Pharmacoepidemiology and Clinical Pharmacology

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Next Generation Health Technology Assessment

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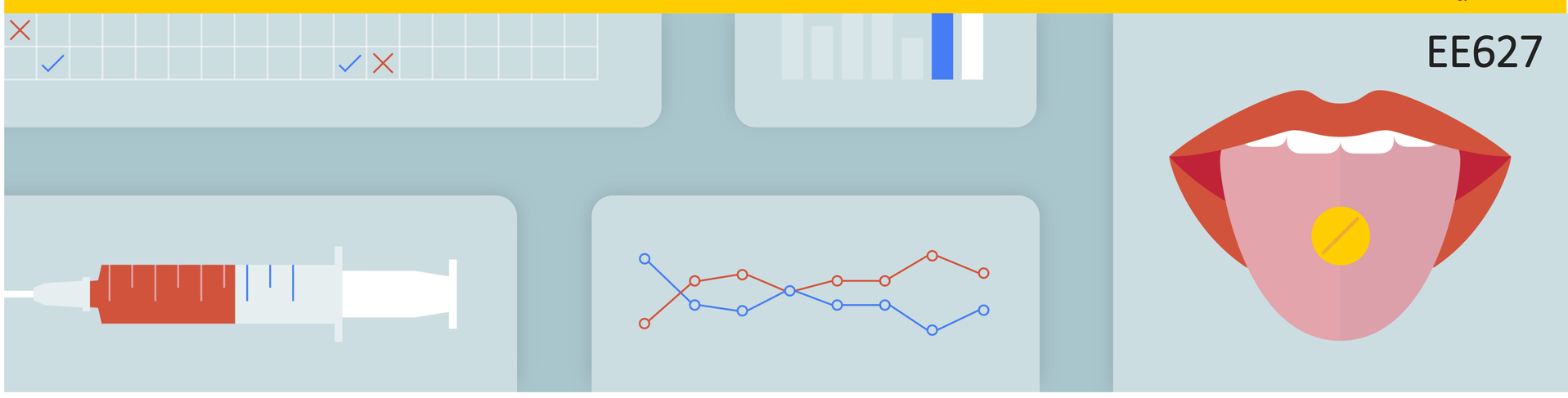

Exploring Diabetes Subgrouping: Pharmacoeconomic Added Value and the Best Strategy

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Introduction

Type 2 diabetes (T2D) is highly heterogeneous in its phenotypes. Although data-driven subgroups are gaining attention, the added value and optimal subgrouping strategy remain understudied.

Research questions

From a pharmacoeconomic perspective
(for aiding reimbursement decision-making in clinical practice)
1. How much does it help having diabetes subgroups?
2. What might be the optimal subgrouping strategy?

Methods

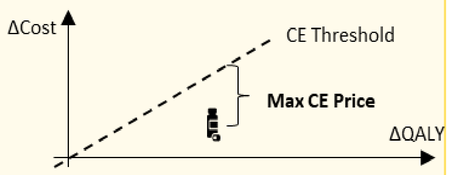
Data: 2,000 randomly selected newly diagnosed T2D from CPRD (UK Primary care data)

	Current	Target
HbA1c (%)	7.5	7
BMI (kg/m^2)	30.9	25
LDL (mmol/L)	2.5	1.4/1.8/2.6/3

Model: UKPDS Outcomes Model[1]

Comparison: Care-as-Usual vs. Treat-to-Guideline-Based Target

Maximum cost-effective price (MCEP):



$$\frac{\triangle \text{ complication cost} + \boldsymbol{MCEP}}{\triangle \text{ QALE}} = \frac{\$100{,}000}{\text{QALY}} = \text{CE Threshold}$$

Subgrouping strategies: (US Healthcare perspective)

Strategy	Information implicitly contained	Learning
K-means[2]	Baseline only	Unsupervised
Rule-based[3]	+Endpoint, expert opinion	Supervised
ADVANCE-based[4]	+Endpoint	Supervised
Latent class-based[5]	+HbA1c follow-up	Unsupervised + Supervised

Results

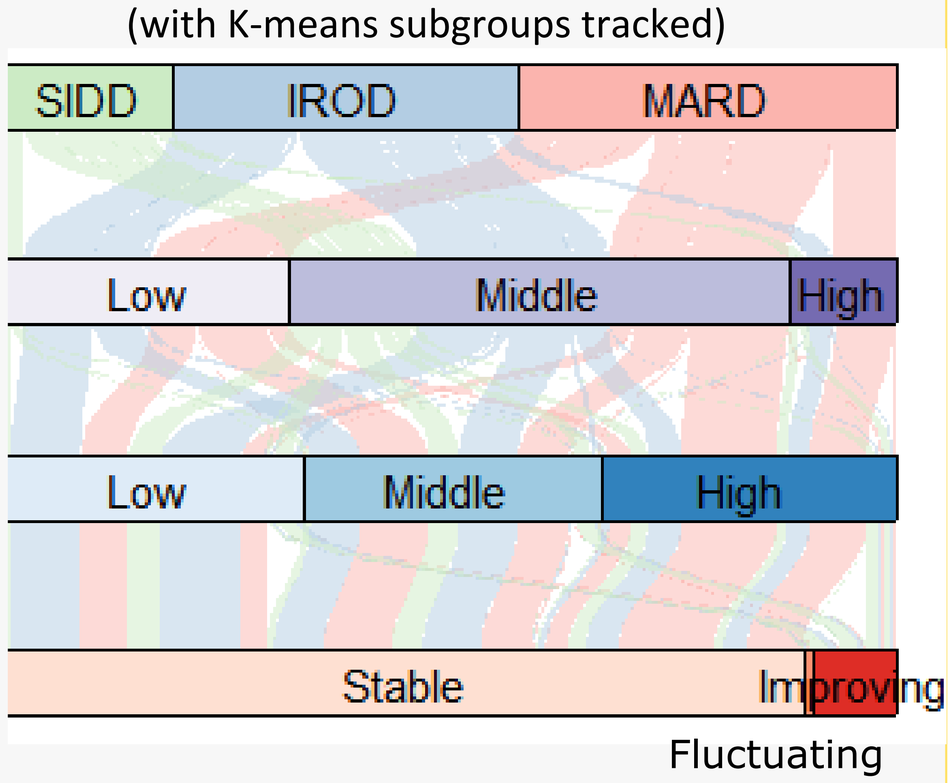
K-means[2]

Rule-based[3]
HbA1c & SCORE
Guideline cutoffs

ADVANCE-based
Prediction model[4]
Risk are divided into tertiles

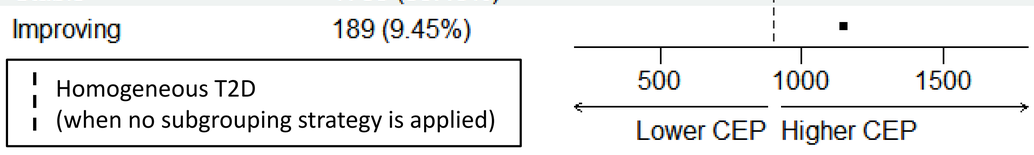
Latent class-based
HbA1c trajectory[5] + Prediction model

Mappings between different subgrouping strategies
(with K-means subgroups tracked)



10 Years hypothetical intensive treatment (HbA1c+LDL+BMI)

Subgroup	Count (Proportion)	Annual Cost-Effective Price ($CEP)*CEP (Diff to min)
HTx K-Means		
MARD	854 (42.7%)	624 (Ref)
SIDD	371 (18.55%)	876 (252)
IROD	775 (38.75%)	1227 (603)
Rule-based		
Low HbA1c and risk	634 (31.7%)	596 (Ref)
Middle HbA1c and risk	1123 (56.15%)	941 (346)
High HbA1c and risk	243 (12.15%)	1540 (945)
ADVANCE Model-based		
Low risk	667 (33.35%)	632 (Ref)
Middle risk	666 (33.3%)	932 (300)
High risk	667 (33.35%)	1150 (518)
HbA1c Latent Class-based		
Fluctuating	22 (1.1%)	853 (Ref)
Stable	1789 (89.45%)	879 (26)
Improving	189 (9.45%)	1152 (299)



*The CEP referred to here is the annualized MCEP, a straightforward indicator.
If a treatment costs less than the CEP in a year, then it is considered cost-effective.

Discussion & Conclusions

- **Mappings** between different subgrouping strategies **vary** → necessity and importance of carefully evaluating subgrouping strategies
- **Subgroup-specific CEP differs** substantially from CEP of **homogenous T2D** → Subgroups support **priority setting and resource allocation**
- **Rule-based risk-driven subgroups** captured **greatest discrimination in CEP** → appear **optimal** from a pharmacoeconomic perspective
- The lesser discrimination of data-driven latent class-based subgroups might be attributed to their current inability to exclude treatment effects, thereby mixing mild individuals with severe individuals who have good control.

References

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