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Development and practical use of a risk-sensitive population segmentation model for healthcare service planning: application in England

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Abstract

Population segmentation can be a powerful tool in healthcare management, in helping to match interventions and resources to individuals of a common health state and condition. However, studies to date indicate a lack of alignment to risk stratification – another key tool in Population Health Management – and insufficient demonstration of how segmentation can be used in practice. In this study, we obtain a five-cohort segmentation derived through four incremental thresholds on the risk-based Cambridge Multimorbidity Score, which is calculated for each member of the 762,117 adult population in and around Bristol, England. Appropriately selecting the four thresholds – 0.09, 0.69, 1.59, 2.95 – yields a segmentation with the convenient property that, with increasing risk, segments halve in size and double in per-person spend. The segmentation has been used to support various planning and management activities within the Bristol healthcare system; two of which are detailed here as case studies in demonstrating the practical value of the segmentation model.

***Keywords**:* *Population health management; Population segmentation; Risk stratification; Healthcare spend; Healthcare utilisation.*

1. Introduction

Population segmentation and risk stratification are regarded as key analytical approaches within the Population Health Management toolkit [1-3]. Essentially, population segmentation refers to the grouping of a population by some measure(s) and is typically used for understanding the high-level health characteristics of a given population. As England's National Health Service (NHS) puts it: "grouping helps understand the distinctive needs of different parts of the population" [1]. Risk stratification concerns the prediction of something occurring, whether it be particular amounts of healthcare spend or utilisation within some period, or the occurrence of outcomes such as death [4,5]. For instance, healthcare systems may use risk stratification to predict the likelihood of individuals attending an Emergency Department in the next month or year, through statistical modelling based upon their demographic and clinical attributes and previous healthcare usage [6]. When such risk predictions are grouped, or arranged into ordinal 'strata', then it can be said that risk stratification constitutes a form of population segmentation [1]. Typically, segments are non-overlapping meaning that each individual within the population can only be a member of only segment, at any one time [7,8].

A recently published risk prediction method is the Cambridge Multimorbidity Score (CMS) which is "a general-outcome multimorbidity score" that can be calculated for each member of a population using data on their long-term conditions [9]. This was found to perform "significantly better" than the more established Charlson Comorbidity Index in predicting family doctor consultations, hospital admissions and mortality [10]. While patient-level risk scoring can, as the authors of the CMS claim, be "valuable to those planning clinical services and policy-makers allocating resources", what is moreover required is the ability to distil such granular information to provide the *bigger picture* necessary to influence decision makers and inform members of the public [11].

To this end, healthcare systems are increasingly turning to segmentation, with the aim of partitioning their populations into a small and manageable number of suitably homogeneous cohorts representing different levels of health need [5,12,13]. Too often, however, there is a lack of alignment between the employed segmentation and risk prediction approaches, specifically regarding the particular measure(s) considered within each. This inconsistency can compromise understanding and interpretability, and so reduce acceptance of the approaches for use in strategic and day-to-day decision making. Uptake has also been limited by a lack of evidence regarding practical use, with many published papers concerning only segmentation development and not its application in practice.

The objective of this study is to develop a risk-sensitive population segmentation of sufficient practical simplicity and relatability to secure widespread on-the-ground use within a major public healthcare system. The purpose is to enhance the quality of current and future service planning activities and decisions through facilitating appropriate consideration of the key health states of the population.

One way to assign individuals to segments is through person-based surveys, in which the surveyor uses information and/or responses from the individual to make an assignment. Chong et al [14] developed a "Simple Segmentation Tool" for categorising adults aged 55 and over into six segments. Four published segmentation methods were evaluated by non-clinician on adults aged 60 and over, with all found to adequately distinguish between healthcare use within six months from assignment [15]. The performance of clinician-mediated survey-based segmentation is evaluated by Duminy et al [16] across 14 European countries. Neelakandan et al [17] use factor analysis on survey responses to obtain a six-segment model for stratifying beliefs relating to the uptake of hypertension screening. And Chalamon et al [18] segment patients into four groups based on their expectations towards the healthcare system. While survey-based segmentation can be useful for direct patient care (e.g., when administered in hospital), it is not readily scalable to larger populations, at which more general healthcare planning decisions are made.

Larger-population segmentations are more easily achieved through querying already-available electronic healthcare data. Data-driven segmentations have been obtained for various diseases, such as diabetes [19] and hypertension [20]; particular population sub-cohorts, including children [21,22]; and for categorising attitudes to healthcare interventions, such as COVID-19 vaccination acceptance [23]. These relatively bespoke segmentations are, however, of limited use for higher-level general service planning.

For whole-population segmentation, or at least segmentation of the large older-adult cohorts that overwhelmingly drive cost, there are both expert-defined and data-defined models. Expert-defined models are those whose segment membership criteria is defined through expert elicitation. These, which can account for 75% of segmentation models [19], include the eight-segment Bridges-to-Health model [24], which has formed the basis of other efforts [14,15]. Other investigators have used expert opinion to partition their adult population into six segments [7,25]. Of the data-defined offers, Low et al [8] and Nnoaham & Cann [26] use cluster analysis to derive their respective five and ten segment models, and Anderson et al [27] use regression modelling to obtain their 16-segment model. (For a more complete literature review of population segmentation approaches, see [11,13]).

However, these studies develop very little in the way of evidence with regard to practical use, in terms of applying the derived segmentations to influence policy or service change. While Low et al [25] claim "our segmentation framework is practical", there is no evidence of practical use. Others talk of how their segmentation "could" or "may" lead to particular interventions [26] with no demonstration provided. But how can managers and practitioners have confidence in the value of segmentation when little-to-no practical demonstration is offered? It is not that any of these studies have failed in their stated aims – just that such aims have not extended beyond development into application. Reflecting on this, Yoon et al [28] state "despite the apparent value and utility of population segmentation frameworks, effective segmentation is limited by the use of different indicators of segmentation, which may not be grounded in practice settings", adding "there appears to be a lack of consensus on the purposes of segmentation".

This paper demonstrates how CMS can conveniently be used to underpin an actionable five-cohort segmentation of the adult population of a major healthcare system in and around Bristol, England. In the next section, the study setting is introduced, alongside the available data and the analytical approach used to obtain the segmentation. Following this, the derived Core Segmentation model is presented, before describing two case studies illustrating real-life application of the segmentation within the healthcare system. Finally, a discussion of strengths and limitations and practical considerations is considered.

2. Methods

2.1 Setting

The setting is a major healthcare system located in and around Bristol, in the south west of England. The Bristol, North Somerset and South Gloucestershire (BNSSG) system covers a one million resident population across a mixture of large metropolitan areas and rural and coastal locations. A higher proportion of younger individuals reside in the main city, which also has a more culturally and ethnically diverse demographic. Rural and coastal areas contain a greater proportion of older individuals and pockets of severe deprivation. Overall, the age profile is similar to that of England [29].

The BNSSG system is, following the latest reforms [30], an Integrated Care System (ICS), comprising NHS funded health care and local authority funded social care. Overseen by an Integrated Care Board, the ICS includes approximately 80 general practices, two large acute hospital trusts, a single community service provider, a single specialist mental health provider, and various social care providers procured by the three constituent local authorities.

2.2 Data

Data were obtained from the System Wide Dataset, which provides patient-level linkable data for the BNSSG population [31]. This is an existing resource that, since August 2019, has joined together primary care, secondary care, mental health, and community services data for 98.3% of the 1.05 million local population (1.7% of the population have opted out).

Primary care data from year-end 2021/22 was used to calculate CMS for the 762,117 individuals in BNSSG aged 17 years or over. Healthcare activity data through 2021/22 was used to calculate total annual spend per individual over primary care, secondary care, mental health, and community services. Any spend directly related to maternity care was excluded since this high-cost activity can be unrelated to a specific long term health condition or health need.

2.3 Segmentation

CMS is used to segment the BNSSG healthcare system's 762,117 adult population into five mutually exclusive groups, referred to within the healthcare system as the Core Segmentation model. Individuals are assigned to the Core Segments based on four incremental thresholds on CMS, such that the lowest-scoring individuals of Core Segment 1 are the most healthy, and the highest-scoring individuals of Core Segment 5 are the least healthy.

By appropriately setting the four thresholds, a segmentation with other convenient properties is sought. First, each higher-order segment should be approximately half the size of its former. That is, Core Segment 2 should contain roughly half as many individuals as Core Segment 1. Second, mean annual healthcare spend per person should double with each higher-order segment. With halving size and doubling spend, this would ensure the third property: that any two segments should have equivalent total spend.

These simple and relatable design principles were considered valuable to catalysing an adequate understanding and ready recollection within the healthcare system's management and with the wider public served. This was driven, in part, by recognition of the previous success of another NHS healthcare system in having attracted interest to their segmentation through illustrating the (decreasing) size and (increasing) spend as two side-by-side inverted pyramids [32]. This was, however, without any specific objective regarding the extent to which segment size was decreasing or segment spend was increasing, and neither was an attempt made to align the segmentation with risk scores.

The analytical approach taken in attempting to achieve the abovementioned three properties firstly involved the identification of all feasible combinations of the four thresholds on CMS, to two decimal places. For example, one threshold combination would be 0.04, 0.54, 1.33, 2.62. The next step involved calculating the ratio of both size and mean healthcare spend between the neighbouring segments, for each of the threshold combinations. The final step was to select the CMS threshold combination which yielded ratios closest to those desired, i.e., halving segment size and doubling segment spend (see the Appendix). This produced the threshold combination 0.09, 0.69, 1.59, 2.95.

3. Results

3.1 The Core Segmentation model

With the ascertained threshold combination on CMS, the segmentation described in Figure 1 was obtained. Given that only one variable was used in describing segment membership, it was somewhat remarkable that such a close match to the abovementioned three properties was achievable: other segmentations typically require the use of many variables to attain the desired characteristics [13]. To illustrate, based on CMS long-term condition weightings [9]: someone with only 'migraine' (0.07) would be in Core Segment 1; someone with only 'migraine' (0.07) and 'hypertension' (0.09) would be in Core Segment 2; someone with only 'Parkinson's disease' (1.29) would be in Core Segment 3;

someone with only ‘dementia’ (2.46) would be in Core Segment 4; and someone with only ‘dementia’ (2.46) and ‘heart failure’ (1.12) would be in Core Segment 5. A descriptive summary of the attributes of the population partitioned by Core Segment is provided in Table 1 (with deprivation measured by the Index of Multiple Deprivation, which ranges from 1 (most deprived) to 10 (least deprived) [33]).

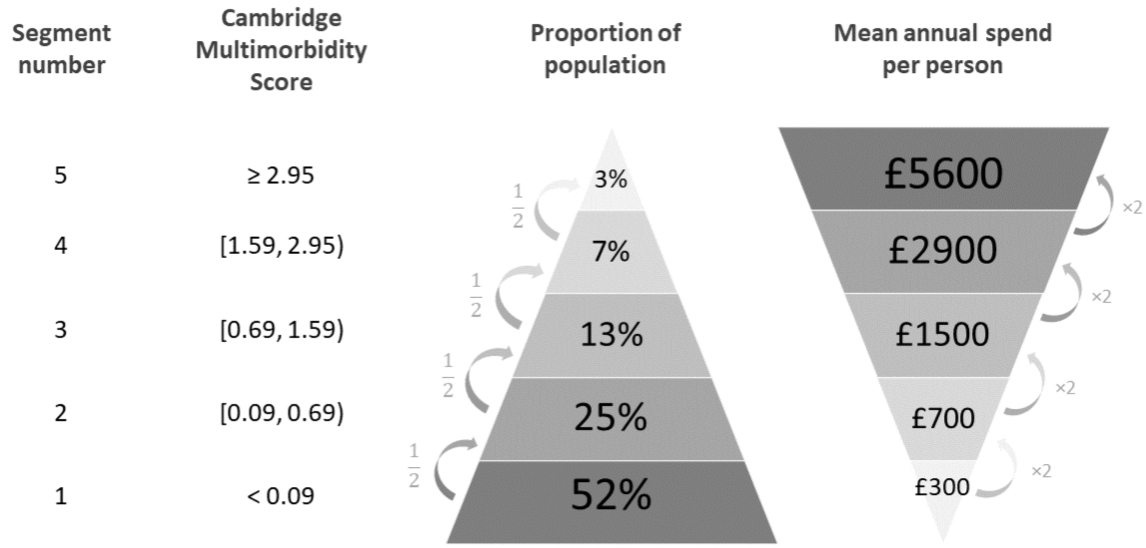

Figure 1. The Core Segmentation model of the BNSSG adult population (n=762,117) using the Cambridge Multimorbidity Score, based on data from financial year 2021/22.

Core Segment	1	2	3	4	5
Age (mean)	39	47	57	66	76
Sex (% male)	54	45	47	46	48
BAME (%)	21	11.7	12.1	9.0	7.6
IMD (mean)	5.9	6.0	5.8	5.6	5.6
BMI (mean)	25	27	28	29	28
CMS (mean)	0.005	0.67	1.1	2.1	4.2

Table 1. Attributes of the BNSSG adult population by Core Segment, based on data as of the end of financial year 2021/22. Abbreviations: BAME is Black, Asian, and Minority Ethnic; IMD is Index of Multiple Deprivation; BMI is Body Mass Index; CMS is Cambridge Multimorbidity Score.

3.2 Identifying patients at risk of potentially avoidable hospital admissions through the Core Segments

Ambulatory Care Sensitive Conditions (ACSCs) are conditions where effective community and primary care and case management could have prevented the need for hospital admission [34]. Although the conditions themselves are well defined and nationally consistent, there has been a deficit of relevant information to help the BNSSG system identify which patients or patient groups may be likely to suffer an ACSC admission, and thus what intervention could be delivered to mitigate such risks. Such information would support healthcare managers in taking proactive and preventative action in primary and community care settings.

Activity data from across BNSSG for the twelve-month period to 30 September 2021 was analysed for a cohort of individuals who had at least one potentially avoidable non-elective admission over the period, as per the ACSC definition used in the NHS [35]. Linking to the Core Segments allowed a descriptive analysis of how ACSC admissions, as well as all non-elective admissions, were distributed according to health state (Figure 2).

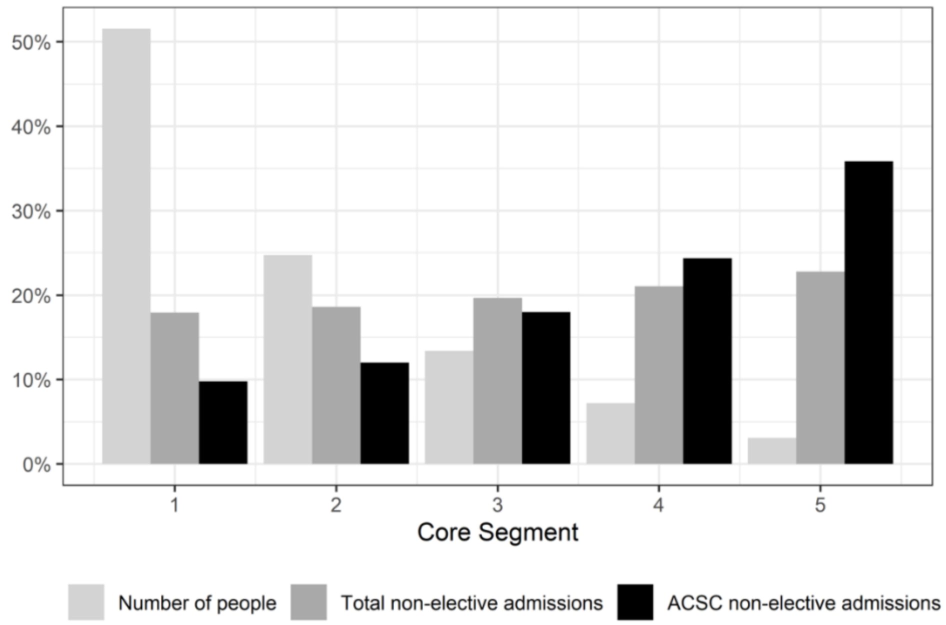

Figure 2. Distribution of ACSC and all non-elective admissions in the BNSSG healthcare system by Core Segment.

As a proportion of segment size (number of people), both total non-elective admissions and ASCS non-elective admissions were significantly different across the Core Segments ($p < 0.01$, proportion test). But while, as a total, non-elective admissions were fairly evenly distributed among the Core Segments, ACSC admissions were highly skewed to the less healthy patients. Indeed, over 50% of all ACSC admissions within the one-year period were from the 10% of the population in Core Segments 4 and 5. Analysing the constituent ACSC conditions revealed a small number of these were responsible for much of the admissions and with most representation from patients in Core Segments 4 and 5, e.g., 82% of all COPD related admissions were from patients of Core Segments 4 and 5 (Table 2).

Table 2. Breakdown of BNSSG non-elective admissions by constituent ACSC conditions.

ACSC condition	**Total non-elective admissions**	**Percentage from Core Segments 4 and 5**
Influenza and pneumonia	1,946	57%
Pyelonephritis and UTIs	1,942	48%
COPD	1,805	82%
Diabetes complications	1,610	43%
Cellulitis	1,557	37%
Congestive heart failure	1,332	75%
Dehydration and gastroenteritis	1,262	43%

Analysing specific ACSC conditions led to identification of the following set of interventions in primary and community care: promoting vaccine uptake for seasonal influenza and COVID-19 if eligible and not yet received; performing structured medication reviews; advanced care planning, including the writing of ‘ReSPECT’ forms (for end-of-life preferences); and chronic disease reviews for the above-mentioned conditions. General practitioners within BNSSG were provided with a targeted list of Core Segment 4 and 5 patients for which these interventions were relevant. The segmentation was useful in conveniently illustrating, for the first time in the BNSSG system, what types of patients were at most risk of ACSC admissions, and how they can be identified for proactive support from primary and community care. The value of a segmentation which holds constant overall segment costs while halving segment size provided confidence that any action would focus on a sufficiently small group of people, who were consuming a disproportionate amount of system resources.

3.3. Modelling longer-term changes in the population health state through the Core Segments

Healthcare policy makers face regular challenges on how to allocate healthcare resources with limited budgets, both in the short and longer term. Mathematical and computer modelling tools can capture, subject to assumptions and simplifications, these interacting factors in estimating the long-term trajectory as well as the implications of different mitigatory measures [36]. However previous studies either focus on population projections for specific types of diseases (e.g., Type 2 diabetes) or specific age groups in the population using dynamic microsimulation models [37,38]. The aim of this project was to develop a mathematical model to support decisions around long-term commissioning needs for the BNSSG healthcare system, by first producing a ‘do nothing’ projection of future healthcare activity and spend. Note that, in a recent study, Duminy et al [16] developed a population segmentation tool that can be used for cross-country comparisons in healthcare, and used it to analyse differences in transition rates between segments and to death using a continuous-time Markov model. However, they do not provide any further segment size nor healthcare related spending projections.

The mathematical model created is a finite horizon discrete-time Markov chain where the state space includes the five Core Segments representing the health state of individuals within the population, in addition to consideration of births, deaths and migration in and out of BNSSG (Figure 3). Essentially, the model accounts for the life-course of individuals as they age and (typically) advance through the Core Segments with declining health. Such movements are extrapolated from the observed Core Segment transition rates in years 2019 through 2022, anchored on demographic projections (birth, deaths, and migrations) contained in data from the Office for National Statistics [39,40].

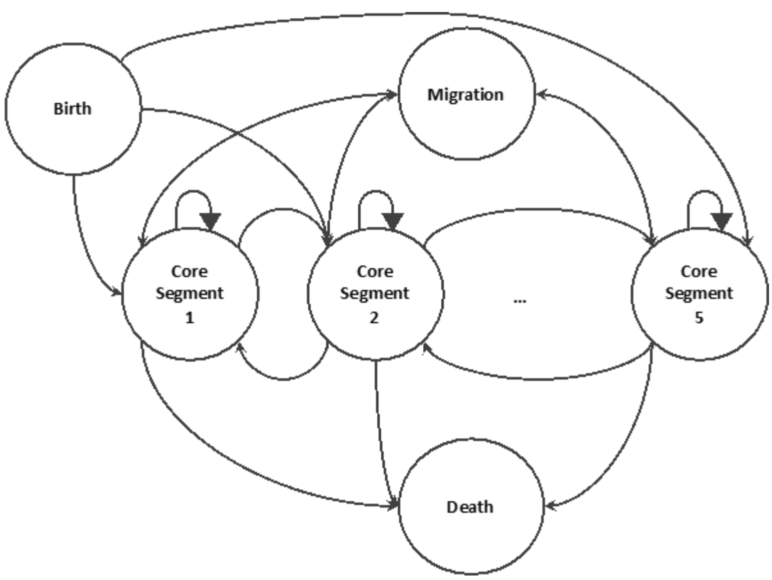

Figure 3. Schematic representation of the Markov chain population model based on the five Core Segments.

Estimates for future population health state, by Core Segment, are detailed in Figure 4 (left-hand side). Core Segment 1 population size decreases slightly over the 20-year time horizon while the size of all other Core Segments increase, with the greatest growth in Core Segments 3 and 4. Attaching current estimates of the average patient spend in each Core Segment yields the cost projections also shown in Figure 4 (right-hand side). The healthcare costs related to Core Segment 1 are expected to decrease slightly, with spend on Core Segments 4 and 5 having the highest projected increase (64% and 70% respectively). Ultimately, while the BNSSG population is expected to increase by 14% over the 20-year horizon, the total cost is expected to increase by 41%, indicating the scale of the challenge required to either or both reduce the increasing multimorbidity of the population or improve technical efficiency in terms of reducing the spend on addressing given health needs. Through use of the Core Segments, the patient groups requiring most attention can be conveniently identified. When fully developed, the model will also consider mitigations to these ‘do nothing’ trajectories, in supporting health leaders weigh up the value of implementing different policies.

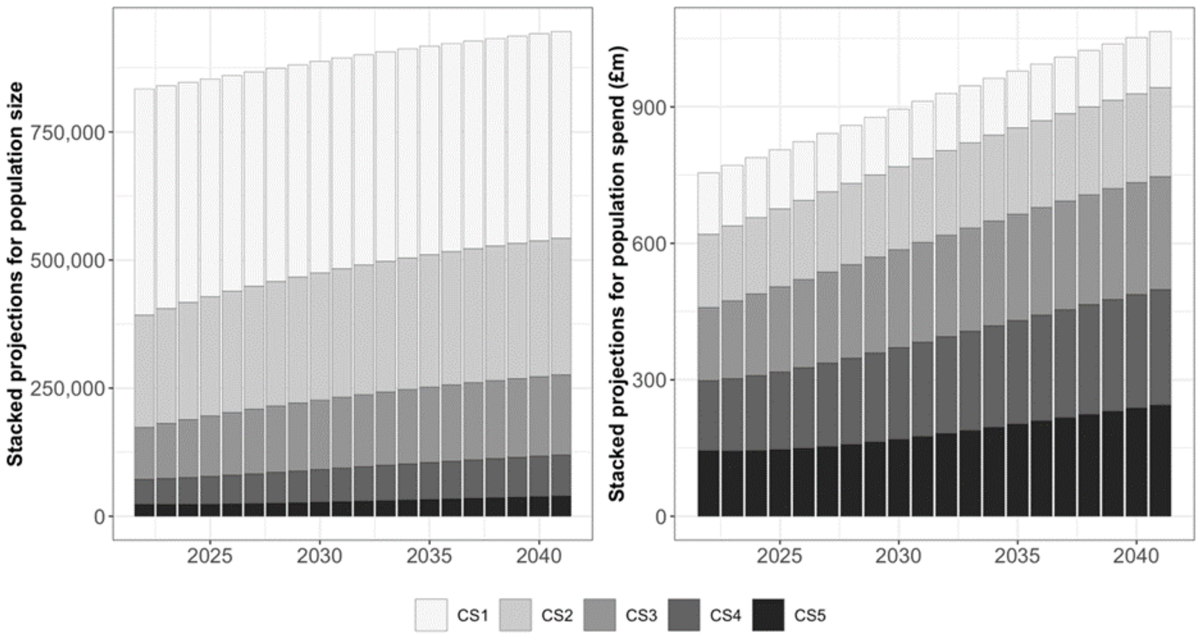

Figure 4. Modelled projections for 2021 to 2041 for BNSSG population size and spend partitioned by Core Segments (CS) 1 to 5.

4. Discussion

In developing a simple and relatable risk-sensitive population segmentation, this study addresses a deficit in the literature regarding the application and practical demonstration of segmentation for general healthcare service planning. The two examples considered here align with the identified purposes of segmentation, as reviewed by Yoon et al [28]: “improving health outcomes, planning for resource allocation, optimising healthcare utilisation, enhancing psychosocial and behavioural outcomes, strengthening preventive efforts and driving policy changes”. Specifically, in targeting proactive primary and community support for patients at greatest risk of admission (Section 3.2), we show the ability of our segmentation to “optimise healthcare utilisation” and for “improving health outcomes”, given the avoidable deconditioning effect of unnecessary hospital admission [41]. In projecting longer-term healthcare activity and costs (Section 3.3), the modelling has revealed the extent of the challenge, in terms of "strengthening preventive efforts" and "planning for resource allocation" in future years.

The "trade-offs between the simplicity and precision of segmentation" is remarked upon by Low et al [7]. Of the various developed population segmentation models [11,13], especially the data-driven ones, it would appear that the effort to date has focused overly on precision, with insufficient appreciation of the importance of the former to achieving demonstrable practical uptake. Simplicity has, in many ways, been key to achieving buy-in to the segmentation from senior decision makers in this current study, who had previously expressed some concern regarding the complexity and arbitrariness of alternative and non-data-driven segmentations such as Bridges to Health [24]. While itself a product of patient-level data for numerous long-term conditions, using just one variable (CMS) – a score already used for risk stratification in the healthcare system – has helped in this regard. So too has the halving size and doubling spend achieved in obtaining the 'inverted pyramids' of Figure 1. While these have before been roughly illustrated in other healthcare systems, this is the first account to the authors' knowledge that has objectively considered the composition of such pyramids in terms of the specific ratios on size and spend.

The balance between "simplicity and precision" also extends to selecting the number of segments – the more segments, the greater stratification of risk, but at the possible expense of stakeholder recognition and relatability. It may, for instance, be challenging to encourage customer buy-in to models which consist of 10 [26] or 16 segments [27]. The choice of five segments in our study reflects a subjective choice pivoted more to achieving simplicity than precision. That said, it falls roughly within the (lower) range of typical segment numbers used in the reviewed literature (Section 1). Also subjective is the naming of segments, as remarked by Low et al [8]. To this end, segments were not named in this current study. Moreover, given the sole use of CMS to define segment membership, the numerical segment names (1-5) reflect the ordinal nature of the segments in terms of increasing risk. Sole use of CMS, while promoting simplicity, does come at the expense of precision. Indeed, in their review of 35 segmentation models, Jeffery et al [2] find "a lack of comprehensive models that integrate data from multiple sources", with many relying solely on diagnostic codes (from which CMS is essentially derived).

In terms of technical limitations regarding the segmentation, it should be noted that three of the 37 long-term conditions used to create the CMS were unavailable in the healthcare system's data. However, the CMS weightings for these conditions – 'chronic sinusitis' (0,13), 'prostate disorders' (0.01), and 'diverticular disease' (-0.02) – are relatively low and clinical opinion was that exclusion would not lead to significant discrepancy in the resulting segmentation. It should also be noted that original development of the CMS was based on a population aged 20 years or over, whereas it is applied here to those aged 17 and over (to align to the 'adult' definition used in the healthcare system). Further research could involve validation of CMS in this slightly younger adult age cohort. While the dataset used in this study accounted for the principal NHS funded healthcare settings – primary care, secondary care, mental health, and community services – it did not include local authority funded social care, accounting for longer-term care needs such as regular home visits and care home placements. Given the far greater utilisation of these services from older and multimorbid individuals, its inclusion may further skew the segmentation profile in terms of the spend and size ratios between the Core Segments.

Readers should also note that there is no guarantee that the identified ratios would hold outside the BNSSG healthcare system studied here. Other systems eager to establish a similar segmentation model should determine their own optimal threshold combination from evaluating a range of possible combinations using the method detailed here (Section 2.3). Inspection and comparison of the different threshold combinations yielded from application to different healthcare systems may be a further research direction for future investigators.

Finally, it should be acknowledged that a high-level segmentation such as the one presented here is no substitute for bespoke approaches given certain questions. For instance, if one wanted to inspect the characteristics of patients with particular long-term conditions then a bespoke segmentation based upon the considered conditions would offer the best route [13]. However, if one seeks to monitor or obtain certain measures for patients of an overall high risk versus low risk then a segmentation like the one presented here could be most suitable. In this respect, our model is similar to that of Low et al [25], whose segmentation "is less about specific disease treatment for a specific patient over a single healthcare encounter, which requires individualisation of management plan by each patient-healthcare provider pair, but more relevant at policy level in planning what types of health services are needed for each segment at population level".

Appendix

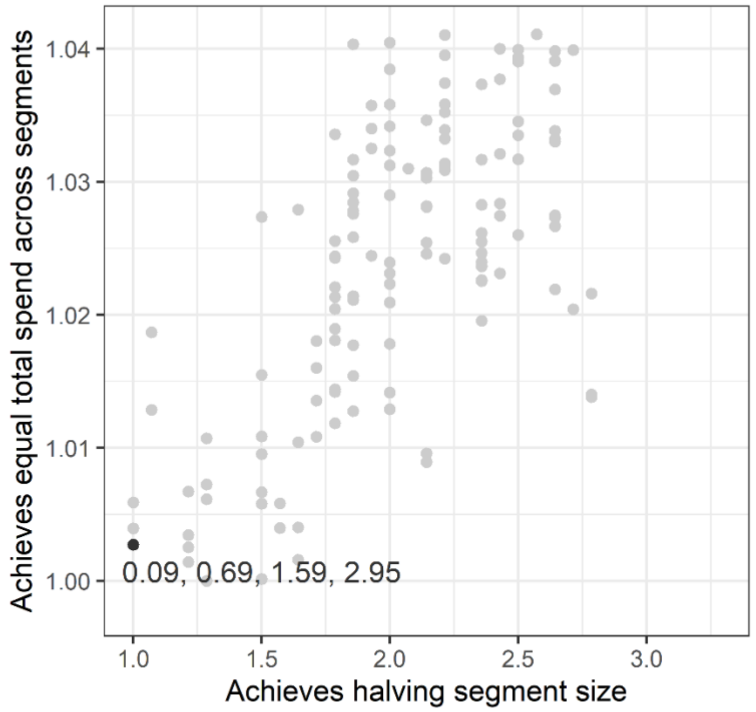

Figure A.1. Best-performing threshold combinations, including the chosen combination as indicated by the black dot (and annotated with the respective threshold values). The two axes are indexed such that the lowest possible value of each 'objective' from any combination is valued at one. An optimal solution is one which minimises both objectives, i.e., one which gets as close as possible to both achieving halving segment size and equal total spend across the segments.

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None to report.

Authorship contribution

RM Wood: Conceptualization, Data Curation, Methodology, Investigation, Visualization, Writing - Original Draft
TA Budiman: Methodology, Investigation, Writing - Review & Editing
N Hassey: Methodology, Investigation, Writing - Original Draft
Z Onen Dumlu: Methodology, Investigation, Visualization , Writing - Original Draft
C Vasilakis: Methodology, Investigation, Writing - Original Draft
FJ Budd: Methodology, Data Curation, Writing - Review & Editing
SE Hollier: Methodology, Investigation, Visualization, Writing - Review & Editing
PM Thomson: Methodology, Data Curation, Writing - Review & Editing
C Kenward: Conceptualization, Methodology, Writing - Review & Editing

Disclosure statement

The authors report there are no competing interests to declare.

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Data availability statement

Data used in this study is protected patient data and not publicly available at the record-level granularity as used in this study.

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