Bristol, North Somerset and South Gloucestershire Clinical Commissioning Group

Understanding the distribution of health needs using Population Segmentation

An applied comparison of methods

Richard Wood
Ben Murch
Adrian Pratt

@BNSSGAnalytics

Population Health Management

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

What is PHM?

"Population Health Management focuses on key outcomes for identified groups. Often these groups share more specific common characteristics, not just a disease diagnosis"

Nuffield Trust

"PHM is the concept of gathering data and insights about population health and wellbeing across multiple care and service settings, with a view to identifying the main health care needs of the community and adapting services accordingly"

Deloitte

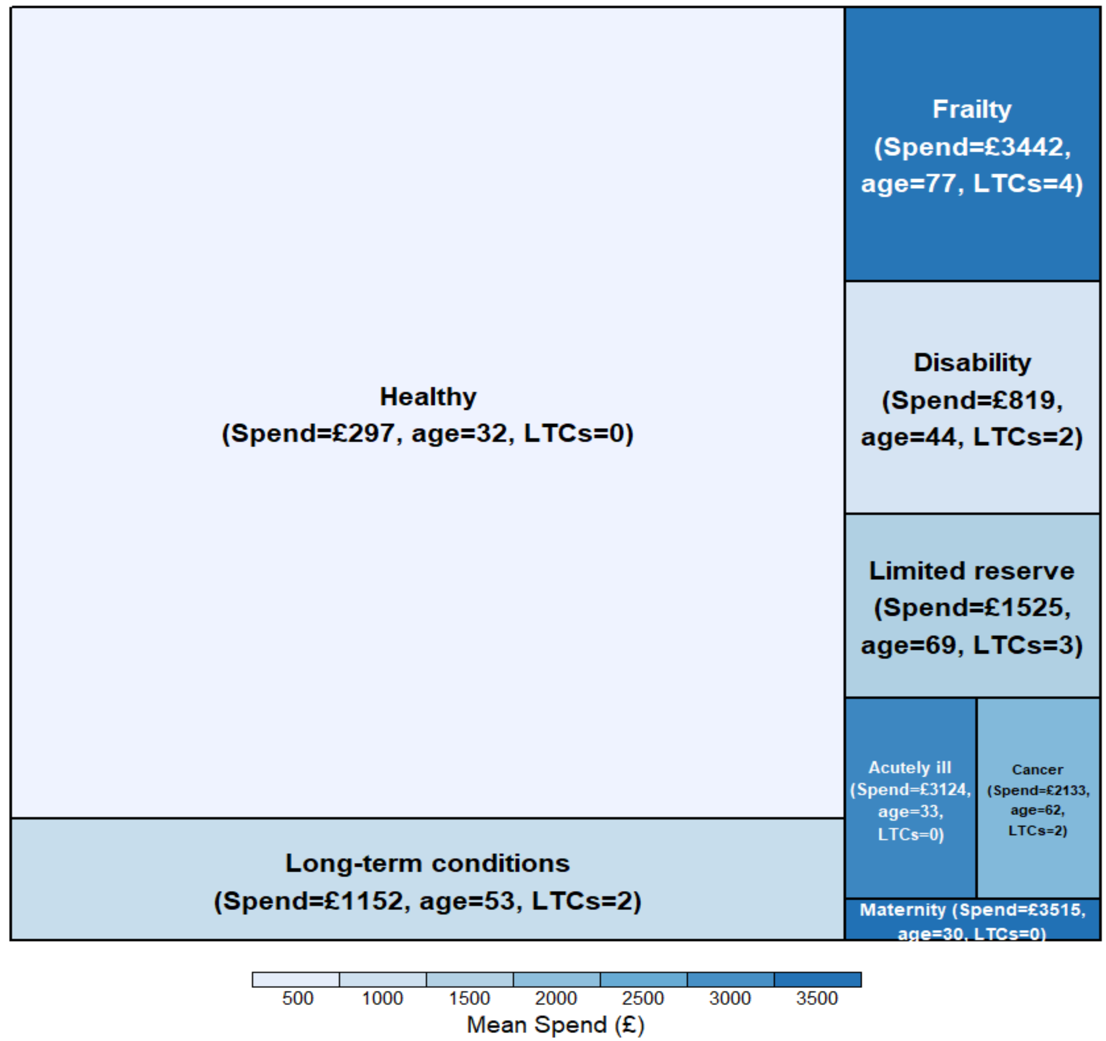
"During 2019, we will deploy PHM solutions to support ICSs to understand the areas of greatest health need and match NHS services to meet them. Over the coming years these solutions will become increasingly sophisticated in identifying those groups of people who are at risk of adverse health outcomes"

NHS Long Term Plan

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Example segmentation

- **Block size** represents segment population
- **Colour depth** represents spend differential



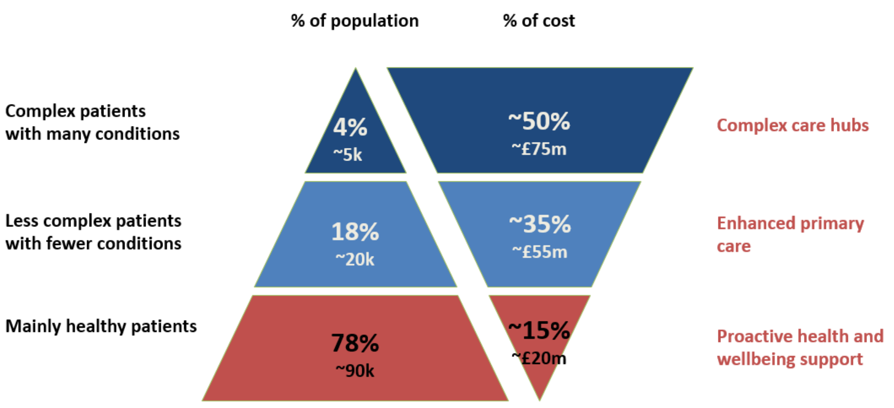
NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Why segment?

- Cut through the complexity of large and unwieldy datasets in making sense of the **key patient-related attributes** that drive the most significant differences in some targeted measure of interest

- **Activity or spend** can be targeted in representing **healthcare need**

- Identified segments thereafter **amenable to tailored interventions**
  - E.g. Complex Care Hub for the most seriously ill patients



From Somerset Symphony project

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Aim

- To review a number of Population Segmentation methods **side-by-side in a consistent manner** using a common dataset…

- …that identify meaningful and interpretable population cohorts which are ***heterogeneous between*** and ***homogeneous within***

- To open up **a range of options** allowing clinicians and managers an informed choice on which approach to use for their situation

Outline of introduction

1. Setting and data
2. Methods
3. Comparison
4. Discussion

Data requirements

- **<u>Attributes</u>**
  Demographic – *age, sex, ethnicity*
  Clinical – *listed chronic conditions, obesity, frailty scores*
  Other – *deprivation, smoking status, housebound*


- **<u>Activity</u>**
  Primary Care contacts – *GP and nurse appointments*
  Secondary Care contacts – *outpatient, inpatient, A+E*
  Prescriptions – *medicines*

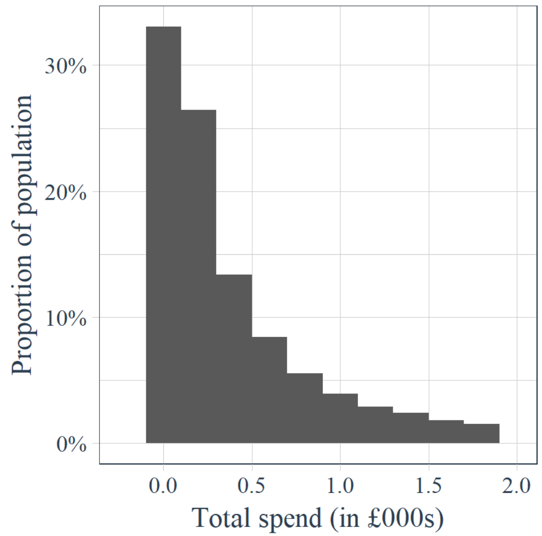

NHS
Bristol, North Somerset
and South Gloucestershire
Clinical Commissioning Group

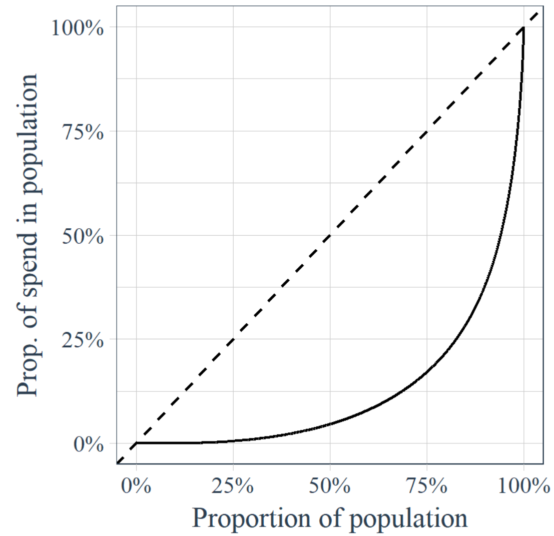
Sample data at a glance (n=51,072)

Highly skewed

Mean £853

Median £240



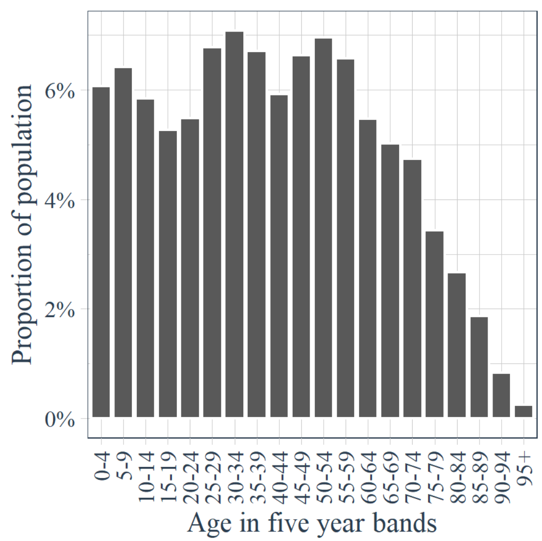


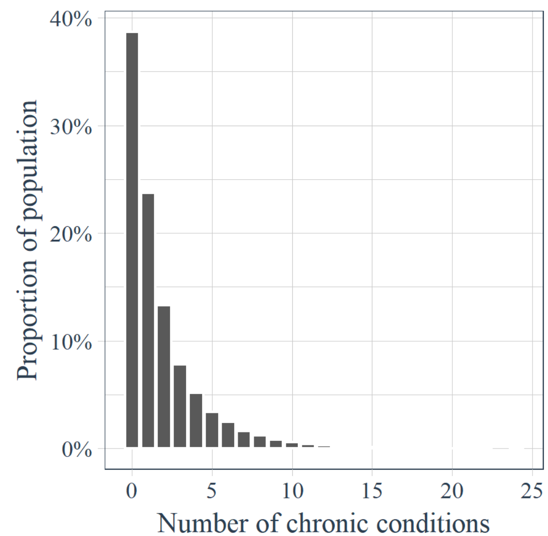
Inequal distribution

Gini 0.75

80/20 rule holds

Multi-modal population in Bristol area





61.3% of people have at least one chronic condition

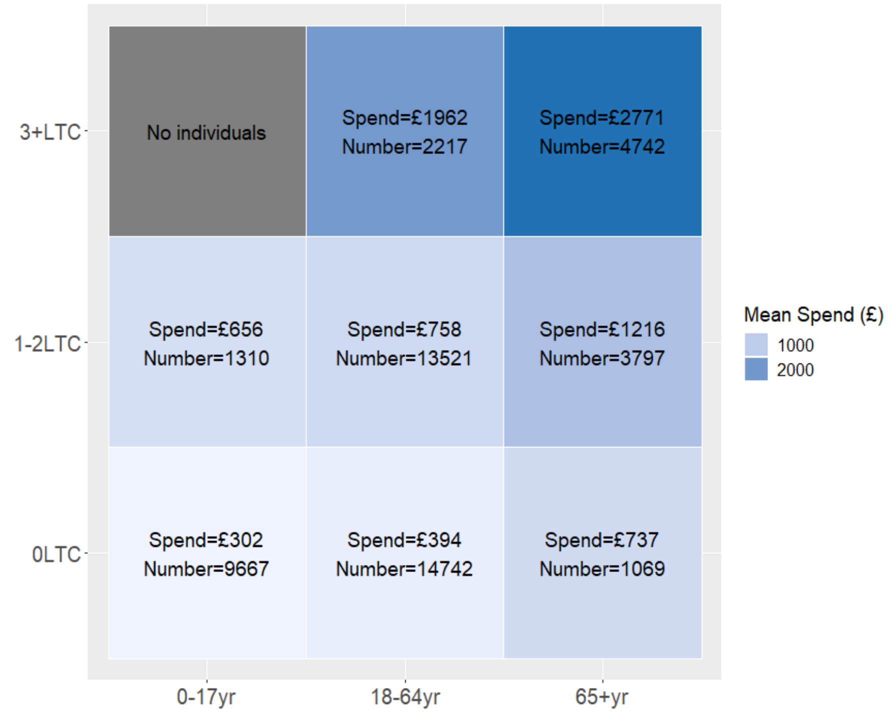
NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Outline of introduction

1. Setting and data
2. Methods
3. Comparison
4. Discussion

Judgemental splits

- Most basic approach
- Simply obtain segments by **making arbitrary splits** on explanatory variables (patient attributes)
- E.g. by age and chronic condition count



1. Age (0-12, 13-17, 18-49, 50-74, 75+)
2. Sex (male/female)
3. Chronic conditions (0-4, 5-9, 10-14, 15+)
4. Age and chronic conditions
   (0-17, 18-64, 65+ by CCs 0-4, 5-10, 11+)

Prescribed binning criteria

- Bin patients according to **preset rules** defining segment membership

- No guarantee that rules will be:
  - Discriminative
  - Relevant to geography/setting
  - Appropriate to targeted measure

- Some rules **not well-defined**

TABLE 1
Population Segments with Typical Patient Examples

Population	Patient and Services
1. Healthy	Mr. Smith, a 37-year-old carpenter, usually books an appointment with his primary care physician each year around his birthday for an annual checkup and necessary screenings. He also may contact his physician's office for acute, self-limiting problems such as a sore throat.
2. Maternal and infant health	Mrs. Brown, a 26-year-old waitress, had regular contact with her gynecologist for contraception and general health monitoring until deciding to become pregnant. A year later, she sought fertility treatment and had monitoring through normal pregnancy and delivery. Her newborn's checkups and immunizations follow national guidelines.
3. Acutely ill	Tom Jones, an 18-year-old high school student, broke his femur while playing football. An ambulance promptly transported him to the local emergency room. Following an uneventful surgical procedure, Tom received physical therapy to rehabilitate his leg and maintain his body strength. He returned as the team quarterback eight weeks later.
4. Chronic conditions, normal function	Mrs. Gomez, a 49-year-old teacher, has hypertension and diabetes. While she has taken classes to learn how to reduce her risks and control these conditions, she still finds that both are occasionally out of control and then makes an appointment with her physician, whose office sends her reminders for immunizations, regular checkups, and monitoring for possible complications.
5. Stable but serious disability	Mr. White, a 56-year-old telemarketer, also is a former paratrooper who is quadriplegic from a gunshot wound to the neck. He lives with his brother in an extensively adapted apartment and has a paid aide for personal care. He has a motorized wheelchair and transportation for shopping and outings. He has been suicidal at various times and often has urinary tract infections. He uses a medical home team for continuity and comprehensive coordination of services, and he and the team work from a negotiated plan of care.

(Continued)

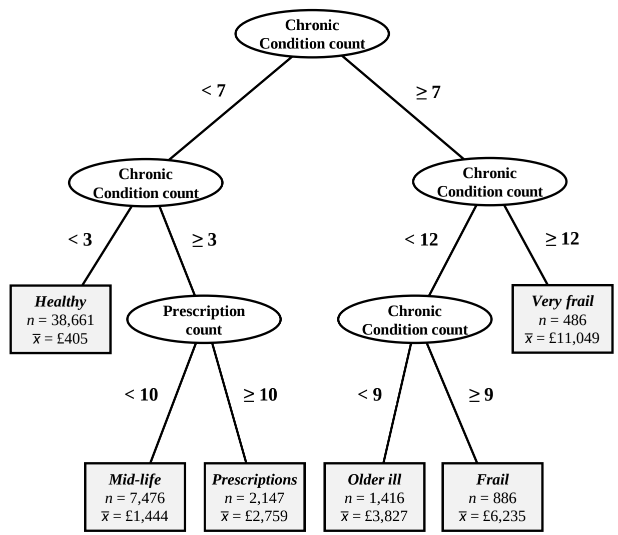
Bridges to Health

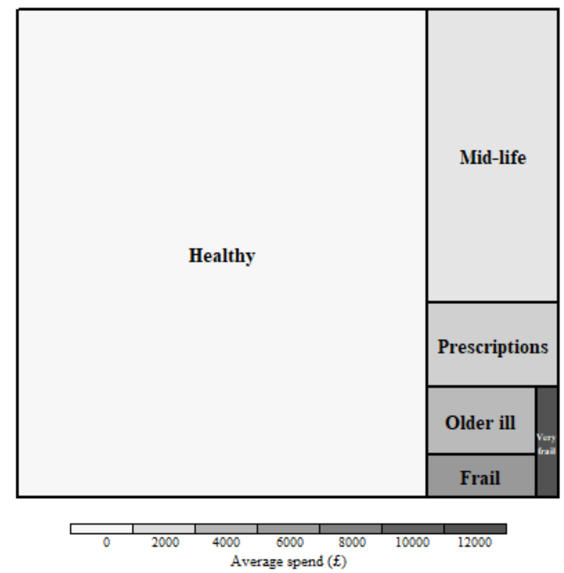
5. Lynn et al, 2017 "Bridges to Health"
6. Low et al, 2017 (Singapore)
7. Joynt et al, 2017 (USA Medicare)
8. Electronic Frailty Index (UK, four levels)

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Decision trees

- A **"derived"** approach
- Objectively **seeks discrimination** in target variable (spend)
- Segment names and definitions may be less intuitive



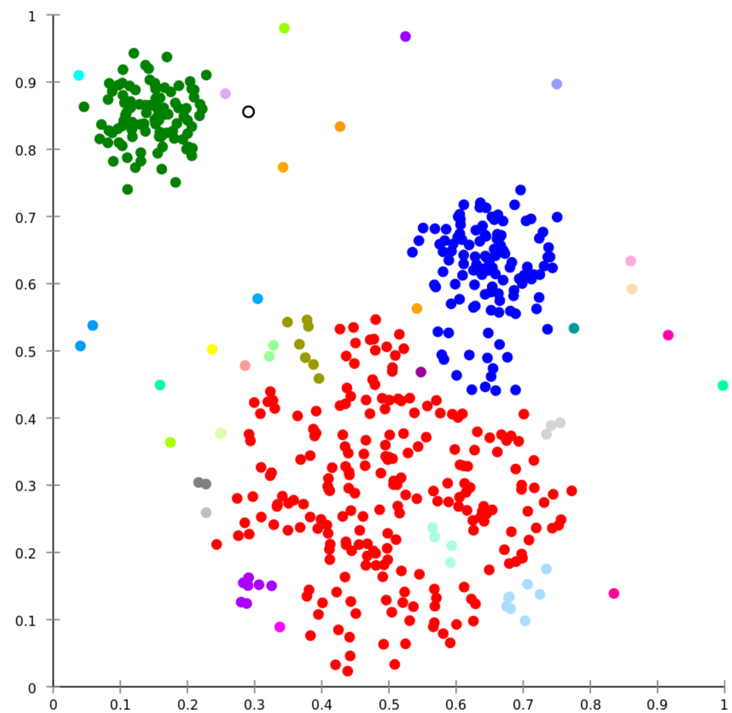


9. CART (Breiman method)
10. Conditional inference trees
11. C5.0 (information gain)
12. CHAID (Chi-square significance testing)

Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Cluster analysis

- Also a derived approach
- Finds groups where observations are **most similar**
- **Non-objective**: similarity driven by attributes and not target
- Need to define “k” upfront



13. k-means (mean Euclidean distance)
14. k-modes (Hamming distance)
15. k-prototypes (numeric + categorical data)
16. k-medoids (sum of square distance)

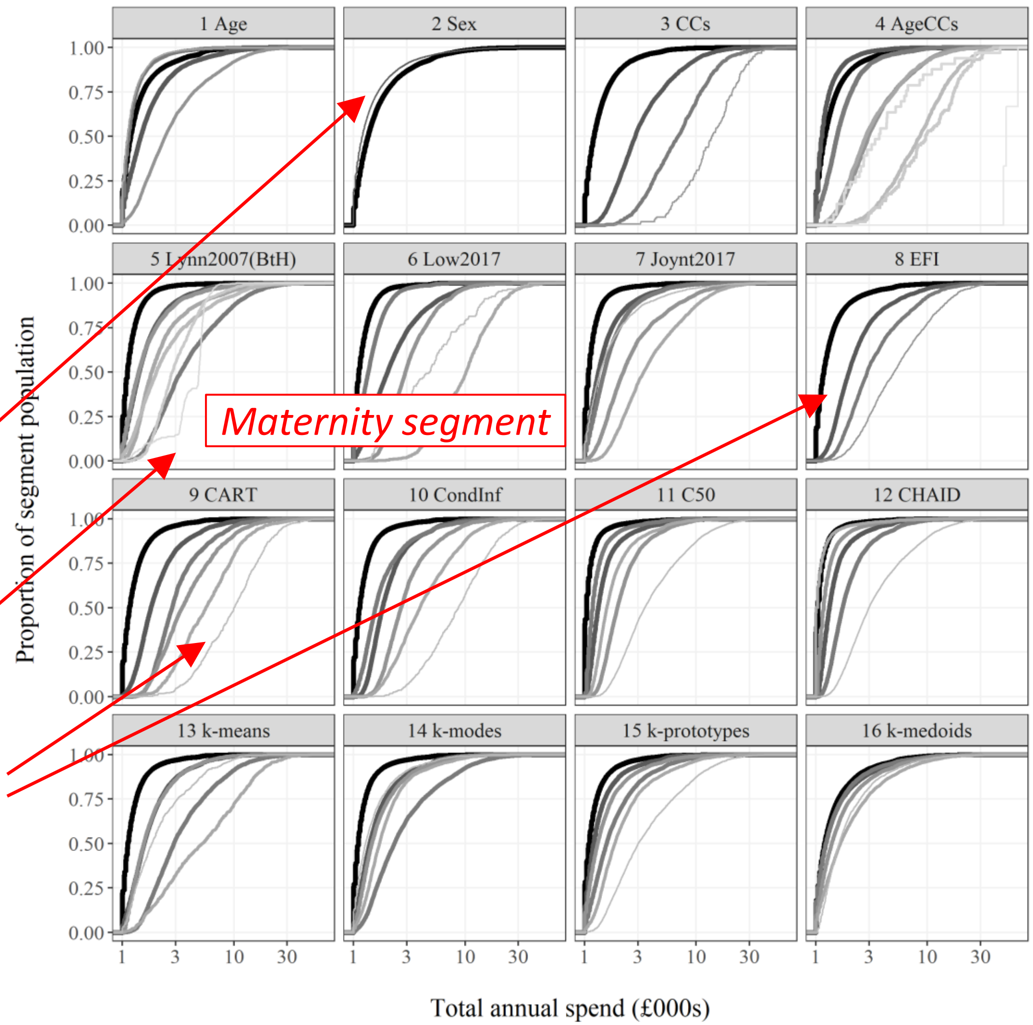
Outline of introduction

1. Setting and data
2. Methods
3. Comparison
4. Discussion

Segment-level spend distributions

- Can understand:
  - Number of segments
  - Spend profile
  - Number in segment

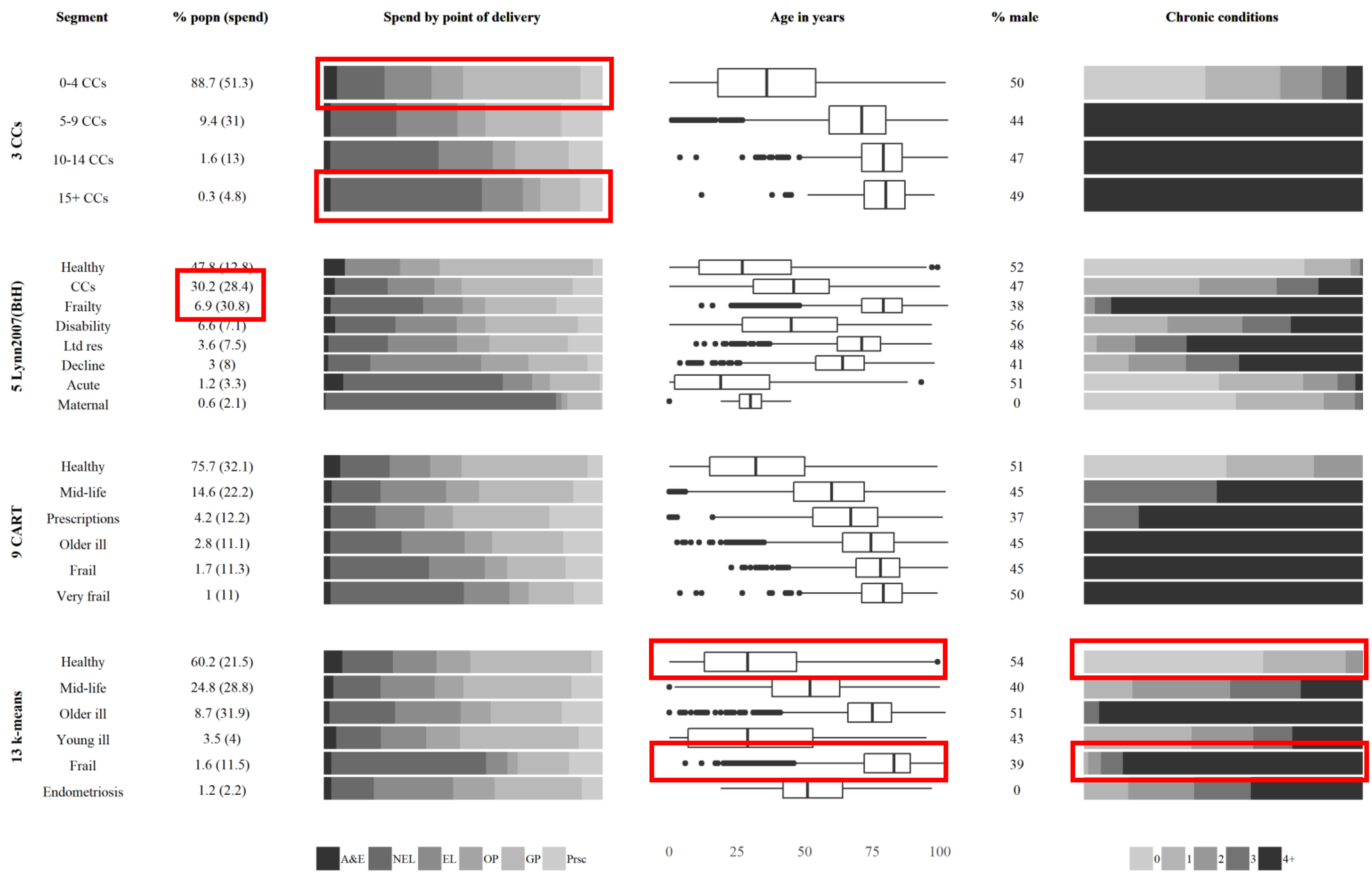
- Rules of thumb:
  - Closer lines = less discrimination
  - More volatility = less homogeneity
  - Consistent progression in line shading = larger less expensive to smaller more costly



NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

3. COMPARISON

Spend and attributes differential



Reduction in variance (spend)

- To be useful for PHM, methods must be **discriminative**

- Assessed through:

$$\sigma_W^2 = \frac{\sum_{i=1}^{N} n_i \sigma_i^2}{\sum_{i=1}^{N} n_i}$$

- A **mixed bag** of results

- Some methods “cheat”

Category	Method	Variance	Reduction
Baseline	*Baseline*	*5,433,321*	-
Judgemental	Age	4,912,301	10%
	Sex	5,418,924	0%
	Chronic conditions	3,516,112	35%
	Age and chronic conditions	3,505,768	35%
Prescribed binning	Bridges to Health	4,275,849	21%*
	Low2017	3,145,663	42%*
	Joynt2017	4,376,765	19%
	Elec Frailty Index	4,319,655	20%
Decision trees	CART	3,352,816	38%
	Conditional infererence	3,403,747	37%
	C5.0	4,017,665	26%
	CHAID	4,180,762	23%
Clustering	K-means	4,088,182	25%
	K-modes	4,647,659	14%
	k-prototypes	4,564,590	16%
	K-medoids	5,331,346	2%

* methods in which activity is used as an explanatory variable

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Outline of introduction

1. Setting and data
2. Methods
3. Comparison
4. Discussion

Considerations for practical use

- **Discrimination vs segment interpretability**
  - CHAID achieves just 4% better discrimination than Joynt2017 method
  - Really worth this given that Joynt has very comprehendible binning rules?
- **Implementation complexity**
  - Performing a judgemental split is trivial
  - Performing FAMD based *k*-medoids requires specialist skillset
- **Availability of explanatory variables**
  - Different methods require use of different variables
  - Derived methods should have lots of candidate variables to choose from
  - Also raises computational issues

Conclusions

- There is **not necessarily a right or wrong method** for descriptive population segmentation – many factors to weigh w.r.t. discrimination and practicality
  - **Cluster analysis** on-the-whole unsuitable – computationally expensive, lacking discrimination, laborious pre-processing
  - **Prescribed binning** e.g. Bridges to Health: unlikely to achieve high levels of discrimination, but may be more interpretable and useful for benchmarking
  - **Decision trees** arguably preferred option since they offer a sound conceptual fit to the problem and promote good, data-derived discrimination
  - Otherwise, if insufficient data or expertise, then **judgemental splits** focusing on the number of chronic conditions should be favoured

Operations Research for Health Care 22 (2019) 100192

Contents lists available at ScienceDirect

Operations Research for Health Care

journal homepage: www.elsevier.com/locate/orhc

A comparison of population segmentation methods

R.M. Wood [a,b,*], B.J. Murch [b], R.C. Betteridge [b,c]

[a] School of Management, University of Bath, Claverton Down, Bath, BA2 7AY, United Kingdom
[b] Modelling and Analytics, UK National Health Service (BNSSG CCG), South Plaza, Marlborough St, Bristol, BS1 3NX, United Kingdom
[c] Data Science, Cerner Limited, 37 North Wharf Road, London, W2 1AF, United Kingdom

HIGHLIGHTS

- Addresses a gap in the literature regarding population segmentation methods.
- Provides a side-by-side comparison of methods used in practice and by researchers.
- Results show that locally-calibrated decision trees offer the best discrimination.
- Findings provide useful advice to healthcare managers on the ground.

ARTICLE INFO

Article history:
Received 6 February 2019
Received in revised form 11 June 2019
Accepted 21 June 2019
Available online 26 June 2019

Keywords:
Population health
Population segmentation
Decision trees
Cluster analysis
Healthcare utilisation

ABSTRACT

This paper presents the first comparison of descriptive segmentation methods for population health management. The aim of descriptive segmentation is to identify heterogeneous segments according to some target observed measure. In healthcare it can be used to understand how utilisation is distributed among a population, and to identify the patient attributes which explain the greatest differences (knowledge of which can help shape segment-tailored services). In reviewing a number of segmentation methods that are both employed on the ground and explored more experimentally within the academic literature, this paper aims to open up a range of options allowing clinicians and managers an informed choice on which approach to use for their situation. Results support the recommendation that decision tree approaches are on-the-whole most suitable, being configurable to local data and providing the best inter-segment discrimination. More basic judgemental splits on patient attributes can be powerful, with the count of chronic conditions being a key variable. Prescribed binning methods such as Bridges to Health are unlikely to achieve high levels of discrimination but do have easily interpretable segments and could be useful for benchmarking. Clustering methods are found to lack discriminative power, which can be attributed to a lack of conceptual appropriateness to the problem.

1. Introduction

Population health has been defined as "the health outcomes of a group of individuals, including the distribution of such outcomes within the group" [1]. Interest in this field has grown in recent years driven by the combination of rising costs of care with increasingly polarised health needs leading to greater inequality in per capita spend and clinical outcome [2]. Facilitated by the rise of big data and the availability of associated analytical methods, this has led to the growth of *population health analytics* as a discipline concerned with quantitatively approaching matters of population health.

One of the principal investigative areas within the field of population health management – and the subject of this paper – is population segmentation. This involves using information about individuals, such as age and sex, to partition a population into similar groups. Ultimately, the aim is to identify meaningful and interpretable population cohorts which are heterogeneous between and homogeneous within. It is important to have such discrimination since it allows the greatest differences to be uncovered.

Population segmentation is an important tool in healthcare since it allows managers and clinicians to cut through the complexity of large and unwieldy datasets in making sense of the key patient-related attributes that drive the most significant differences in some targeted measure of interest – clinical outcome, waiting time, or utilisation as measured through activity or spend. These insights can help determine the nature and scale of intervention that may be required for cohorts of the population

* Corresponding author at: Modelling and Analytics, UK National Health Service (BNSSG CCG), South Plaza, Marlborough St, Bristol, BS1 3NX, United Kingdom.
E-mail address: richard.wood16@nhs.net (R.M. Wood).

https://doi.org/10.1016/j.orhc.2019.100192
2211-6923/

Wood, R. M., Murch, B. J., & Betteridge, R. C. (2019). A comparison of population segmentation methods. Operations Research for Health Care, 100192.

@BNSSGAnalytics

richard.wood16@nhs.net

NHS
Bristol, North Somerset and South Gloucestershire
Clinical Commissioning Group

Outline of today's workshop

1. Understanding the data
2. Basic segmentation by age
3. Inclusion of long-term conditions alongside age
4. Decision tree segmentation
5. Bridges to Health segmentation
6. Report generation via Rmarkdown
7. Further work on R-based PHM suite