0	224.0	224.0	224.0	224.0
Minimum	1.0	0.0	15.4	15.2	2.0	0.0	0.1
Maximum	8.0	1.0	68.5	59.6	40.0	9.4	34.0
Range	7.0	1.0	53.1	44.4	38.0	9.4	33.9
1st quartile	3.0	0.5	34.6	25.4	20.0	0.5	0.5
Median	4.0	0.7	43.2	31.8	27.0	1.1	1.5
3rd quartile	5.0	0.9	56.8	37.8	33.0	2.2	3.1
Mean	3.9	0.7	44.6	32.6	25.9	1.6	2.9
Standard deviation	1.3	0.2	13.0	9.5	8.4	1.6	4.8

7.2 | Impact of static resilience indicators on PaJR calls

7.2.1 | PaJR alerts per call

Overall resilience (CFI) appeared to be a superior to resilience (CD_RISC) as predictor of high vs low levels of alerts per call and together they predicted ROC above the level initially selected as significant. CFI was a significant predictor of high vs low PaJR alerts per call dichotomised at median 1.1 with a non-significant contribution from CD-RISC dichotomised (ROC: 0.72). The model with all the variable of high vs low PaJR alerts per call dichotomised at median 1.1 demonstrated the contribution of mental and physical health and quality of life. The baseline measures in the model that best predicted alerts per call were mental health (SF12-MSC), physical health (SF12-PSC), and quality of life (ICECAP-O) with (ROC: 0.84). Thus, frailty CFI was an adequate predictor, but a combination of physical and mental health and quality of life was accurately predicted alerts (see Figure 3A,B and Table 4).

7.2.2 | Impact of static indicators on acute hospital admissions

Frailty (CFI) is the best predictor of an acute hospital admission (ROC: 0.66) in a logistic regression with CD-RISC. Adding all baseline variables into the logistic regression model CD-RISC, SF12-MSC, SF12-PSC, and ICECAP-O improved model (ROC: 0.67) slightly. Including all two-way interactions among all variable improved the model (ROC: 0.70) to an acceptable level of prediction indicating a very complex process underpinning acute hospital admission. Nevertheless, without any medical or clinical metrics in the model, acute admissions were predictable by self-reported biopsychosocial measures (Figure 4 and Table 5).

7.3 | Stressors and dynamic indicators

PaJR alerts per call represented a simple dynamic indicator of stressors. Total PaJR alerts were at a higher level over the 10 days prior to an acute admission compared with all calls in the whole sample. Average PaJR alerts/all calls = 1.64/call vs PaJR alerts/call in 10 days prior to an admission = 3.01. Chi-square significant difference alpha = 0.05.

Nevertheless, the static measures do not provide "real time" indicators on which to act. Further analysis indicated that patterns of an increasing rate of PaJR alerts and acute admissions were highly correlated. Two-sample Kolmogorov-Smirnov test/two-tailed test: D 0.194 *P*-value (two-tailed) < 0.0001 alpha 0.05. The *P*-value is computed using an exact method. Fifty-one patients had no admissions and 172 have at least one admission.

7.3.1 | Individual cases—identifying when individuals are at risk

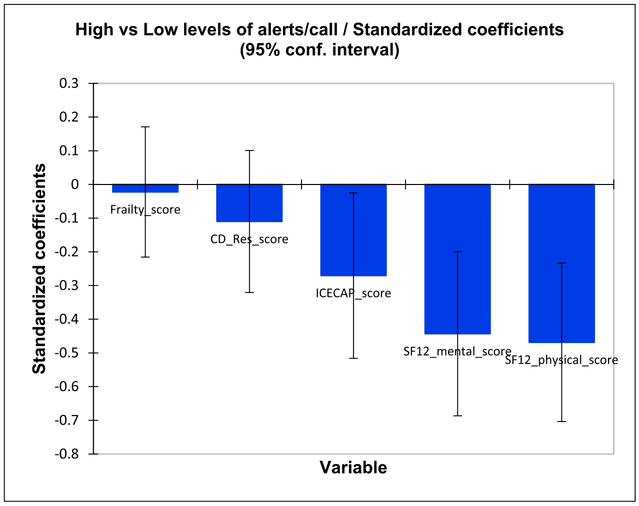
Alerts have been demonstrated to represent a dynamic biopsychosocial trajectory emergent from underlying frailty (CFI) and physical and mental health and quality of life.

Four cases with more than 25 calls were randomly selected—Patient IDs 20, 1024, 1227, and 1040 to demonstrate alert patterns in journeys which can be described in time series. These patterns demonstrated shifts which increase or reduce risks of acute admission. Such patterns identify the individual at risk in a cohort. Such

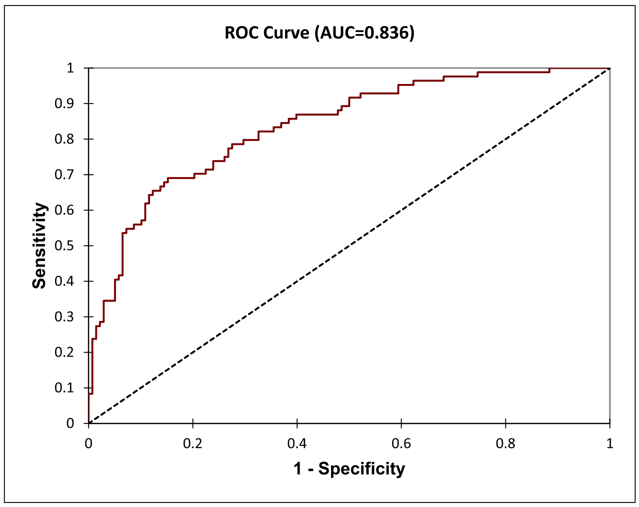
TABLE 3 Correlation matrix of CD-RISC,CFI, ICECAP O, SF-12_MCS, and SF-12_PCS

Correlation Matrix (Pearson):					
Variables	CFI	ICECAP	SF12_MCS	SF12_PCS	CD-RISC
CFI	1	−0.216	−0.031	−0.244	−0.150
ICECAP	−0.216	1	0.112	0.280	0.453
SF12_MCS	−0.031	0.112	1	0.013	0.071
SF12_PCS	−0.244	0.280	0.013	1	0.159
CD-RISC	−0.150	0.453	0.071	0.159	1

Values in bold are different from 0 with a significance level alpha = 0.05.



(A)

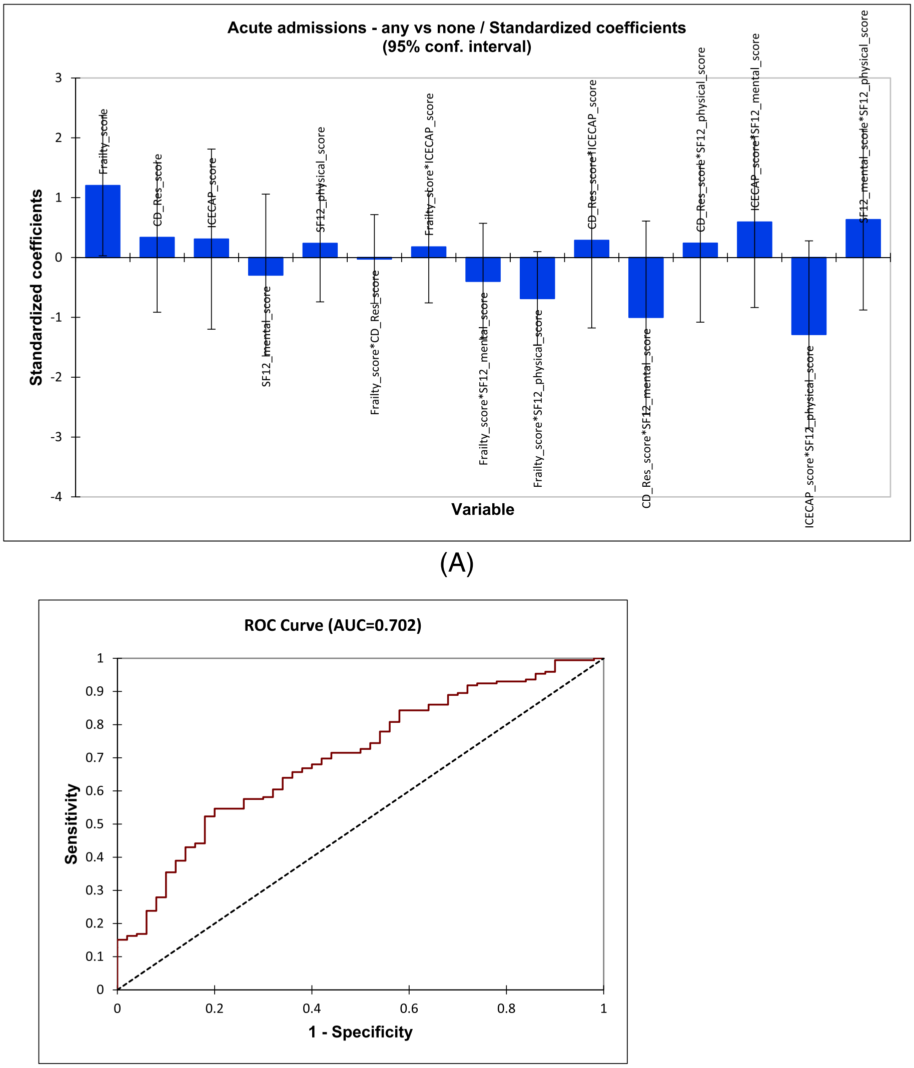


(B)

FIGURE 3 A, Best model of high vs low PaJR alerts using logistic regression with baseline measures Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey Scores Mental (MSC) and Physical (PSC) and ICECAP-O. B, PaJR alerts high versus low-dichotomised at median 1.1 (logistic-regression) with predictors Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC); SF-12v2 Health Survey Scores Mental (MSC) and Physical (PSC), and ICECAP-O

TABLE 4 High vs low levels of alerts per call (log-Reg)

Source	Value	Standard Error	Wald Chi-Square	Pr > Chi^2	Wald Lower Bound (95%)	Wald Upper Bound (95%)
Frailty	−0.022	0.099	0.051	0.821	−0.216	0.171
CD-RISC	−0.110	0.107	1.045	0.307	−0.320	0.101
ICECAP	−0.270	0.125	4.653	0.03*	−0.516	−0.025
SF12-MSC	−0.443	0.124	12.699	0.000**	−0.687	−0.199
SF12-PSC	−0.468	0.120	15.238	< 0.0001****	−0.704	−0.233



(B)

FIGURE 4 A, Emergency admits any versus none logistic regression predicted by Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey Scores Mental (MSC) and Physical (PSC), and ICECAP-O with two-way interactions. B, Any vs none acute admits (ROC) predicted by emergency admits any versus none (log-reg) Clinical Frailty Index (CFI); Connor Davis Resilience (CD-RISC): SF-12v2 Health Survey Scores Mental (MSC) and Physical (PSC), and ICECAP-O

patterns may signify dynamic indicators in future research (Figure 5; Table 6).

8 | DISCUSSION

Resilience and intercorrelated health perceptions metrics were investigated in the context of the intervention arm of the MW/HLCC service innovation to reduce the avoidable hospitalization days—acute non-surgical admissions were the key target. The relevance of a theoretical stressor—resilience—health perceptions-QOL model to inform innovative complex adaptive care in unstable health journeys was explored. Modelling the predictive capacity of baseline (and common) metrics on the HLCC cohort in MW intervention arm was explored. This cohort was already predicted to have a 30% chance of having ≥3 admissions in the next 12 months.

TABLE 5 Emergency admits any versus none (log-reg)

Standardized Coefficients (Emergency Admits Any Vs None):						
Source	Value	Standard error	Wald Chi-square	Pr > Chi^2	Wald lower bound (95%)	Wald upper bound (95%)
CFI	1.202	0.599	4.029	0.045*	0.028	2.375
CD_RISC	0.335	0.637	0.276	0.599	−0.914	1.584
ICECAP	0.307	0.768	0.159	0.690	−1.199	1.813
SF12_MSC	−0.293	0.689	0.180	0.671	−1.644	1.058
SF12_PSC	0.236	0.499	0.224	0.636	-0.741	1.213
CFI*CD_RISC	−0.024	0.378	0.004	0.948	−0.766	0.717
CFI*ICECAP	0.176	0.477	0.137	0.712	−0.758	1.110
CFI*SF12_MSC	−0.397	0.494	0.645	0.422	−1.364	0.571
CFI*SF12_PSC	−0.685	0.399	2.945	0.086	−1.466	0.097
CD_RISC*ICECAP	0.286	0.746	0.147	0.701	−1.177	1.749
CD_RISC*SF12_MSC	−0.999	0.821	1.483	0.223	−2.607	0.609
CD_RISC*SF12_PSC	0.238	0.673	0.125	0.723	−1.080	1.557
ICECAP*SF12_MSC	0.592	0.728	0.661	0.416	−0.835	2.019
ICECAP*SF12_PSC	−1.285	0.798	2.595	0.107	−2.848	0.278
SF12_MSC*SF12_PSC	0.632	0.770	0.674	0.412	−0.877	2.141

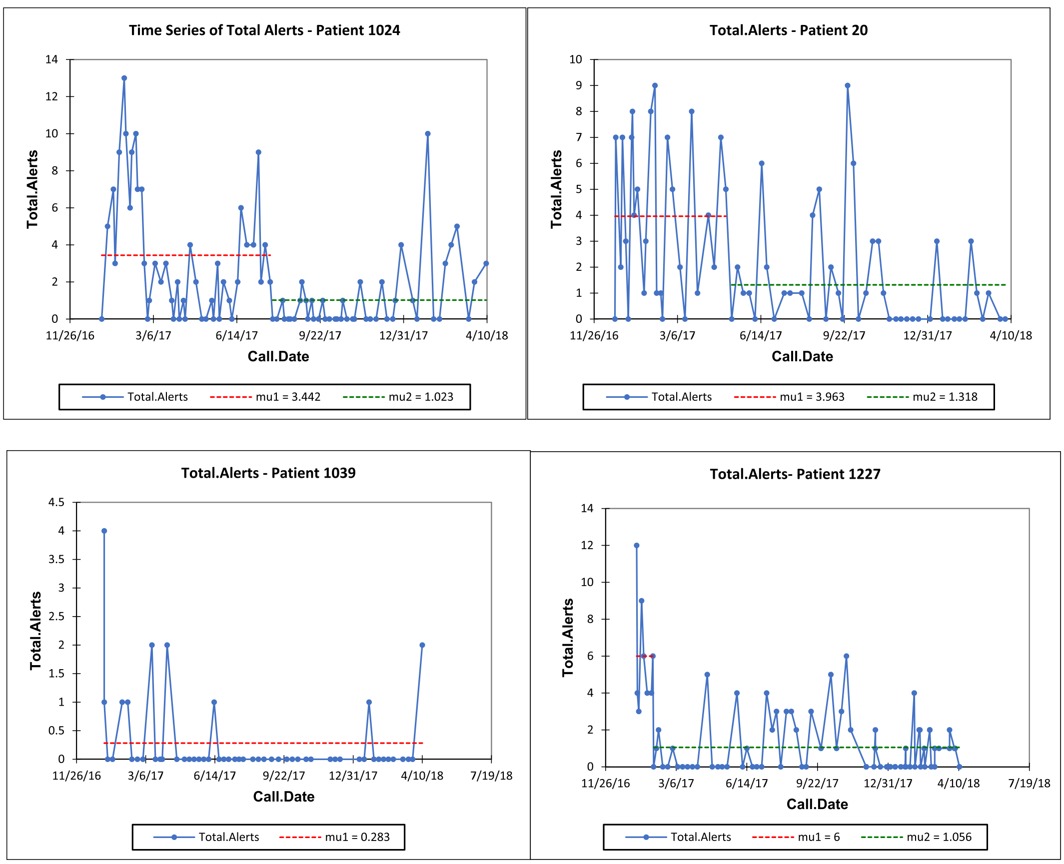


FIGURE 5 Graph of dynamics of time series analysis of alerts reflecting physical and psychosocial stressors for patients 20, 1024, 1039, and 1227. Homogeneity tests enable you to determine if a series may be considered as homogeneous over time, or if there is a time at which a change occurs. mu1 is the first series, and mu2 is the second series after a date (t) when there is a statistically significant change in levels of alerts

All variables in the Theoretical Model for Static and Dynamic Indicators of Acute Admissions predicted live and ongoing PaJR alerts per call and most importantly acute admissions. However, how to incorporate such knowledge into everyday clinical practice is a work-in-progress. Perhaps, paying attention to those with worse scores in different dimensions on entry to the MW service and providing more tailored care would be productive. The relationship between reported PaJR alerts/problems as recorded in outbound calls and stressors is implied but forms the basis for triggers to activate services. Nevertheless, PaJR alerts are not stable and represent the presence of non-linear

TABLE 6 Dynamics of alerts—time series patient 20. Homogeneity test using Pettitt's test. H0: Data are homogeneous. Ha: There is a date at which there is a change in the data. If the computed *P*-value is lower than the significance level alpha = 0.05, null hypothesis H0 is rejected, and Ha is accepted

Pettitt's test (Total.Alerts):	PID 20	1024	1039	1227
K	641.0	925.0	196.0	530.0
T (date of change)	3/5/17	24/7/17	6/4/17	1/2/17
P-value (two-tailed)	0.001	0.000	0.065	0.070
Alpha	0.05	0.05	0.05	0.05

dynamic physical and psychological stressors that emerge from a complex adaptive system. Dynamic indicators of stressors reported as PaJR alerts demonstrate fluctuations which can be identified retrospectively or at best in real time. PaJR alerts on average, doubled in the 10 days before an admission. This is an average phenomenon, and some people had admissions with few alerts—seeking comfort from the hospital system, while others may have stabilized without an emergency admission. Some people with similar patterns of non-life threatening but impactful illness may attend their GP while others see the emergency department as a source of reassurance, perhaps. Dynamic patterns of homogeneity of higher levels of PaJR alerts in sections of patient journeys represent greater instability.

This study takes place in the context of a specific case finding method HLCC using "big data" from a public hospital system data base. Moreover, all similar service interventions take place in complex adaptive systems with different populations, health and community services, and GP care, even the same service will change over time. The numbers in this analysis are relatively small, and the impact of diagnosis—such as Heart Failure or Chronic Obstructive Pulmonary Disease is not assessed in this analysis. Baseline measures in the analysis may contribute more information if repeated periodically. Only two service parameters were modelled—alerts and acute admissions—and there are many others. An interesting question for further research is "how does the responsiveness of health services and their threshold for admissions and capacity to respond to complex unpredictable health needs change over time?". Nevertheless, as part of formative evaluation of the live MW and HLCC service program, useful information about resilience and QOL psychometrics is likely to inform its ongoing improvement. More stratification and structuring of care from the outset may be possible; however, time series analysis of PaJR alerts reflecting physical and psychosocial stressors would seem to be necessary. While there are many caveats, this snapshot of a dynamic system and retrospective coherence may inform other services about the likely nature of the dynamics rather than provide protocols or standardized approaches.

A literature on systemic resilience is emerging.[17,18,26] Greater frailty was associated with greater variation in self-rated health, greater correlation between physical and mental health, and autocorrelation.[17,27] While the settings, context, and measures of this study are different from the study of Gijzel et al,[17] the principles would seem coherent. Frailty (CFI) was an important predictor or worse outcomes and interrelated with psychosocial resilience (CD-RISC) rather than either alone. The best predictors of admissions involved two-way interactions between all the baseline indicators. PaJR alerts have an inbuilt measure of instability in illness in medical, medication, social support, and self-care domains[7] corresponding with higher levels of alerts. Homogeneity measures are a proxy for autocorrelation and the cases presented demonstrating patterns of homogeneity or autocorrelation in phases of higher and lower levels of alerts or self-reported risk. These PaJR alerts could be understood as a barometer of the interaction among stressors, resilience and health perceptions. This formative evaluation study opens up the prospect of further theoretical development and theory testing, as more data becomes available and different populations and settings are involved.

9 | CONCLUSION

Self-reported health and stressors as both static and dynamic indicators have the potential to inform threshold models of admission risk in ways that could be clinically useful. Static baseline indicators are predictors of the high levels of stressors and admissions in the identified HLCC high-risk cohort and offer the possibility of some stratification and structuring of care. Given the dynamic nature of unstable journeys, however ongoing monitoring of physical and psychosocial stressors is important for detection and reaction to imminent hospitalization. One can only see so far into murky waters. Ongoing research will continue to explore and understand resilience, stressors, and health perceptions related to acute admissions.

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