A Process Cube based Approach of Process Mining in Analysing Frailty Progression Exploiting Electronic Frailty Index

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Abstract: Process mining is a data analytics technique that is used in healthcare to develop insights into care processes, care pathways and disease progression using event data extracted from Health Information Systems. The most widely used application is process discovery where models of healthcare processes are automatically inferred and visualized. These have been applied to frailty, a common geriatric condition in elderly people typically described in terms of progression through a number of stages. In this paper we use the Electronic Frailty Index which is calculated using 36 indicators of frailty deficits. We use process mining to analyse frailty progression using data from the SystmOne GP system used in UK primary care. We propose an approach for analysing frailty progression using a process cube analysis through slicing and dicing sets of attributes related to clinical frailty events. Different combinations of process cube dimensions allow us to model and analyse a comprehensible frailty progression. We illustrate the method through a case study investigating the association between frailty stages and three common issues; falls, hypertension and polypharmacy.

1 INTRODUCTION

Frailty affects us all. In the UK frailty is recognised as a geriatric condition affecting 26% of people over 85 (Clegg *et al.*, 2013). With an aging global population, the impact of frailty on elderly people, their families and society has attracted the attention of researchers. Frailty affects health outcomes, quality of life as well as rising costs associated with healthcare and the support required for daily living (Han *et al.*, 2019).

Frailty is often described in terms of an accumulation of health characteristics, called deficits, that reduce physical capability (Clegg and Young, 2011; Xue, 2011). As physiological functions of the body decline the body is more susceptible to internal and external events that can further worsen the condition. As a result, frailty leads to an increase risk of hospital admissions, institutionalisation, dependency and other adverse health consequences (Fried *et al.*, 2004).

Process mining is a data analytics technique that is used in healthcare to develop insights into care processes, care pathways and disease progression using event data extracted from Health Information Systems (HIS). The three types of process mining are process discovery, which reveals how processes occurs; conformance checking, identifying differences between models of the process and the data from actual events; and process enhancement, which includes steps to improve the actual process (van der Aalst, 2016). Process mining can be seen as the overlap between the two disciplines of data mining and process analysis (van der Aalst, 2011). Example applications of process mining in healthcare include patient safety, process improvement and exploration of care pathways (Mans *et al.*, 2013; Kurniati *et al.*, 2020; Kusuma *et al.*, 2020). In earlier work we investigated applications of process mining to frailty and identified a limited literature base and opportunities to help better understand frailty progression through the use of routine healthcare data (Farid *et al*., 2019). In this paper we develop a method

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suitable for understanding frailty progression and illustrate the method through a case study investigating the association between frailty stages and three common issues: falls, hypertension and polypharmacy.

2 BACKGROUND

2.1 Process Mining

Patient level information about the delivery of healthcare, treatments and outcomes encoded within HIS can be used to identify common patterns that can be used to generate insights to inform practitioners, healthcare providers and health informatics research. Process mining applies this process-based approach by using a log of relevant events extracted from HIS. Three types of process mining are common: i) *process discovery*, to create process models from the log of events, ii) *conformance checking* to ensure the model produced is highly representative of the log and iii) *enhancement*, steps taken to improve the process (van der Aalst, 2016).

2.2 Process Cube

Process mining can be extended with the concept of process cubes used to scope and organise event data based on classic Online Analytical Processing (OLAP) procedures including dice, slice, drill down and roll up (van der Aalst, 2013). Process cubes are used to characterise large datasets where each dimension is linked to properties of patients and events. In our analysis we used gender, time (in one-year increments) and a range of clinical concepts. Figure 1 shows the view of our process structure with three dimensions.

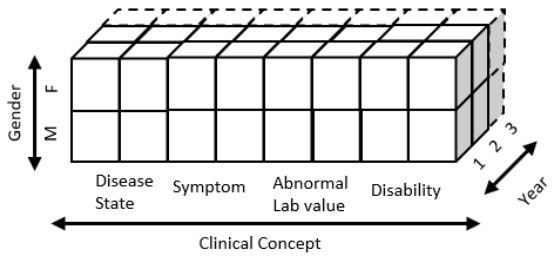


Figure 1: Structure of the process cube for the dataset.

The four common process cube operations following the standard OLAP procedures are slice, dice, drill down and roll up. Slice operations select parts of the values from a dimension while eliminating the dimension from the sub-cube. The second operation, dice is like a slice operation without removing any dimensions from the process cube. Drill down and roll up are operations that deal with changing the level of a dimension's granularity.

2.3 Frailty in Elderly People

Even though frailty is common in elderly people and associated with natural aging, it is not an unavoidable process. Frailty is recognised as a dynamic process where the people transition from fit to moderate frailty and to more advanced frail states over time (Gill *et al.*, 2006; Lang *et al.*, 2009). Frailty is generally seen as a trajectory with progression highly likely to end in a frail state (Setiati *et al.*, 2019). However, frailty progression varies widely between individuals, their health and their circumstance and understanding this complex variation is imperative. An improved understanding of frailty progression may help clinicians identify those at high risk of deterioration and to develop effective intervention plans.

2.3.1 Electronic Frailty Index

A variety of frailty assessment tools have been developed with supporting guidance and resources including PRISMA-7, Tillburg Frailty Indicator, SHARE-FI (Pialoux, Goyard and Lesourd, 2012) and the Electronic Frailty Index (eFI) (Clegg *et al.*, 2016). The eFI has now been adopted across UK primary care settings and is embedded within General Practitioner (GP) primary care systems such as SystmOne, it is in regular use by GPs to assess the level of frailty and is calculated automatically using data from the patient's record (Lansbury *et al.*, 2017).

2.4 Related Work

Disease progression, also known as disease trajectory, has been modelled effectively as a network graph where nodes represent the first report of a disease and edges show the direction (trajectory) of disease progression (Pescosolido, 2013; Jensen *et al.*, 2014). The practicality of applying process mining to study disease progression has been demonstrated by (De Toledo *et al.*, 2019) and (Kusuma *et al.*, 2020). However, work on frailty progression based on the clinical assessment and/or demographics records have not utilised process mining techniques so far (Chamberlain *et al.*, 2016; Rogers *et al.*, 2017; Verghese *et al.*, 2021). While these works analyse

disease patterns, no performance indicators such as intervals between disease progress were discussed.

3 METHODOLOGY

Process Mining Project Methodology (PM2) is the general methodology used to conduct this work (Van Eck *et al.*, 2015). It comprises of six phases. The focus of work is established by creating research questions as a guideline in phase (I) planning. In phase (II) data extraction is done by selecting appropriate event data and defining a scope of work. Next, data processing and transformation in phase (III) is performed in refining the data to create event logs in next phase (IV) of mining and analysis. The evaluation phase (V) is done by diagnosing and verifying the work findings. The last phase (VI) process improvement and support was not relevant to this work. Several iterations were done involving the last three phases of the methodology. These included the implementation of two process cube operations in different iterations.

4 CASE STUDY

The dataset used as our case study is from General Practices from the city of Bradford in West Yorkshire, England. The primary care professionals use SystmOne to record clinical findings during consultation which includes history, symptoms, diagnosis, observations, referrals, and treatments. The case study following the PM2 methodology explained in previous section, the activities executed at each stage are described below.

4.1 Phase I: Planning

The planning phase involved developing the research questions to explore frailty progression. They were derived from a review of previous studies and confirmed by clinical domain experts working in frailty care in the local region. The domain experts identified three commonly acknowledged clinical problems with frailty progression which are hypertension, falls and polypharmacy. Our aim was to determine the association between frailty stages with these areas of concern. The research questions were:

RQ1) Can process mining detect and quantify the differences in frailty progression?

RQ2) Is it possible to uncover the differences in sequence of deficits of concern using process mining?

RQ3) Can process mining determine variations between patterns of concern?

4.2 Phase II: Extraction

Anonymised patient record data was extracted by the connected Bradford research data service www.bradfordresearch.nhs.uk/our-research-teams/connected-bradford/ Data was extracted from the SystmOne electronic health care record system for participating GP practices and loaded into an SQL server database management system for analysis. The extract covered Electronic Health Records (EHR) from elderly patients aged 65 years for a period of 1 January 2003 until 31 August 2018. Data for 86,919 elderly patients with over 2 million events records were extracted.

Three inclusion criteria were employed to obtain a patient cohort appropriate for the work. The first criterion was to include patients who had at least one year's data within the dataset, the second was for patients aged over 84 years with their final frailty category in the middle or later stage of frailty, and the third inclusion criterion was the maximum average of frailty deficits accumulation is three in a year. The last inclusion criterion follows Bartosch, McGuigan and Akesson (2018) who found that most frail elderly people experienced about 6%-7% of deficits increment in a year. This phase identified two cohorts of patient with three deficits of concern (n = 8,547) and without (n = 3,848).

4.3 Phase III: Data Processing and Transformation

The third phase of this work involved the preparation of event logs suitable for loading into process mining tools. The processing step included creating views based on the structure of data and research aim to investigate the association between frailty progression and deficits of concern. Other data processing and transformation steps includes frailty index score identification at each visit to General Practice, log enriching and securing the sequence of the events that shared similar timestamp details. Each of the transformation steps are explained as follows:

- *Calculation of Electronic Frailty Index (eFI) score* - Frailty scores were determined at every visit that the patient made to the General Practice based on those frailty deficits identified at the time of the visit.

- *Log Enriching* – Following Clegg et al. (2016) frailty is classified into four stages known as fit (0 – 4 deficits), mild (5 – 8 deficits), moderate (9 – 12 deficits), and severe (13 or more deficits). The log was enriched by creating additional events for the transition between each stage.
- *Securing the Events Sequence* – Where the transition to a new frailty stage has the same timestamp as a frailty deficit the order is assumed to be frailty stage first. In this work, only the first occurrence of deficits associated with frailty are considered.

We used the commercial process mining tool Fluxicon Disco (https://fluxicon.com/disco) and the popular open-source tool ProM (https://www.promtools.org). The processed event logs of the two cohorts were loaded into the process mining tools to produce visual models of frailty progression.

4.4 Phase IV: Mining and Analysis

The fourth phase involves process mining and analytical techniques implemented on the patient cohorts during the mining and analysis. Control-flow and time are two process mining perspectives applied in this work. In addition to process mining techniques using process cube and variant analysis, an analytical technique is performed to analyse the frailty progression. Process mining and analytical techniques will be discussed in detail below.

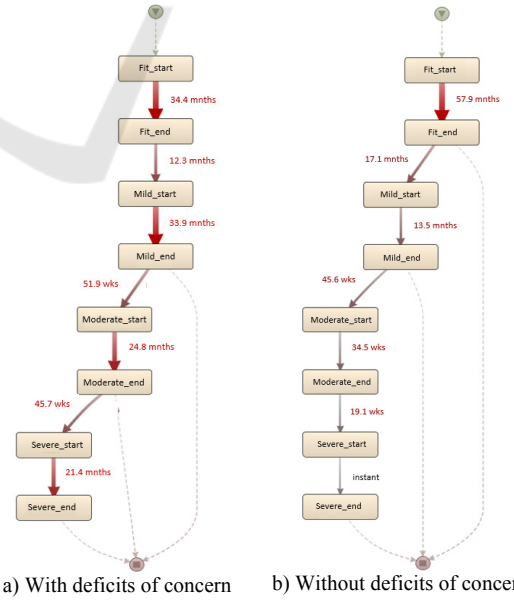
4.4.1 Process Cube based Analysis

A process cube based analysis is implemented to produce a simplified and understandable process models for frailty progression. The dice operation of process cube techniques was applied where we only consider the dimension of clinical concepts. The traces to create event log are retrieved from the attributes of events and frailty stages. Table 1 shows the descriptive statistics generated from the process cube of one dimension; a) sub-cohort with the deficits of concern and b) sub-cohort without the deficits of concern.Table 1 shows the measurement values for conformance checking produced using the plugin in ProM called *Replay a Log on Petri Net for Conformance Analysis* and *Measure Precision and Generalization*. Fitness measures how much the model allows behaviour recorded in the event log, precision measures the behaviour allowed in the model but not being expressed in the event log, lastly generalization measures the future behaviour expressed by the process model (Buijs, van Dongen and van der Aalst, 2012). Both models are highly representative from the event logs, and high precision indicate that models only represent behaviour of the event log. Furthermore, generalization (0.53, out of 1) in the model without deficits of concern is medium which demonstrates medium possibility for it to accept behaviour that does not present in the log.

Table 1: The descriptive statistics of two sub-cohorts following one dimension of process cube.

	Cohort *a*	Cohort *b*
# patients	8,547	3,848
# events	30,754	5,385
Events per patient	3.6 (~4)	1.4 (~1)
Trace Fitness	0.96	1.00
Precision	1.00	1.00
Generalisation	0.77	0.53

The process discovery of sub-cohorts is illustrated in Figure 2 using the performance view of Disco. The thickness of the edges indicates the longer mean duration within frailty stages or transition points. The transition point is defined as the interval between end of current frailty stage to the start of the next frailty stage. The transition point from fit stage to mild stage is recognised as point 1, from mild to moderate stage is point 2 and point 3 is from moderate to severe stage. It is observed that mean duration is shorter in Figure 2(b) within both frailty stage and transition point, except for the fit frailty stage.



a) With deficits of concern b) Without deficits of concern

Figure 2: Process models generated from Disco with mean duration executed in between activities.

The evaluation of duration distributions of frailty stages and transition points were computed using the independent *t*-test. The general hypothesis is that time taken to reach the subsequent stages is influenced by the presence of deficits of concern

Table 2: The descriptive statistics in segments of stages with highlighted cells showing statistical significance between sub-cohorts.

Frailty Stages	Cohort *a*	Cohort *b*	*p*-value
	Median Duration (IQR) in months		
Fit	26.6 (13.3 - 47.1) *N* = 8,547	**46.6 (25.0 - 81.9)** *N* = 3,848	**0.00**
Mild	**27.8 (14.3 - 47.8)** *N* = 8,514	1.0 (0 - 18.6) *N* = 1,432	**0.00**
Moderate	**19.2 (5.8 - 36.3)** *N* = 7,023	0.0 (0.0 – 9.9) *N* = 101	**0.00**
Severe	11.1 (0.0 – 33.7) *N* = 3,335	0.0 (0.0 – 0.0) *N* = 2	0.25
Transition Point	Median Duration (IQR) in months		*p*-value
1	7.0 (2.1 – 16.6) *N* = 8,514	**9.0 (2.6 – 23.6)** ***N* = 1,432**	**0.00**
2	6.7 (2.0 – 16.5) *N* = 7,023	5.5 (1.7 – 14.6) *N* = 101	0.32
3	6.0 (1.9 – 14.6) *N* = 3,335	4.4 (3.6 – 5.2) *N* = 2	0.49

Table 2 demonstrates numerical measurements of two sub-cohorts comprises of median duration between segments of stages with the Interquartile Range (IQR) at 25% and 75%. The statistical significance component is highlighted in Table 2 using a chosen p-value of less than 0.05. It defined by the time taken to reach the subsequent stages from current stage. In segment I (Fit) the duration is between the start of the fit to the end of the fit stage, segment II (Mild) between the start of the mild to the end of the mild stage, segment III (Moderate) between the start of the moderate to the end of the moderate and the last segment IV (Severe) is between the start to the end of severe stage.

The comparison between sub-cohorts in general showed statistically significant differences in frailty stages of fit, mild, and moderate. Whereas transition point 1 is the only statistically significant difference found between sub-cohorts. It is observed that the duration is longer in sub-cohort *b* at mild and moderate stage, while sub-cohort *a* experienced a longer duration in the fit stage.

4.4.2 Variant Analysis

The association between the deficits of concern is further investigated using different process cube operations. A slice operation is implemented to pick specific value as the attributes from selected dimension of cube. The disease state of clinical concept is chosen where the value of attributes are the deficits of concern.

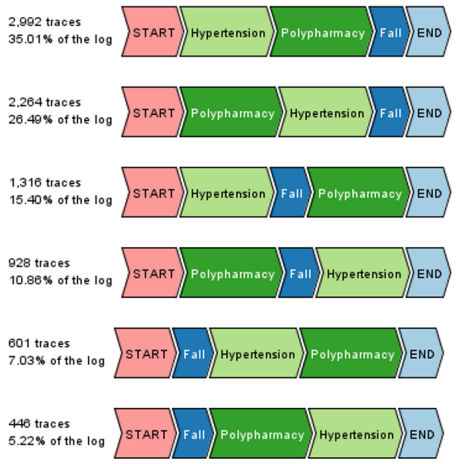


Figure 3: Trace variants with the deficits of concern generated from the ProM.

Figure 3 shows the trace variant from the sub-cohort with deficits of concern. The goal of trace variant analysis is to generate the pattern of sequence between deficits fall, hypertension and polypharmacy. It reveals that the trace variants follow three distinct patterns based on when an elderly person has their first fall event. The dominant pattern is that a fall happens after both hypertension and polypharmacy occurred (61%), while the second most common pattern is that a fall is recorded in between hypertension and polypharmacy (23%) and third pattern is that a fall precedes hypertension and polypharmacy (16%).

Table 3: The descriptive statistics of pattern of sequence. The duration of y value indicates year and m indicates month. *PoS is for Pattern of Sequence.

PoS*	# Cases	Case Portion	Mean Case duration	Median Case Duration [IQR]
I	5,256	F: 60 Mi: 815 Mo: 2,190 Se: 2,236	10y, 6m	11y,1m [8y,1m – 13y,6m]
II	2,244	F: 9 Mi: 464 Mo: 1,004 Se: 767	9y, 10m	10y,2m [7y,2m – 12y,9m]
III	1,047	F: 9 Mi: 212 Mo: 494 Se: 332	9y, 6m	10y,0m [6y,6m – 12y,5m]

The statistical significance difference test is assessed on case duration of all three patterns of sequence using Analysis of Variance (ANOVA).

Next, post-hoc test, Tukey significant difference is conducted to find which pattern is different. The hypothesis to test if there is difference among patterns of sequence with case duration.

Table 3 shows three patterns of sequence derived from trace variant 1 and 2 (from Figure 3) for pattern of sequence I, trace variant 3 and 4 for pattern of sequence II and last two variants from Figure 3 for pattern of sequence III. The case portion column presents the acronym for a patient in the fit category as 'F', in the mild category as 'Mi', in the moderate category as 'Mo' and in the severe category as 'Se'.

The general observation between the three process models is that the combination of an individual deficit of hypertension and/or polypharmacy usually happened before reaching the Mild frailty stage. Though, it occurred only in pattern of sequence I and II (from Figure 3 and 4), it is affecting about 84% of cases from sub-cohort *a*.

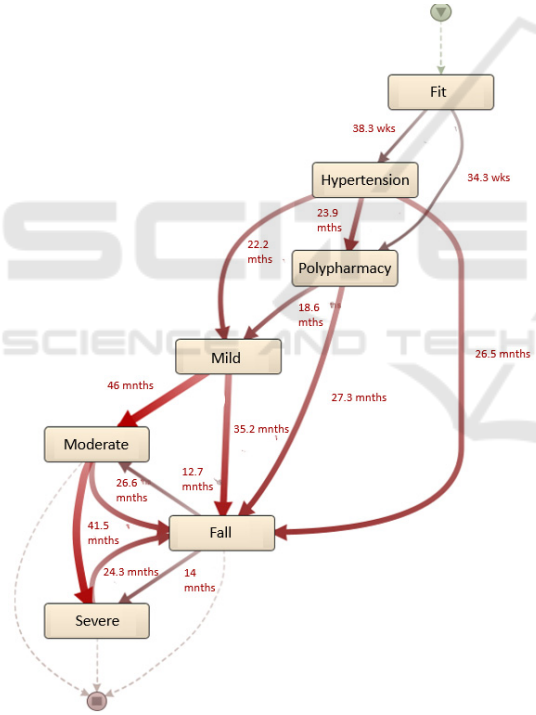


Figure 4: Process model from Pattern of Sequence I.

On the other hand, the difference that we can observe based on 50% frequent path illustrated from three patterns in Figure 4-6 is that a fall occurred before reaching the initial frailty stage for pattern of sequence II (Figure 5) and III (Figure 6). While a fall in pattern sequence I (Figure 4) commonly happened after reaching mild stage. Furthermore, it appears that the average duration of reaching the final frailty stages is shortest in pattern of sequence I (Figure 4).

It took about 14 months to enter the final frailty stage, severe. The transition to severe stage is observed after a fall had occurred. Meanwhile, in pattern of sequence II (Figure 5) the average duration (43.6 months) to reach the severe stage is longer than pattern of sequence III in Figure 6 (42.5 months).

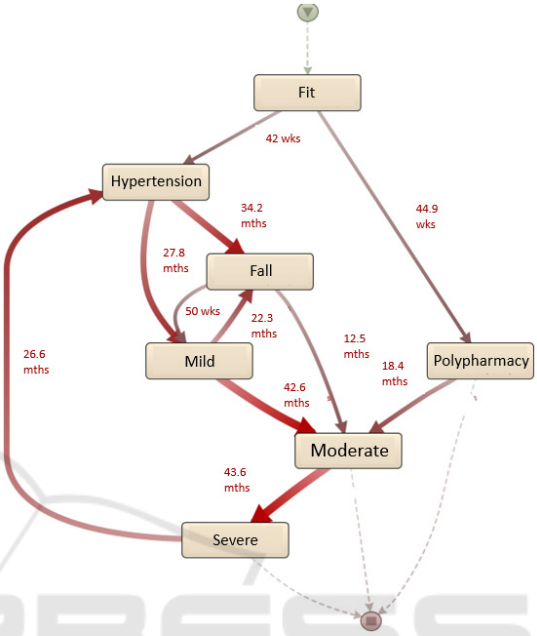


Figure 5: Process model from Pattern of Sequence II.

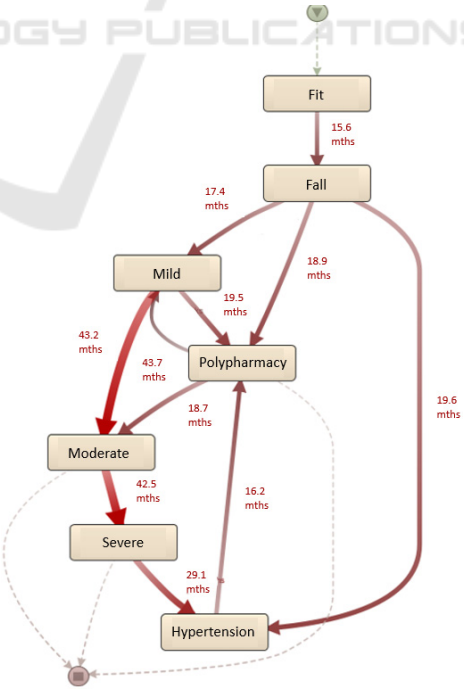


Figure 6: Process model from Pattern of Sequence III.

Although the pattern of sequence I has the longest mean and median case duration, the elderly patients with this pattern of sequence experienced quicker change to the severe frailty stage.

4.5 Phase V: Evaluation

The last phase is evaluation with the goal to evaluate the feasibility of the approach taken in the work. The results from the implementation of a process cube and descriptive statistical analysis produced insight on the variation of frailty progression towards deficits of concern. The RQ1 acts as a baseline in driving the rest of the work to achieve the aim of incorporating the process cube and variant analysis. Furthermore, discussions with domain experts at the early stage of work helped us focus on the critical matters underlying frailty progression in elderly.

Based on the observation from process models (Figure 3-5), pattern of sequence I recorded the longest case duration but with the shortest interval to reach the severe frailty stage. It suggests that patients with the pattern of sequence I are becoming severe more quickly especially when a fall occurred after reaching the moderate frailty stage. Apart from that, longest mean case duration recorded for patient with pattern of sequence I as a high proportion of patients (43%) have their final frailty stage as severe, in Table 3 compared to pattern of sequence II (34%) and III (32%). This reflects findings that patients with severe frailty are at greater risk of hospital admission and longer duration of hospital stays (Clegg *et al.*, 2016). These factors contribute to the increased mean case duration within the study period.

5 DISCUSSION AND LIMITATIONS

This work explored the association of deficits of concern with frailty progression. Falls, hypertension, and polypharmacy are deficits of concern and three widely known issues prevalent in the elderly. The implementation of process cube for exploiting the slicing operation found variations in frailty progression between cohorts of patient with and without deficits of concern which answered RQ1. The approach enabled analysis of progression at each frailty stage, and this was illustrated using process models. The slicing operation supports filtering based on specific values within a dimension to discover sequences for the deficits of concern. Trace variant analysis identified patterns that addressed RQ2. The relationship between falls, hypertension and polypharmacy was explored. RQ3 is answered by comparative analysis from the process models. Statistical analysis supports the findings.

This is the first study which includes process mining techniques to determine the association of frailty progression with deficits of concern. Polypharmacy often appears in the initial stage of frailty suggesting that it could possibly correlate with early frailty progression from fit to mild. While we can identify correlations, we should be cautious of making causal assumptions, it may be worsening frailty that leads to polypharmacy. On the other hand, there is anecdotal evidence from clinical domain experts that polypharmacy may be a risk factor for falls. One limitation with the eFI method is that, once a deficit has occurred once, it is permanently identified as a deficit so reducing polypharmacy would not reduce the eFI score. The eFI score is a useful tool to indicate frailty but it is not a definitive assessment of a patient's true condition.

6 CONCLUSIONS AND FUTURE WORK

We have established an approach for exploring the association between frailty progression and three deficits of concern: falls, hypertension and polypharmacy using process mining techniques and routine patient records data from primary care. The approach comprises of analysis based on process cubes and trace variant analysis to explore the sequence of deficits of concern and identify emerging patterns of frailty progression. This study contributes insights for the process mining community and practitioners within frailty domain.

While a process and data driven approach has been our focus in this work, future work is needed to explore the interaction of frailty progression with the presence of polypharmacy at multiple points along study duration. To achieve this, a more extensive process mining and statistical investigation is required.

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researchers. IRAS ID: 227117 REC reference: 17/EM/0254.

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