Profiling unmet post–acute care needs of an inpatient population in Hong Kong: can real-world data and machine learning algorithms bring precision to tertiary prevention in the community?

Eman Leung, Jingjing Guan, Frank Youhua Chen, Sam CC Ching, Hector Tsang, Martin CS Wong, Olivia Lam, Yinan He, Sarah TY Yau, Yilin Liu, CB Law, NY Chan, YF Wong, YH Chow, CT Hung, EK Yeoh, Albert Lee *

A B S T R A C T

Introduction: Case-mix systems aim to optimise acute care resource allocation, yet patients within the same groups often exhibit substantial variability in utilisation. This study aimed to examine how incorporating measures of clinical complexity and post–acute care utilisation—both critical to rehospitalisation risk and accurate resource planning—into case-mix stratification could improve the precision of acute care resource allocation.

Methods: Through iterative applications of unsupervised and supervised machine learning models, we extracted typical patient profiles from the study populations, analysed post–acute care utilisation patterns, and assessed the 28-day rehospitalisation rates resulting from different pairings between clinical profiles and post–acute care service utilisation patterns.

Results: Across various disease systems and age-groups, patients discharged without receiving algorithm-selected post–acute care (ie, No Service groups [NS groups]) showed significantly higher 28-day rehospitalisation rates relative to their corresponding segments in the same medoid case-mix groups (CMGs; pooled odds ratio [OR]=19.27; P<0.001). The NS groups also demonstrated higher rates of having two or more chronic diseases (pooled OR=1.84; P<0.001) and—for the 50-64–year-old population—resource-intensifying co-morbidities (pooled OR=1.23; P=0.05). Patients displaying higher rates of resource-intensifying co-morbidities compared with their ≥65-year-old counterparts (such as when the medoid CMG was renal failure or chronic obstructive pulmonary disease) also exhibited significantly higher 28-day rehospitalisation rates than the ≥65–year-old NS groups sharing the same medoid CMGs.

Conclusion: These findings support a precision-driven approach to designing rehospitalisation prevention programmes that target individuals aged 50 to 64 years discharged with specific clinical profiles, and developing and allocating human capital for these targeted prevention programmes.

Hong Kong Med J 2025;31:462–73
https://doi.org/10.12809/hkmj2411474

[1,2] **E Leung,** PhD
[3] **J Guan,** PhD
[1] **FY Chen,** PhD
[2] **SCC Ching,** BBA
[4] **H Tsang,** PhD
[2] **MCS Wong,** MD, FHKAM (Family Medicine)
[2] **O Lam,** MPH
[2] **Y He,** MPH
[2] **STY Yau,** MPH
[2] **Y Liu,** MPH
[5] **CB Law,** MB, BS
[5] **NY Chan,** MB, BS
[5] **YF Wong,** PhD
[6] **YH Chow,** BSocSc
[2] **CT Hung,** FHKAM (Anaesthesiology)
[2] **EK Yeoh,** FHKAM (Medicine)
[2,4,7] **A Lee *,** MD, FHKAM (Family Medicine)

[1] *Department of Management Sciences, City University of Hong Kong, Hong Kong SAR, China*
[2] *The Jockey Club School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong SAR, China*
[3] *EpitelligenceHK, Hong Kong SAR, China*
[4] *Department of Rehabilitation Science, Hong Kong Polytechnic University, Hong Kong SAR, China*
[5] *Kowloon West Cluster, Princess Margaret Hospital and North Lantau Hospital, Hong Kong SAR, China*
[6] *Kwai Tsing Safe Community and Healthy City Association, Hong Kong SAR, China*
[7] *Centre for Health Education and Health Promotion, The Jockey Club School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong SAR, China*

* Corresponding author: alee@cuhk.edu.hk

香港入院患者未獲滿足的急性期後護理概況：真實數據及機器學習演算法能否精準幫助社區三級預防？

梁以文、關菁菁、陳友華、程俊翔、曾永康、黃至生、林芷而、赫軼男、邱芷蕊、劉依林、羅振邦、陳藝賢、黃玉芳、周奕希、熊志添、楊永強、李大拔

引言：病例組系統旨在優化急症護理資源分配，惟同一病例組內患者的資源使用情況往往存在明顯差異。本研究旨在探討於病例組分層中納入臨床複雜度及急性期後護理使用情況這兩項對再入院風險及資源規劃準確度均具關鍵影響的指標，能否提高急症護理資源分配的精準度。

方法：本研究透過反覆運用非監督及監督式機器學習模型，從研究群組中擷取典型患者概況，分析急性期後護理服務的使用模式，並評估不同臨床概況與急性期後護理服務使用組合所產生的28天再入院率。

結果：在不同疾病系統及年齡層中，出院時未獲演算法選定的急性期後護理患者（即無服務組）的28天再入院率，顯著高於其所屬中位病例組內相應分段的患者為高（合併比值比=19.27；P<0.001）。無服務組中同時患有兩種或以上慢性疾病的比例亦較高（合併比值比=1.84；P<0.001），而在50至64歲群組中，無服務組出現高資源需求共病的比率亦較其相應分段為高（合併比值比=1.23；P=0.05）。在若干中位病例組配對中（例如中位病例組為腎衰竭或慢性阻塞性肺病時），50至64歲無服務組患者不僅有較高的高資源需求共病比率，其28天再入院率亦顯著高於同屬該病例組的65歲或以上無服務組患者。

結論：本研究結果支持以精準為導向的策略，包括針對具有特定臨床概況的50至64歲出院患者設計再入院預防計劃，以及按此等目標性預防計劃的群組特徵培訓及分配所需的人力資源。

Introduction

To standardise clinical practices and inform targeted policy decisions, major health systems segment their populations into case-mix groups (CMGs). With expert input and analytical methods, CMGs are designed with optimal granularity—balancing individual-level clinical care decisions and population-level acute care resource allocation[1]—and judicious parsimony, selecting indicators from the wealth of information extracted from patient electronic health records (see online supplementary Table 1 for a comparison of major healthcare systems' case-mix frameworks).

However, clinical case-mix systems often provide imperfect estimations of their populations' acute care utilisation.[2-4] It has been suggested that critical drivers of acute care admissions and 28-day rehospitalisations, such as clinical complexity,[5,6] are not often included as indicators for stratifying patients. Also, the linkage between case mixes of populations and their respective post–acute care (PAC) needs has not been established, although PAC can reduce rehospitalisations and mitigate the rehospitalisation risk associated with clinical complexity.[7] In fact, not only have the PAC needs of patients discharged under various case-mix classifications remained unexplored, but studies examining the effects of PAC on acute care utilisation often fail to consider the diversity of PAC service types[8,9] and their differential effects on patients with distinct clinical profiles.[10-12]

Therefore, this study aimed to identify the factors contributing to the discrepancy between the objectives of case-mix systems—optimising the efficient allocation of acute care resources—and the observed heterogeneity in acute care utilisation among patients within the same CMGs. Specifically, although clinical complexity and PAC utilisation influence the rehospitalisation risk of discharged patients—which in turn affects the accuracy of population-level acute care resource planning—they are not typically included in case-mix systems for patient stratification. Thus, we examined the heterogeneity and relationships among clinical complexity, PAC utilisation, and rehospitalisation risk within homogeneous patient segments. These segments were partitioned from the study population using conventional case-mix parameters and acute care utilisation metrics. Given this context, we hypothesised that among patients within the same homogeneous segments, those who did

New knowledge added by this study

- Our novel machine learning analyses revealed that ambulatory care–sensitive conditions such as chronic obstructive pulmonary disease and general digestive symptoms were the diagnoses received by patients who were 'typical' (ie, the medoid) of the studied inpatient population and its subpopulations of patients with unmet post–acute care needs.
- Higher proportions of patients aged 50 to 64 years in the subpopulations had histories of two or more chronic illnesses prior to the index hospitalisation, had resource-intensifying co-morbidities at the index hospitalisation, and rehospitalised within 28 days after being discharged.

Implications for clinical practice or policy

- Tertiary prevention programmes targeting specific profiles of individuals aged 50 to 64 years who are discharged into the community can help relieve the burden on hospital services.
- The integration of post–acute care utilisation data and clinical complexity indicators into population stratification can improve the precision of tertiary prevention planning and resource allocation across community and hospital settings.

not receive effective PAC would exhibit the highest rates of 28-day rehospitalisation. Additionally, we hypothesised that greater clinical complexity would increase the likelihood of rehospitalisation occurring before receipt of any effective PAC.

Methods

Study population

In this study of an inpatient population of 197 805 individuals (aged >50 years) discharged into the community, a combination of unsupervised and supervised learning algorithms was deployed (Fig 1). First, unsupervised learning algorithms were applied to identify typical patients (ie, medoids) using a comprehensive set of clinical parameters (including discharged patients' CMGs) and acute care utilisation data.[13] Patients similar to typical patients in terms of these parameters were clustered into the same segments. Each resulting segment was labelled according to the Major Clinical Category (MCC)[13] assigned to its medoid. According to case-mix methodologies adopted by major healthcare systems (eg, CMG+ of Canada[13]), the MCC reflects the primary body system or medical specialty involved and provides a high-level overview of the patient's condition. Within each MCC, patients are further classified into more specific CMGs based on detailed clinical and resource utilisation characteristics. We therefore expected that patients within the same segment would share the same MCC as the medoid, although their CMGs might differ. Consequently, each segment was labelled with the medoid's MCC. The International Classification of Diseases codes constituting each CMG and the corresponding MCC for each are shown in online supplementary Table 2.

Study design

Second, with additional features representing the types and timing of PAC service utilisation, 28-day rehospitalisation outcome–supervised machine learning algorithms (Unbiased Recursive Partitioning with Surrogate Splitting [URPSS][14]) were applied to recursively partition clinically homogeneous segments into subpopulations, each characterised by homogeneous PAC utilisation. The URPSS has previously been used to compare the effects of clinical profiles and acute care utilisation on 28-day rehospitalisations with those of different PAC service types, isolating the unique contribution of patients' clinical and acute care factors.[15] In this study, we adopted a complementary approach by isolating each PAC service type's unique contribution to 28-day rehospitalisation while adjusting for the influence of the end user's clinical profile and acute care utilisation. To achieve this approach, we

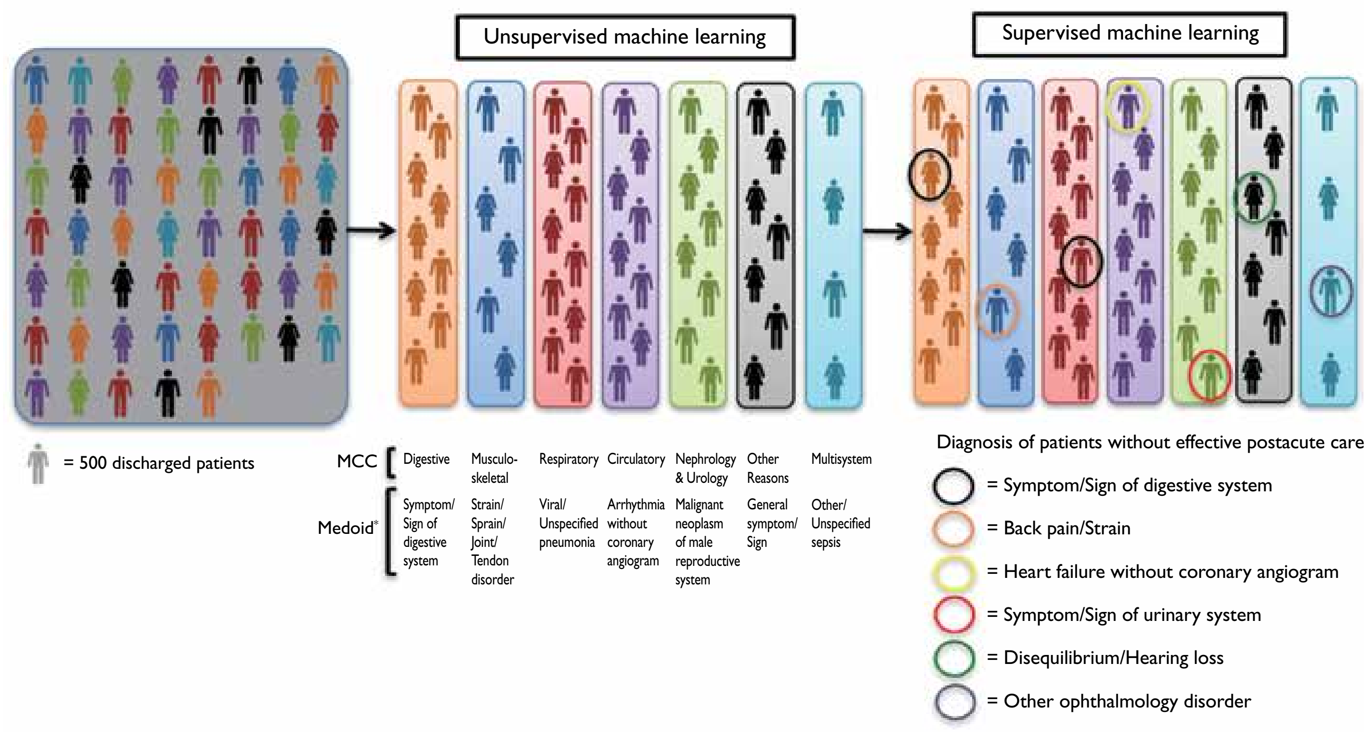

FIG 1. Methodology
Abbreviation: MCC = Major Clinical Categories
* Representative diagnosis in the segment

first partitioned the population into segments with homogeneous clinical and acute care utilisation profiles. Within each segment, the URPSS algorithm was then applied to infer the effects of PAC on 28-day rehospitalisation, contingent on patients' clinical and acute care characteristics. A detailed description of the hybrid machine learning approach used to disentangle post-acute from acute influences is provided in the online Appendix.[14-16]

Among the different subpopulations partitioned from each segment, one inevitably remained unpartitioned by any feature representing the PAC services for which the algorithm found significant conditional inferences on 28-day rehospitalisation. We hypothesised that this unpartitioned subpopulation—representing patients whose acute care needs (as reflected by the comprehensive segmenting features of clinical and acute care utilisation parameters) were homogeneous with others in the same segment but who lacked any 28-day rehospitalisation–mitigating PAC services—would exhibit the highest clinical complexity and 28-day rehospitalisation rates. These groups of discharged patients, whose rehospitalisation risk was high but who lacked algorithm-selected PAC services, are hereafter referred to as the No Service groups (NS groups).

In conjunction with the 28-day rehospitalisation rate, the prevalence of clinical complexity—reflected by the presence of two or more chronic illnesses diagnosed prior to the index hospitalisation and by acute care resource-intensifying co-morbid diagnoses at index hospitalisation[5,6]—was also compared between the NS groups and their corresponding segments. We hypothesised that greater clinical complexity would be associated with an increased likelihood of patients being rehospitalised before receiving any effective PAC. Comparisons were also made between populations aged 50-64 years and 65 years or above. Research has shown that adults aged 50 to 64 years face unique health challenges and experience care gaps not observed among those aged 65 years or above.[16] In particular, care gaps predominantly affecting the 50-64 age-group have been linked to inaccuracies in predicting patients' acute care needs using case-mix models,[17] which were primarily developed from inpatient populations aged 65 years and older.[18-21]

Although many comparisons could be made between the NS groups and their corresponding segments across all segments partitioned from the 50-64–year-old or ≥65–year-old populations—and between the NS groups or segments of the two populations—comparisons were restricted to the NS groups and their corresponding segments that shared the same medoid CMGs, to ensure homogeneity in clinical and acute care utilisation profiles between the subgroups being compared. Similarly, comparisons between the 50-64–year-old and ≥65–year-old NS groups or between the 50-64–year-old and ≥65–year-old segments were confined to pairs with the same medoid CMGs. The odds ratios (ORs), 95% confidence intervals (95% CIs), and P values resulting from comparisons between each same-CMG pair for clinical complexity and 28-day rehospitalisation were calculated from a subset of the descriptive statistics reported in online supplementary Tables 3 (for the 50-64–year-old age-group) and 4 (for the ≥65–year-old age-group). In addition to the presence of data regarding the prevalence of clinical complexity and 28-day rehospitalisations, these supplementary tables include the comprehensive set of features that: (1) constitute the CMGs adopted in this study, (2) segment the 50-64–year-old and ≥65–year-old populations, and (3) partition each segment to identify its corresponding NS groups. These features encompass diagnoses, age, sex, resource-intensive interventions received at index acute care hospitalisation, and resource-intensifying co-morbidities diagnosed at index acute care hospitalisation. Given that the contributions of these features to clinical profile variability had already been adjusted for through multiple iterations, they were unlikely to be selected by the URPSS algorithm to split a segment into subpopulations. Our focus therefore remained on demonstrating the high prevalence of clinical complexity and 28-day rehospitalisation among the NS groups, rather than on features not selected by the URPSS.

We tested our hypotheses regarding the elevated risks of the NS groups compared with their parent segments (particularly for the 50-64–year-old population) through selected paired comparisons and omnibus testing. By aggregating results across different same-CMG pairs, we followed the standard epidemiological practice of utilising all available evidence from various subgroups within a single sample to maximise the robustness and generalisability of estimates while adjusting for inherent sample stratification.[22,23] Indeed, whereas analysis of an entire sample may overlook underlying confounding factors, a strong focus on stratified subgroup analyses can lead to misinterpretations that inflate the effects of confounding variables on outcomes and distort the relationships between risk factors and outcomes.[24,25] To quantify the likelihood of clinical complexity and 28-day rehospitalisation rates in the NS groups versus their parent segments, we pooled ORs using the Mantel-Haenszel formula[26] across same-CMG pairs within each age population and between the 50-64–year-old and ≥65–year-old populations (calculated from the ORs and associated 95% CIs and P values reported in Table 1). This approach allowed us to evaluate overall differences in co-morbidity, chronic illnesses, and 28-day rehospitalisations between age-groups and between

TABLE 1. Likelihood of study parameters in the No Service groups and 50-64–year-old population

	Medoid CMG	Likelihood of study parameters in NS groups (full segment as reference category)					
		Co-morbidity level		Chronic illnesses		28-day rehospitalisation	
		OR (95% CI)	P value	OR (95% CI)	P value	OR (95% CI)	P value
50-64 years	Inflammatory and reactive arthropathy	1.70 (1.15-2.52)	<0.001	2.16 (1.81-2.57)	<0.001	28.57 (23.90-33.94)	<0.001
	Chronic obstructive pulmonary disease	1.06 (0.82-1.38)	0.66	1.90 (1.67-2.15)	<0.001	26.43 (21.89-31.95)	<0.001
≥65 years	Chronic obstructive pulmonary disease	0.71 (0.58-0.86)	<0.001	1.62 (1.49-1.76)	<0.001	11.46 (10.37-12.67)	<0.001
	Symptom or sign of digestive system	0.50 (0.41-0.61)	<0.001	1.63 (1.49-1.79)	<0.001	19.38 (17.15-21.83)	<0.001
	Dementia	1.22 (1.00-1.48)	<0.05	2.14 (1.90-2.41)	<0.001	20.64 (17.85-23.88)	<0.001
	Medoid CMG	Likelihood of study parameters in 50-64–year-old population (≥65–year-old population as reference category)					
		Co-morbidity level		Chronic illnesses		28-day rehospitalisation	
		OR (95% CI)	P value	OR (95% CI)	P value	OR (95% CI)	P value
Full segment	Symptom or sign of digestive system	0.61 (0.56-0.66)	<0.001	0.07 (0.06-0.08)	<0.001	0.94 (0.89-0.99)	<0.001
	Chronic obstructive pulmonary disease	0.78 (0.70-0.87)	<0.001	0.32 (0.30-0.34)	<0.001	0.91 (0.85-0.96)	<0.001
	General signs or symptoms	0.38 (0.33-0.44)	<0.001	0.27 (0.25-0.29)	<0.001	0.95 (0.88-1.02)	0.13
NS group	Heart failure	0.96 (0.79-1.18)	0.71	0.39 (0.34-0.45)	<0.001	0.69 (0.59-0.82)	<0.001
	Renal	63.11 (50.26-79.38)	<0.001	0.47 (0.40-0.54)	<0.001	1.35 (1.06-1.70)	0.01
	Chronic obstructive pulmonary disease	1.17 (0.84-1.61)	0.36	0.37 (0.32-0.43)	<0.001	2.11 (1.69-2.64)	<0.001
	Disequilibrium	0.42 (0.31-0.57)	<0.001	0.34 (0.28-0.40)	<0.001	1.79 (1.45-2.22)	<0.001

Abbreviations: 95% CI = 95% confidence interval; CMG = case-mix group; NS group = No Service group; OR = odds ratio

the NS groups and their corresponding segments. The Mantel-Haenszel formula has been applied in diverse clinical contexts involving a single patient sample or population, including a targeted patient group with traumatic brain injury,[27] a regional population admitted from multiple hospitals with different major diagnoses,[28] and a case-control study combining matched and unmatched control groups.[29] Results reported below include pooled ORs, 95% CIs, P values, and, where applicable, *Q* statistics with corresponding P values to indicate significant heterogeneity among pooled ORs.

Results

Below, we describe the clinical profiles of typical patients (medoids) in the 50-64–year-old and ≥65–year-old populations and their corresponding population segments. We then report the order in which the URPSS algorithm selected PAC services based on their unique statistical importance in classifying 28-day rehospitalisation. We also characterise the clinical profiles of patients who received none of the URPSS-selected PAC services (ie, the NS groups). Finally, we compare the rates of resource-intensifying co-morbidities, the presence of two or more chronic diseases, and 28-day rehospitalisations between the NS groups and their corresponding segments, as well as between the 50-64–year-old and ≥65–year-old populations.

Profiles of typical patients and associated segments in the 50-64–year-old and ≥65–year-old populations

The Calinski–Harabasz index indicated that the optimal number of segments was seven for the 50-64–year-old population and eight for the ≥65–year-old population.[30] Our analyses revealed that the seven typical patients identified in the 50-64–year-old population belonged to the same MCCs as their counterparts in the ≥65–year-old population: Circulatory, Digestive, Nephrology and urology, Musculoskeletal, Respiratory, Multiple systems of diseases and disorders, and Other reasons for hospitalisation. Additionally, four MCCs shared between the two age-groups were characterised by identical CMGs: Symptom or sign of digestive system (Digestive), Malignant neoplasm of urinary system (Nephrology and urology), Chronic obstructive pulmonary disease (Respiratory), and General symptom or sign (Other reasons for hospitalisation). In the ≥65–year-old population, we identified an eighth segment, whose typical patient's CMG was dementia, belonging to the MCC of Diseases and disorders of the mental system.

Utilisation of post–acute care services and associated 28-day rehospitalisation rates

Tables 2 and 3 report the type, sequence (reflecting the descending rank order of marginal contribution feature importance), and associated 28-day rehospitalisation rates of each PAC service selected by the URPSS algorithm. With areas under the receiver operating characteristic curve ranging from 0.85 to 0.93, the URPSS algorithms classified 28-day rehospitalisation outcomes in every segment partitioned from the two populations using features selected for their unique contributions to outcomes. Among all features in the pool to which the URPSSs were applied (online supplementary Table 5), only PAC-related features were selected to split segments that had previously been partitioned from the population using other features (eg, sex) that were unrelated to PAC.

Our analyses revealed that, compared with all other PAC services, specialist outpatient clinics (SOPCs) had the greatest marginal contribution to 28-day rehospitalisation outcomes among patients with similar clinical profiles and acute care utilisation patterns, even after adjusting for the effects of the segments' patient clinical profiles and acute care utilisation patterns on 28-day rehospitalisations through conditional inference. Additionally, SOPCs' contribution to 28-day rehospitalisation was not conditional on the effects of other features. Consequently, the lowest 28-day rehospitalisation rates were observed among SOPC attendees across all homogeneous population segments. Nevertheless, although SOPCs had the highest marginal contribution feature importance—and were associated with the lowest 28-day rehospitalisation rates—in all segments across both populations, the 28-day rehospitalisation rates among SOPC attendees were higher in every segment of the 50-64–year-old population compared with the corresponding segments of the ≥65–year-old population (mean difference between segments with the same MCC profiles: 9.5%).

As shown in Tables 2 and 3, the 28-day rehospitalisation rates were consistently the highest among subpopulations within each segment that remained unsplit after the sequential selection and partitioning by features representing PAC services that the URPSS identified as highly important to 28-day rehospitalisation outcomes (ie, the NS groups). For example, among the 50-64–year-old population, the mean difference in 28-day rehospitalisation

TABLE 2. Sequence of services selected by Unbiased Recursive Partitioning with Surrogate Splitting and associated 28-day rehospitalisation rates in each 50-64–year-old segment*

Segment		SOPC†	PC	CONV	NTR	FUMC‡	REHAB	Day patient§	No service
Circulatory	Ranking of URPSS selection	1	NS	NS	NS	NS	NS	NS	
	Readmission rate‖	4.53%	NS	NS	NS	NS	NS	NS	80.09%
Digestive	Ranking of URPSS selection	1	4	NS	3	NS	NS	2	
	Readmission rate‖	20.60%	65.45%	NS	12.50%	NS	NS	27.27%	89.62%
Nephrology and urology	Ranking of URPSS selection	1	3	NS	2	NS	NS	4	
	Readmission rate‖	11.35%	65%	NS	15.63%	NS	NS	76.92%	100%
Musculoskeletal	Ranking of URPSS selection	1	2	NS	NS	NS	NS	NS	
	Readmission rate‖	15.88%	50%	NS	NS	NS	NS	NS	80.50%
Respiratory	Ranking of URPSS selection	1	3	NS	2	NS	NS	4	
	Readmission rate‖	23.60%	63.46%	NS	21.74%	NS	NS	52.38%	90.33%
Other reasons for hospitalisation	Ranking of URPSS selection	1	3	NS	2	NS	NS	NS	
	Readmission rate‖	17.33%	57.14%	NS	14.29%	NS	NS	NS	84.41%
Multisystem	Ranking of URPSS selection	1	NS	NS	NS	NS	NS	NS	
	Readmission rate‖	25.62%	NS	NS	NS	NS	NS	NS	83.67%

Abbreviations: CONV = convalescent inpatient service; FUMC = follow-up medical consultation; NS = not selected; NTR = nursing transitional care; PC = primary care; REHAB = Rehabilitation Day Programme; SOPC = specialist outpatient clinic

* Subgroup of patients lacking the selected acute and post-acute service

† Refers to ambulatory follow-up care

‡ Refers to follow-up care

§ Refers to acute day patient service

‖ Refers to 28-day rehospitalisation probability

TABLE 3. Sequence of services selected by Unbiased Recursive Partitioning with Surrogate Splitting and associated 28-day rehospitalisation rates in each ≥65–year-old segment*

Segment		SOPC†	PC	CONV	NTR	FUMC‡	REHAB	Day patient§	No service
Circulatory	Ranking of URPSS selection	1	NS	2	3	NS	NS	NS	
	Readmission rate‖	6.65%	NS	69.40%	48.10%	NS	NS	NS	85.60%
Digestive	Ranking of URPSS selection	1	2	NS	3	NS	NS	NS	
	Readmission rate‖	8.52%	44.30%	NS	4.80%	NS	NS	NS	84.29%
Nephrology and urology	Ranking of URPSS selection	1	2	NS	4	NS	NS	3	
	Readmission rate‖	9.97%	43.15%	NS	99.70%	NS	NS	54.47%	99.26%
Musculoskeletal	Ranking of URPSS selection	1	2	NS	3	NS	NS	NS	
	Readmission rate‖	5.72%	54.69%	NS	25.00%	NS	NS	NS	86.09%
Respiratory	Ranking of URPSS selection	1	2	NS	3	NS	NS	4	
	Readmission rate‖	9.24%	2.10%	NS	25.00%	NS	NS	62.20%	81.50%
Other reasons for hospitalisation	Ranking of URPSS selection	1	2	3	4	NS	5	6	
	Readmission rate‖	4.13%	25.71%	80.90%	67.08%	NS	42.86%	44.83%	74.72%
Multisystem	Ranking of URPSS selection	1	2	4	3	NS	NS	5	
	Readmission rate‖	8.15%	35.64%	83.56%	71.25%	NS	NS	62.79%	76.58%
Mental health	Ranking of URPSS selection	1	NS	NS	NS	2	NS	NS	
	Readmission rate‖	4.49%	NS	NS	NS	38.60%	NS	NS	82.80%

Abbreviations: CONV = convalescent inpatient service; FUMC = follow-up medical consultation; NS = not selected; NTR = nursing transitional care; PC = primary care; REHAB = Rehabilitation Day Programme; SOPC = specialist outpatient clinic

* Subgroup of patients lacking the selected acute and post-acute service

† Refers to ambulatory follow-up care

‡ Refers to follow-up care

§ Refers to acute day patient service

‖ Rate refers to 28-day rehospitalisation probability

rates between the NS groups and those in the same segments who received SOPC care (the PAC service with the greatest feature importance) was 70.01%; the mean difference between the NS groups and their corresponding full segments was 66.69%. Similarly, among the ≥65–year-old population, the mean difference between the NS groups and patients in the same segments who received SOPC care was 76.28%; the mean difference between the NS groups and their corresponding full segments was 62.26%. Notably, whereas the NS groups consistently showed the highest 28-day rehospitalisation rates among all subpopulations, the NS groups of the 50-64–year-old population exhibited a greater mean difference in 28-day rehospitalisation rates compared with their ≥65–year-old counterparts (by a mean difference of 2.99%).

Clinical complexity and 28-day rehospitalisation of the No Service groups and their corresponding segments in the populations aged 50-64 years and ≥65 years

The above analyses identified a subpopulation (ie, the NS groups) within each segment that exhibited high 28-day rehospitalisation rates but lacked effective PAC services. To provide a more in-depth understanding of the NS groups, we compared 28-day rehospitalisation rates, the prevalence of resource-intensifying co-morbidities, and the presence of two or more chronic illnesses between the NS groups and their corresponding segments, as well as between the 50-64–year-old and ≥65–year-old populations. Not all NS groups' typical patients shared the same CMGs as the medoids of their corresponding segments, nor were the same CMGs shared between the medoids of the 50-64–year-old and ≥65–year-old populations. Chronic obstructive pulmonary disease (COPD) was the only CMG consistently identified as a medoid CMG in both populations and their corresponding subpopulations. Therefore, a more detailed analysis was conducted on the segment and subpopulation with COPD CMGs to illustrate factors contributing to the differences between NS groups and their corresponding segments, and between the 50-64–year-old and ≥65–year-old populations.

Table 1 reports the ORs (and their associated 95% CIs and P values) for resource-intensifying co-morbidities, the presence of two or more chronic illnesses, and 28-day rehospitalisations of NS groups relative to their corresponding 50-64–year-old or ≥65–year-old population segments sharing the same medoid CMGs. As shown in the table, even when diseases of different systems were considered across both populations, the NS groups exhibited significantly higher rates of 28-day rehospitalisation compared with their same-medoid-CMG segments (pooled OR=19.27, 95% CI=17.86-20.79; P<0.001); they also showed a greater prevalence of having two or more chronic illnesses (pooled OR=1.84, 95% CI=1.64-2.07; P<0.001).

Although resource-intensifying co-morbidity is also a measure of clinical complexity, it was not more likely to be found among NS groups than among their same–medoid-CMG segments. Follow-up analyses revealed that the pooled OR for the ≥65–year-old population was heterogeneous (*Q* statistic=39.97, P<0.001), whereas the *Q* statistic for pooled ORs in the 50-64–year-old population was not statistically significant. Upon closer examination, the rate of resource-intensifying co-morbidity was indeed higher in NS groups of the 50-64–year-old population than in their same–medoid-CMG segments (pooled OR=1.23, 95% CI=1.00-1.52; P=0.05); it was lower in the NS group population aged ≥65 years than in their corresponding segments (pooled OR=0.76, 95% CI=0.68-0.85; P<0.001).

The observation that the 50-64–year-old population exhibits higher clinical complexity and 28-day rehospitalisation rates compared with their ≥65–year-old counterparts was directly examined among same–medoid-CMG pairs of the 50-64–year-old and ≥65–year-old population segments, as well as among pairs of NS group populations aged 50-64 years and ≥65 years (Table 1). Whereas the 50-64–year-old population showed higher rates of resource-intensifying co-morbidity and 28-day rehospitalisation compared with the ≥65–year-old population at both the segment and NS-group levels, these differences were not statistically significant (pooled ORs=1.27, 95% CI=0.55-2.93, and 1.18, 95% CI=0.84-1.65, respectively). Follow-up analysis revealed substantial heterogeneity in the pooled statistics, attributable to significant variation among the pooled ORs of NS-group pairs (*Q* statistics=7.81-9.43; all P<0.05). Follow-up segment-level analyses also showed significantly lower prevalence of all study parameters in the 50-64–year-old population compared with the ≥65–year-old population: OR=0.56 (95% CI=0.52-0.59; P<0.001), OR=0.22 (95% CI=0.20-0.24; P<0.001), and OR=0.93 (95% CI=0.89-0.96; P<0.001) for rates of resource-intensifying co-morbidity, the presence of two or more chronic illnesses, and 28-day rehospitalisation, respectively.

Given the high heterogeneity of pooled ORs for the NS-group CMG pairs, differences in the prevalence of study parameters between the 50-64–year-old and ≥65–year-old populations were examined within individual NS-group pairs. Follow-up analyses revealed that, although not all NS-group CMG pairs showed higher rates of resource-intensifying co-morbidity or 28-day rehospitalisation in the 50-64–year-old population, those that did—such as when the medoid CMG was renal failure or COPD—also showed significantly higher 28-day rehospitalisation rates compared with their ≥65–year-old counterparts sharing the same medoid CMGs. For example, in the case of renal failure, the ORs were 63.11 (95% CI=50.26-79.38; P<0.001) and 1.35 (95% CI=1.06-1.70; P=0.01) for resource-intensifying co-morbidity and 28-day rehospitalisation rates, respectively (Table 1).

Finally, to consider differences in study parameter prevalence between the NS group and its corresponding segment when comparing clinical complexity and 28-day rehospitalisation outcomes between the 50-64–year-old and ≥65–year-old populations, we examined cases in which the CMG was COPD. Chronic obstructive pulmonary disease was the only CMG that served as the medoid of both the population segment and the corresponding NS group for the 50-64–year-old and ≥65–year-old populations, allowing us to adjust for differences in study parameter prevalence between the NS group and its full segment when comparing the two age-groups. Our analyses revealed that, relative to the statistics of the full segments, the ORs for resource-intensifying co-morbidity, two or more chronic illnesses, and 28-day rehospitalisation rates were significantly greater in the 50-64–year-old NS group than in the ≥65–year-old counterparts [ratios of ORs=1.50 (95% CI=1.06-2.11; P=0.02), 1.17 (95% CI=1.01-1.37; P=0.04), and 2.34 (95% CI=1.84-2.96; P<0.001), respectively].

Discussion

Unmet post–acute care needs and age-related disparities

Patients aged 50 to 64 years who were discharged without receiving algorithm-selected PAC services (ie, the NS groups) were generally more likely to be rehospitalised within 28 days of discharge than their counterparts who shared similar clinical and acute care utilisation profiles but received such services. In some cases, the 50-64–year-old NS groups were rehospitalised at even higher rates than the ≥65–year-old NS groups. Under these circumstances, the 50-64–year-old NS groups also exhibited higher rates of resource-intensifying co-morbidity. This elevated co-morbidity among patients aged 50-64 years who experienced more frequent rehospitalisation than their ≥65–year-old counterparts was exemplified by

NS groups whose clinical and acute care utilisation profiles resembled the CMGs of typical patients with renal failure and COPD—the same CMGs characterising typical patients in the ≥65–year-old NS groups. In the case of COPD, the rates of co-morbidity, chronic illnesses, and rehospitalisation within the full segment could be directly considered when comparing the 50-64–year-old and ≥65–year-old NS groups.

Ambulatory care–sensitive case-mix profiles and preventable rehospitalisation

Similar to COPD, the majority of typical patients' CMGs in the full segments and NS groups identified in the present study were considered ambulatory care–sensitive conditions (ACSCs),[31] for which hospitalisations are potentially avoidable through timely and effective ambulatory care. Because avoidable hospitalisations among ACSC patients could be prevented with better access to ambulatory and primary care services, it has been argued that resources should be redistributed from acute care to these services.[32] Our findings provide rare empirical support for this argument. By comparing rehospitalisation rates among subpopulations of patients with homogeneous clinical profiles and acute care utilisation patterns but differing PAC assignments, we demonstrated, at a population level, the benefits of ambulatory care (eg, specialist follow-up and in-home nursing transitional care) and primary care in reducing rehospitalisation rates among typical patient profiles whose CMGs were ACSCs.

Notably, even ACSCs may progress into more acute diagnoses, with a higher likelihood of co-morbidity and elevated 28-day rehospitalisation rates. For instance, whereas Angina or Arrhythmia were the CMGs of typical patient profiles in the full patient segments of the 50-64–year-old and ≥65–year-old populations, respectively, the CMG of their NS groups' typical patient profile was Heart Failure; these patients exhibited higher rates of co-morbidities and 28-day rehospitalisation. Similarly, Digestive Malignancy was the CMG of the typical patient profile in a 50-64–year-old NS group, which showed higher rates of co-morbidities and 28-day rehospitalisation than its corresponding full patient segment, whose typical CMG was Symptom or Sign of the Digestive System.

Post-discharge service gaps and policy implications

Despite such evidence, these services remain largely unavailable for individuals in the studied populations. For example, the average wait time for SOPC appointments ranges from 9 to 111 weeks,[33] in sharp contrast to the median interval between discharge and rehospitalisation among NS patients, which is 14 days. Given the constraints on healthcare professional availability in the public sector, reducing SOPC wait times may be challenging. Therefore, by quantifying the benefits of different PAC services for various patient profiles, the findings presented here suggest the need for the following policy actions: (1) procure specialist follow-up services from the private sector and ensure effective public–private service coordination within the parallel public and private tracks of the healthcare system studied; and (2) enhance the provision of less scarce, near-equivalent alternatives available in the community, rather than relying solely on medical specialists.

Multi-morbidity in adults aged 50 to 64 years and the case for multidisciplinary tertiary prevention

In addition to the higher rehospitalisation rates identified in the present study, typical patient profiles with ACSC CMGs that lacked effective PAC services also exhibited a high prevalence of co-morbidities. The rates of co-morbidities and 28-day rehospitalisations were particularly high among individuals aged 50 to 64 years who fit these patient profiles. This finding aligns with recent studies showing that younger patients with diabetes—also a chronic ACSC—have significantly greater co-morbidities and worse outcomes than their older counterparts.[34] Furthermore, we found that younger patients not only have more complex health needs but also benefit less from conventional PAC services and are more likely to be rehospitalised before receiving ambulatory or primary care. This finding is consistent with current literature, which indicates that effective rehospitalisation prevention programmes for chronically ill patients with multiple health problems,[35] especially younger patients, require a multidisciplinary approach to address diverse needs such as smoking cessation,[36] rather than the conventional 'assess-and-advise' primary care model of rehospitalisation prevention.[37]

Indeed, most evidence supporting the benefits of multidisciplinary primary care for chronic conditions is derived from intervention studies targeting diseases that also represented the CMGs of typical patients identified in our study populations—particularly those who did not receive PAC services deemed effective in reducing 28-day rehospitalisation. For example, multidisciplinary pulmonary rehabilitation programmes, which are most effective in preventing rehospitalisation among patients with COPD, include not only clinician-led physical rehabilitation but also health-related education, advice regarding exercise programmes, targeted interventions addressing cognitive and behavioural issues, and personalised care plans tailored to individual needs.[38,39] Similarly, community-based cardiac rehabilitation programmes that integrate cardioprotective therapeutics with psychosocial care and lifestyle management are most effective in preventing rehospitalisation among patients with angina and arrhythmia—conditions that are often underdiagnosed in acute care settings yet associated with high rehospitalisation rates and natural progression to heart failure if left untreated.[40] Furthermore, effective pain management programmes for patients with pain-related musculoskeletal conditions—such as the inflammatory and reactive arthropathy CMGs assigned to our typical patient profiles—are multidisciplinary in nature and combine physiotherapy with approaches that promote active coping and self-management.[41]

Precision-driven tertiary prevention: case management and population stratification

Patients with multiple chronic health conditions benefit most from multidisciplinary care but often require treatment from numerous healthcare professionals across both primary and secondary care settings. To mitigate the risk of care fragmentation redundant patient assessments, a case management approach has been advocated as a holistic means of addressing the complex needs of such patients (Fig 2). For example, patients with COPD have diverse and evolving care needs throughout their care journey,[39] requiring care that is not only multidisciplinary but also integrated through case management. Effective case management for patients with COPD involves healthcare professionals who address the most pressing needs at the initial stage of the care journey assuming the role of case manager, supported by community health practitioners who coordinate other professional services as required.[42]

Given the complexity of multidisciplinary care needs in patients with multiple chronic conditions, and the challenge of delivering the right intervention from the right healthcare professionals to the right patients at the right time, the training and provision of case management can be enhanced through a precision-driven approach. By leveraging advanced data analytics and machine learning, such an approach can accurately identify care needs and service gaps to improve the integration of multidisciplinary care.[43,44] The approach used in the present study—segmenting patient populations based on diagnostic profiles and patterns of acute and PAC service utilisation through iterative applications of unsupervised and 28-day rehospitalisation outcome–supervised machine learning algorithms—can profile unmet needs and service gaps among patient populations discharged into the community. Thus, our study adds value to a body of literature largely focused on identifying homogeneous inpatient segments solely based on diagnoses[45-51] or cost,[52] aimed at improving acute care management.

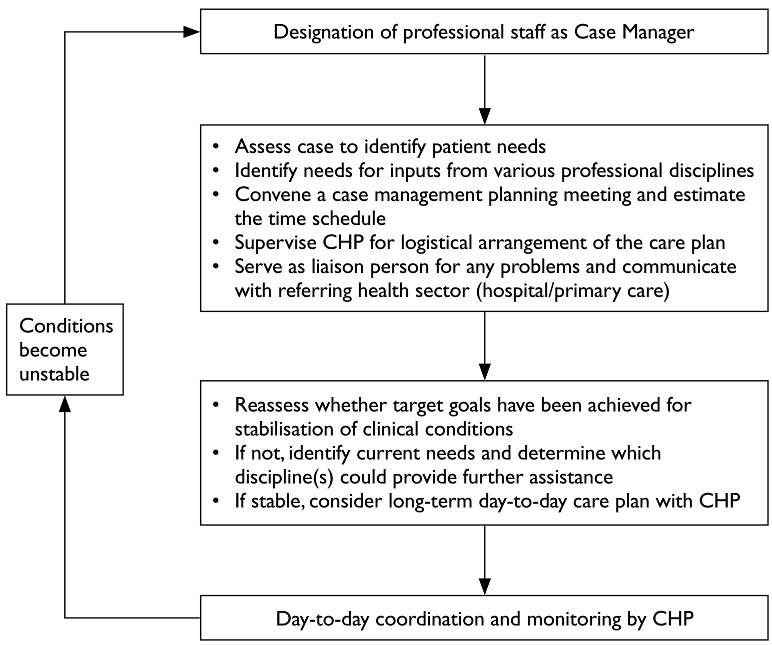

FIG 2. Case management
Abbreviation: CHP = community health practitioner

Limitations

This study has several limitations. First, the data were solely derived from public hospitals as information from private hospitals and other healthcare providers outside the public system was not accessible. However, it is worth noting that public hospitals account for over 90% of inpatient services. Second, the coding system may not capture all patient health conditions because it mainly focuses on chief complaints. Finally, the lack of socio-demographic data limits the ability to generate more precise predictions.

Conclusion

This hybrid machine learning analysis of electronic health records of discharged patient population showed that patients aged 50 to 64 years with typical ambulatory care–sensitive case-mix profiles who did not receive algorithm-selected PAC services had substantially higher levels of multimorbidity and increased risk of 28-day rehospitalisation compared with clinically similar peers receiving such care. Integrating PAC utilisation and clinical complexity indicators into case-mix stratification can enable precision tertiary prevention and guide the development of targeted, multidisciplinary, case-managed services in the community.

Author contributions

Concept or design: E Leung, A Lee, J Guan.
Acquisition of data: E Leung, J Guan, SCC Ching.
Analysis or interpretation of data: E Leung, J Guan, SCC Ching.
Drafting of the manuscript: E Leung, A Lee, FY Chen.
Critical revision of the manuscript for important intellectual content: All authors.

All authors had full access to the data, contributed to the study, approved the final version for publication, and take responsibility for its accuracy and integrity.

Conflicts of interest

As the Chief Editor of the journal, MCS Wong was not involved in the peer review process. Other authors declared no conflicts of interest.

Funding/support

This research was supported by the Strategic Public Policy Research Funding Scheme of the Hong Kong SAR Government (Project No.: S2019.A4.015.19S) awarded to A Lee and E Leung; the Community Involvement Fund of the Home Affairs Department, Hong Kong SAR Government, through Sham Shui Po District Council (Project Nos.: 220179 and 220180) awarded to E Leung and A Lee; and the General Research Fund of the Research Grants Council of Hong Kong (Project No.: 9043763) awarded to FY Chen. The funders had no role in the study design, data collection/analysis/interpretation, or manuscript preparation.

Ethics approval

This research was approved by the Joint Chinese University of Hong Kong–New Territories East Cluster Clinical Research Ethics Committee, Hong Kong (Ref No.: SBRE-22-0386). The requirement for patient consent was waived by the Committee due to the use of unidentifiable information of participants in the research.

Supplementary material

The supplementary material was provided by the authors and some information may not have been peer reviewed. Accepted supplementary material will be published as submitted by the authors, without any editing or formatting. Any opinions or recommendations discussed are solely those of the author(s) and are not endorsed by the Hong Kong Academy of Medicine and the Hong Kong Medical Association. The Hong Kong Academy of Medicine and the Hong Kong Medical Association disclaim all liability and responsibility arising from any reliance placed on the content. To view the file, please visit the journal online (https://doi.org/10.12809/hkmj2411474).

References

1. Vuik SI, Mayer E, Darzi A. A quantitative evidence base for population health: applying utilization-based cluster analysis to segment a patient population. Popul Health Metr 2016;14:44.
2. Caldon LJ, Walters SJ, Reed JA, Murphy A, Worley A, Reed MW. Case-mix fails to explain variation in mastectomy rates: management of screen-detected breast cancer in a UK region 1997–2003. Br J Cancer 2005;92:55-9.
3. Hof S, Fügener A, Schoenfelder J, Brunner JO. Case mix planning in hospitals: a review and future agenda. Health Care Manag Sci 2017;20:207-20.
4. Şentürk D, Chen Y, Estes JP, et al. Impact of case-mix measurement error on estimation and inference in profiling of health care providers. Commun Stat Simul Comput 2020;49:2206-24.
5. Tumlinson A, Altman W, Glaudemans J, Gleckman H, Grabowski DC. Post–acute care preparedness in a COVID-19 world. J Am Geriatr Soc 2020;68:1150-4.
6. Lee MC, Wu TY, Huang SJ, Chen YM, Hsiao SH, Tsai CY. Post–acute care for frail older people decreases 90-day emergency room visits, readmissions and mortality: an interventional study. PLoS One 2023;18:e0279654.
7. Jamei M, Nisnevich A, Wetchler E, Sudat S, Liu E. Predicting all-cause risk of 30-day hospital readmission using artificial neural networks. PLoS One 2017;12:e0181173.
8. Siddique SM, Tipton K, Leas B, et al. Interventions to reduce hospital length of stay in high-risk populations: a systematic review. JAMA Netw Open 2021;4:e2125846.
9. McGilton KS, Vellani S, Krassikova A, et al. Understanding transitional care programs for older adults who experience delayed discharge: a scoping review. BMC Geriatr 2021;21:210.
10. Cao YJ, Wang Y, Mullahy J, Burns M, Liu Y, Smith M. The relative importance of hospital discharge and patient composition in changing post–acute care utilization and outcomes among Medicare beneficiaries. Health Serv Insights 2023;16:11786329231166522.
11. White HK. Post–acute care: current state and future directions. J Am Med Dir Assoc 2019;20:392-5.
12. Geng F, Liu Z, Yan R, Zhi M, Grabowski DC, Hu L. Post–acute care in China: development, challenges, and path forward. J Am Med Dir Assoc 2023;25:61-8.
13. Canadian Institute for Health Information. Case Mix Decision-Support Guide: CMG+. Ottawa: Canadian Institute for Health Information; 2015.
14. Hothorn T, Hornik K, Zeileis A. Unbiased recursive partitioning: a conditional inference framework. J Comput Graph Stat 2006;15:651-74.
15. Guan J, Leung E, Kwok KO, Chen FY. A hybrid machine learning framework to improve prediction of all-cause rehospitalization among elderly patients in Hong Kong. BMC Med Res Methodol 2023;23:14.
16. Choi NG, DiNitto DM, Choi BY. Unmet healthcare needs and healthcare access gaps among uninsured U.S. adults aged 50-64. Int J Environ Res Public Health 2020;17:2711.
17. Hof S, Fügener A, Schoenfelder J, Brunner JO. Case mix planning in hospitals: a review and future agenda. Health Care Manag Sci 2017;20:207-20.
18. Fetter RB, Shin Y, Freeman JL, Averill RF, Thompson JD. Case mix definition by diagnosis-related groups. Med Care 1980;18(2 Suppl):iii, 1-53.
19. Centers for Medicare & Medicaid Services (CMS), HHS. Medicare program; changes to the hospital inpatient prospective payment systems and fiscal year 2008 rates. Fed Regist 2007;72:47130-8175.
20. Fries BE, Schneider DP, Foley WJ, Gavazzi M, Burke R, Cornelius E. Refining a case-mix measure for nursing homes: Resource Utilization Groups (RUG-III). Med Care 1994;32:668-85.

21. Pope GC, Kautter J, Ellis RP, et al. Risk adjustment of Medicare capitation payments using the CMS-HCC model. Health Care Financ Rev 2004;25:119-41.
22. Aschengrau A, Seage GR. Essentials of Epidemiology in Public Health. 3rd edition. Burlington [MA]: Jones & Bartlett Publishers; 2013.
23. Tripepi G, Jager KJ, Dekker FW, Zoccali C. Stratification for confounding—part 1: the Mantel-Haenszel formula. Nephron Clin Pract 2010;116:c317-21.
24. Shrier I, Pang M. Confounding, effect modification, and the odds ratio: common misinterpretations. J Clin Epidemiol 2015;68:470-4.
25. Knol MJ, Le Cessie S, Algra A, Vandenbroucke JP, Groenwold RH. Overestimation of risk ratios by odds ratios in trials and cohort studies: alternatives to logistic regression. CMAJ 2012;184:895-9.
26. Mantel N, Haenszel W. Statistical aspects of the analysis of data from retrospective studies of disease. J Natl Cancer Inst 1959;22:719-48.
27. Sudhakar SK, Sridhar S, Char S, Pandya K, Mehta K. Prevalence of comorbidities post mild traumatic brain injuries: a traumatic brain injury model systems study. Front Hum Neurosci 2023;17:1158483.
28. Lloyd T, Deeny SR, Steventon A. Weekend admissions may be associated with poorer recording of long-term comorbidities: a prospective study of emergency admissions using administrative data. BMC Health Serv Res 2018;18:863.
29. le Cessie S, Nagelkerke N, Rosendaal FR, van Stralen KJ, Pomp ER, van Houwelingen HC. Combining matched and unmatched control groups in case-control studies. Am J Epidemiol 2008;168:1204-10.
30. Caliński T, Harabasz J. A dendrite method for cluster analysis. Commun Stat 1974;3:1-27.
31. Lin PJ, Zhong Y, Fillit HM, Cohen JT, Neumann PJ. Hospitalizations for ambulatory care sensitive conditions and unplanned readmissions among Medicare beneficiaries with Alzheimer's disease. Alzheimers Dement 2017;13:1174-8.
32. Grabowski DC, Mor V. Nursing home care in crisis in the wake of COVID-19. JAMA 2020;324:23-4.
33. Hospital Authority. Waiting time for stable new case booking at specialist out-patient clinics. 2024. Available from: https://www.ha.org.hk/haho/ho/sopc/dw_wait_ls.pdf. Accessed 5 Jul 2024.
34. Hong SN, Mak IL, Chin WY, et al. Age-specific associations between the number of co-morbidities, all-cause mortality and public direct medical costs in patients with type 2 diabetes: a retrospective cohort study. Diabetes Obes Metab 2023;25:454-67.
35. Fong BY, Law VT, Lee A. Primary Care Revisited: Interdisciplinary Perspectives for a New Era. Singapore: Springer; 2020.
36. Al Quait A, Doherty P. Does cardiac rehabilitation favour the young over the old? Open Heart 2016;3:e000450.
37. Lorig K, Holman H, Sobel D, Laurent D. Living a Healthy Life with Chronic Conditions: Self-management of Heart Disease, Arthritis, Diabetes, Asthma, Bronchitis, Emphysema and Others. 3rd edition. Boulder [CO]: Bull Publishing Company; 2006.
38. Bourbeau J, Julien M, Maltais F, et al. Reduction of hospital utilization in patients with chronic obstructive pulmonary disease: a disease-specific self-management intervention. Arch Intern Med 2003;163:585-91.
39. Cravo A, Attar D, Freeman D, Holmes S, Ip L, Singh SJ. The importance of self-management in the context of personalized care in COPD. Int J Chron Obstruct Pulmon Dis 2022;17:231-43.
40. Dalal HM, Doherty P, Taylor RS. Cardiac rehabilitation. BMJ 2015;351:h5000.
41. Soares JJ, Sundin O, Grossi G. The stress of musculoskeletal pain: a comparison between primary care patients in various ages. J Psychosom Res 2004;56:297-305.
42. Tong KW, Fong KN. Community Care in Hong Kong: Current Practices, Practice-Research Studies and Future Directions. Hong Kong: City University of Hong Kong Press; 2014.
43. Talias MA, Lamnisos D, Heraclides A. Editorial: Data science and health economics in precision public health. Front Public Health 2022;10:960282.
44. Leung E, Lee A, Tsang H, Wong MC. Data-driven service model to profile healthcare needs and optimise the operation of community-based care: a multi-source data analysis using predictive artificial intelligence. Hong Kong Med J 2023;29:484-6.
45. Chong JL, Lim KK, Matchar DB. Population segmentation based on healthcare needs: a systematic review. Syst Rev 2019;8:202.
46. Mechanic R. Post–acute care—the next frontier for controlling Medicare spending. N Engl J Med 2014;370:692-4.
47. Nnoaham KE, Cann KF. Can cluster analyses of linked healthcare data identify unique population segments in a general practice-registered population? BMC Public Health 2020;20:798.
48. Lafortune L, Béland F, Bergman H, Ankri J. Health status transitions in community-living elderly with complex care needs: a latent class approach. BMC Geriatr 2009;9:6.
49. Liu LF, Tian WH, Yao HP. Utilization of health care services by elderly people with National Health Insurance in Taiwan: the heterogeneous health profile approach. Health Policy 2012;108:246-55.
50. Eissens van der Laan MR, van Offenbeek MA, Broekhuis H, Slaets JP. A person-centred segmentation study in elderly care: towards efficient demand-driven care. Soc Sci Med 2014;113:68-76.
51. Joynt KE, Figueroa JF, Beaulieu N, Wild RC, Orav EJ, Jha AK. Segmenting high-cost Medicare patients into potentially actionable cohorts. Healthc (Amst) 2017;5:62-7.
52. Davis AC, Shen E, Shah NR, et al. Segmentation of high-cost adults in an integrated healthcare system based on empirical clustering of acute and chronic conditions. J Gen Intern Med 2018;33:2171-9.