Unstable Health Journeys and Potentially Avoidable Hospitalisations (PAH)
A work-in-progress!!!

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Unstable Health Journeys and PAH

- Resilience – systemic and psychosocial - in unstable journeys – tipping to PAH
- Contribution of baseline indicators to predict journeys and PAH in HLCC
- Dynamic indicators in unstable journeys
- Segmenting impactability in HLCC cohort?
- Where to from here?
My Journey

My experience of serious chronic illness

The Care of Chronic Illness in General Practice PhD ANU 1993-1998

Health Care Planning and Medication MMR DVA/DoHA Canberra

Co-ordinated Care Trials/Divisions Australia

Primary Care Health Transition/Aboriginal Health Transition Canada

Innovation – NDRC Ireland, 1871 Chicago

MonashWatch et al
My Network

Professor Donald Campbell, Keith Stockman and Narelle Hinkley
MonashWatch, Dept. of Medicine, Nursing and Allied Health, Monash Health

Professors Lucy Hederman and Carl Vogel
O’Reilly Institute, Trinity College Dublin, Ireland

Kevin Smith and John-Paul Smith
University of Queensland & PHC Research Pty Ltd

Joachim Sturmberg
Foundation President, ISSCSH International Society of Systems and Complexity Sciences for Health

Marten Scheffer, Wageningen University and Research Centre and international collaboration – systemic resilience

And many others.......Sally Phillips, Dee Grady, NAPCRG SIG, JECP, Vector Institute and York University, Toronto etc.
How can we best address unstable health journeys leading to PAH?

Unstable journeys are dynamic adaptations to continual illness/disease/frailty/life challenges.

Stressors, shocks or challenges to unstable journeys can have catastrophic, cumulative, (un)predictable consequences or promote adaptation.
Resilience theories

• System (body) responsiveness – pathophysiology, co-morbidities, drugs, ‘frailty’, disease dynamics*

• Psychosocial ‘coping’ and adaptation to stressors
  • “both an individual capacity to navigate their health and resources & a condition of individual’s family, community, and culture to provide resources in culturally meaningful ways”
  Michael Ungar (The International Resilience Project)

A new frontier in health.
Resilience dynamics in unstable journeys tipping to PAH

Acute and chronic stressors
- Disease/symptoms flare, medication, services, treatment effects, loneliness, environment, weather, legal, money, etc.

Social structure environment
- Close relationships, social support, housing, finances, transport, health and social services, primary care

Multimorbidity Self-care
- Medications, nutrition, alcohol, activity, sleep, social engagement, treatment and lifestyle caregiver support

Psychosocial Resilience
- Coping, self-regulation, mental health, personality, self-care, loneliness

Systemic Resilience
- Organ-based disease, multiple systems, cognitive capacity

Mental Health-related crises
- Depression, anxiety, severe symptoms, alcohol, medications, environment

Physical morbidity and mortality
- Disease exacerbation, comorbidities, medication

Acute Admission
Potential Baseline Predictors of tipping in HLCC (logistic regression) in MonashWatch HLCC intervention group

**Stressors – which and when?**
- Biological, psychosocial, environmental

**Systemic resilience**
- Disease, Rockwood Frailty
- SF12 Physical

**Psychosocial resilience**
- CD_res_score
- SF12 Mental
Acute Admission DRGs – many in PAH list in 240 intervention MW
Acute Admission DRG Categories – in 240 intervention MW
Challenges of Impacting Disease in PAH

- Post Hospital Syndrome* - systemic resilience
- Multimorbidity – systemic resilience
- Frailty – systemic resilience
- Psychosocial resilience

Predictors Length of Stay greater LOS per journey (PAH) in MW Acute Admissions (logistic regression)
Baseline Predictors Length of Stay $\geq 1\text{day} / 30\text{days}$ (PAH) in MW Acute Admissions $n=244$ (logistic regression)
Predictors Length of Stay (1-5)/30days (PAH) in MW Acute Admissions (logistic regression) n=244
<table>
<thead>
<tr>
<th>Source</th>
<th>Chi-sq (Wald)</th>
<th>Pr &gt; Wald</th>
<th>Chi-sq (LR)</th>
<th>Pr &gt; LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frailty_score</td>
<td>6.120</td>
<td>0.013</td>
<td>6.566</td>
<td>0.010</td>
</tr>
<tr>
<td>SF12 mental score</td>
<td>5.224</td>
<td>0.022</td>
<td>5.466</td>
<td>0.019</td>
</tr>
<tr>
<td>Age*Frailty_score</td>
<td>7.842</td>
<td>0.005</td>
<td>8.945</td>
<td>0.003</td>
</tr>
<tr>
<td>age*CD_Res_score</td>
<td>7.086</td>
<td>0.008</td>
<td>8.445</td>
<td>0.004</td>
</tr>
<tr>
<td>Frailty_score*ICECAP_score</td>
<td>5.707</td>
<td>0.017</td>
<td>6.111</td>
<td>0.013</td>
</tr>
<tr>
<td>SF12mental_score*SF12_physical_score</td>
<td>4.167</td>
<td>0.041</td>
<td>4.233</td>
<td>0.040</td>
</tr>
<tr>
<td>CD_Res_score*call/30 days</td>
<td>4.107</td>
<td>0.043</td>
<td>4.411</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Predictors Length of Stay (1-5)/30days versus other (PAH) in MW Acute Admissions (logistic regression) n=244
Tipping points in unstable journeys

• Predicting ‘nearness’ to a potential ED visit or PAH allows timely journey interventions

• Dynamical indicators of resilience (instability and closeness to tipping points) in time series of self-reported physical, mental, and social health were strongly correlated with systemic and/or psychosocial resilience in older adults\(^1\), depression\(^2\), and survival\(^3\)


Supervised care guides (CG) conduct semi-structured phone conversations to track individual journeys and context with online data entry of regular self-reports.

Analysis of patient and caregiver’s conversation data with algorithms.

Aims – to ‘predict’ real-time alerts of instability that trigger emergencies & less urgent long term biopsychosocial issues.

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

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].

Paddy’s journey in Ireland

A complex trajectory – systemic and psychosocial resilience

Related to caregiver falling and breaking 1 ankle and spraining another
Red alert/flag = high risk disease concerns
Other alerts = less acute chronic biopsychosocial problems

Algorithms ‘learned’ and ‘learning’ from > 20,000 outbound phone calls in PaJR database of outbound call summaries and call recordings
Days very well spent.

The daughter

Hospital back out.

Calls from doctors.

More tests needed.

Seems to be a stroke.

Need to go to the hospital.

Handbook.

Breathing.

Lung problems.

Sleeping.

Feels better.

Pity the poor thing.

Says the doctor.

Medication.

Health.

Week.

Blink.

Hops.

Droplet.

Glasses.

Need.

Eating.

Taking.

Blood.

Tests.

Action.

Virus.

Diabetes.

Breathless.

Bing.

Biotics.
Predicting Tipping points in PaJR/MW

- All calls averages
  - All alerts/flags $1.64$/call
  - Potential urgent event red alerts/flags $0.4$/call
- 10 days before acute admission
  - All alerts/flags $3.01$/call
  - Potential urgent/immed event red alerts/flags $0.8$/call
- Machine learning and natural language processing algorithms can improve individual predictions based on group and individual journeys
Can we predict impactable subgroups from HLCC enrolled cohort at outset?


- Dynamic Indicators of resilience and change in a short trial may be the way forward to test Impactability
Who can benefit? Who is impactable?

• A moral and ethical question as well as a technical question
  • Who is impactable - systemic or biopsychosocial resilience - when admitted to hospital or ICU? Why the question in HLCC if costs are contained?

• Risk of victim blaming
  • Opioid seeking? or demoralisation and poor mental health?
  • Rejection of services due to health system inflexibility and alienation?
  • Poor adherence because root cause of problem not addressed
  • Acopia or ‘just old’ versus overwhelmed
Baseline data - *simple* yet poorly predicts the unstable journey

A more *complicated* approach – perhaps frailty and disease could narrow the scope of HLCC intervention

• BUT we have the opportunity to learn and understand the *complex* dynamics underlying PAH

• Dynamic indicators identify unstable journey patterns/tipping points using what data we collect more effectively

• People in HLCC generally have unstable physical and mental health and deserve better care!!!
Where to next?

Understanding the individual with instability & PAH in context: moving from the diagnosis to enabling and optimizing their journey.
Dynamic Indicators in Unstable Journeys Time Series

• What is known practically
  • It is difficult to predict how and when people will reach a tipping point in a disease (biopsychosocial environmental) journey but there are likely to be early warnings. It is not known how best to monitor and predict deteriorations in a timely manner to improve efficiencies.

• Future opportunities
  • Artificial Intelligence and data analytics
  • IT Systems e.g. heart rate or bi-polar disease monitoring or sensors
  • New Theoretical Approaches – Dynamic Indicators of Resilience
Resilience in unstable journeys with risk of PAH

• HLCC Chronic Care Links - empirical algorithms based on literature and data analytics predicts unstable journeys with risk of PAH
  • Strengths – real world predictions, adaptable with feedback, have access to live information; opportunities to link with other data sets e.g. MBS, myhealthrecord, GP notes or other indicators e.g. Charlson Index
  • Weaknesses – local variation hospital ecosystems e.g. Dandenong vs E. Grampians or Clayton; coarse-grained at individual journey or local small area
  • Opportunities to stratify subgroups in HLCC based on needs if useful?
    • Disease type, Frailty, Chronic Pain, End of life, Alcohol and/or Drug dependence, Mental illness, live alone, poverty?
    • Scales – Frailty, SF-12, CD_res_score, QOL, Compliance??, Impactability??
Monitoring unstable journeys

Monitoring journeys – lots of potential IT options

• Community care and primary care REQUIRE TIMELY TOUCH POINTS* between contacts – expensive in professional-time

• Telehealth – monitoring biometrics eg HR useful but limited real world uptake outside specific diseases at present

• Smart phones still developing for self-monitoring eg psychosis, alcohol

*2-3 days lead time to provide broad contextual information across multiple potential triggers or challenges.
Health journey analytics ongoing

How to individualise/personalise alerts for each individual?

How to cluster different capacity for engagement and impactibility in groups?

How to utilise call data recordings?

How to make contact more natural?

How to ensure quality in scaled up services with respect to CG’s, coaches and local services?

How to utilise other technologies – e.g. video, smart phones and sensors?