Casemix classification for Dutch homecare payment

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Agenda

- Introduction
- Developing an instrument to collect data
- Improving the casemix model
- Closing remarks

Introduction

Towards a new homecare payment system

From fee-for-service to a **prospective payment system** for home care with the aim to:

- ✓ Align with current policy incentives for (home) care
- ✓ Incentivize quality of care
- ✓ Increase personalized, integrated care

Casemix classification as essential aspect of a prospective payment system to prevent risk selection by providers.

Towards a new homecare payment system

One of the challenges in developing casemix classification for homecare in the Netherlands

Lack of standardized data

The need for a **separate questionnaire** to collect **standardized, objective data** on relevant predictors of homecare use.

Collecting data for casemix classification

The **Case-Mix Short Form questionnaire**

Illness prognosis	Illness prognosis
Daily functioning	Meal preparation
	Eating and drinking
	Continence
	Toileting
	Mobility
	Dressing
	Washing/showering
	Medication use
Cognitive functioning	Cognitive skills for daily decision making
Social support	Informal care

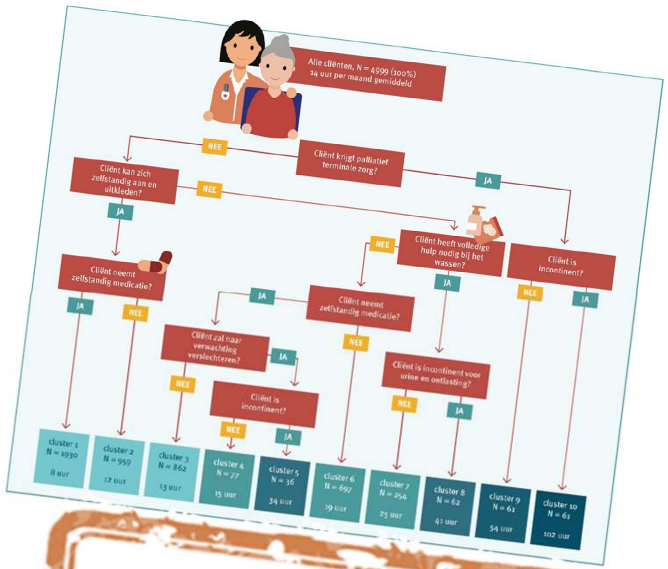
Casemix classification based on CM-SF data

The CM-SF questionnaire shows **promising results** in predicting homecare use.

Main predictors relate to a client's **daily functioning** and if a client receives **palliative care**.

Can we improve?

- Better alignment of client groups to daily practice.
- Increase explained variance.



Explains 21% of variance in weighted home care use

Goals of today's presentation

Gain insight into **(other) client characteristics that are relevant to predict homecare use**, according to nurses and healthcare purchasing experst (i.e. insurers), and **how these can be measured**.

by
Anne van den Bulck

Present the **data-driven** and **expertise-driven** approach that was followed to develop an **improved case-mix model** given the client characteristics identified.

by
Maud de Korte

Identifying relevant predictors of homecare use

Methods to identify predictors

Two-round **Delphi-study** according to the RAND/UCLA Appropriateness Method.

Assessing relevance of client characteristics on a 9-point Likert scale

11 characteristics of the CM-SF
+
Characteristics suggested by the experts

Expert panel meeting

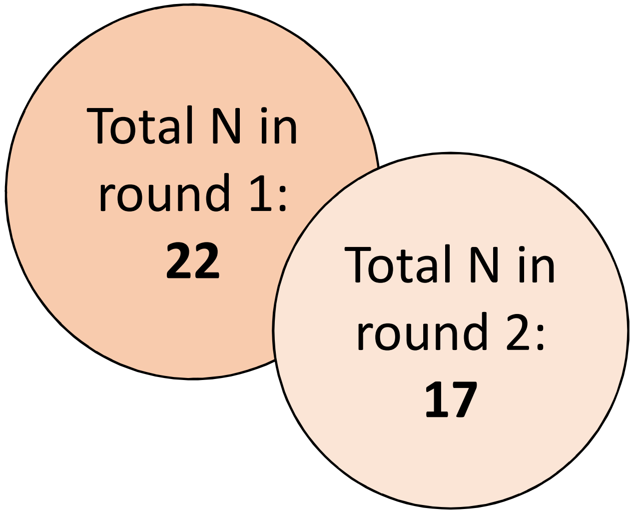
Re-assessing relevance of client characteristics

Methods to identify predictors

Two separate groups of **participants** in the Delphi-study:

- **District nurses**
  Round 1: 16
  Round 2: 12

- **Insurers**
  Round 1: 6
  Round 2: 5



Methods to identify predictors

Analyzing scores using a combination of **medians** and **interquartile ranges** (IQR).

Median 1-3	Irrelevant	IQR≤2	Consensus
Median 4-6	Uncertain	IQR >2	No consensus
Median 7-9	Relevant		

➔ Relevance = median 7-9 AND consensus
➔ Uncertainty = median 4-6 AND/OR no consensus
➔ Irrelevance = median 1-3 AND consensus

Results

Final relevance of the 11 client characteristics from the CM-SF:

- **4 client characteristics** were found **consensually relevant**.

Client characteristic	Relevant?	Consensus?	Conclusion
Continence	Uncertain	No	Uncertain
Toileting	Yes	No	Uncertain
Mobility	Yes	No	Uncertain
Dressing	Uncertain	No	Uncertain
Washing/showering	Yes	Yes	Relevant
Eating and drinking	Yes	Yes	Relevant
Meal preparation	Uncertain	No	Uncertain
Medication use	Yes	No	Uncertain
Cognitive skills for daily decision making	Yes	Yes	Relevant
Informal care	Yes	No	Uncertain
Illness prognosis	Yes	Yes	Relevant

Results

Client characteristics suggested by the experts:

142 initial suggested client characteristics

↓ *ordening, clustering and defining*

Final list of **53 suggested client characteristics**

↓

Selection of 11 suggested characteristics

Results

Final relevance of the 11 suggested client characteristics:

- **6 client characteristics** were found **consensually relevant**.

Client characteristic	Relevant?	Consensus?	Conclusion
Multimorbidity	Yes	Yes	Relevant
Skin problems	Yes	No	Uncertain
Vision and hearing	Uncertain	No	Uncertain
Malnutrition	Uncertain	Yes	Uncertain
Mental functioning	Yes	Yes	Relevant
Resilience	Yes	Yes	Relevant
Dementia	Uncertain	No	Uncertain
Self-management and self-direction	Yes	No	Uncertain
Learning ability	Yes	Yes	Relevant
Social network	Yes	Yes	Relevant
Need for technical nursing care	Yes	Yes	Relevant

Results

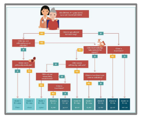
According to nurses and insurers, homecare use could be predicted better by **including other more holistic predictors** in case-mix classification.

- **11 out of 22** client characteristics assessed as consensually relevant.
- Suggested client characteristics were relevant relatively more often.

Developing an instrument to collect data on relevant predictors

Developing CM-SF version 2.0

Criteria for client characteristics to be **included in version 2.0**:

1.  Characteristics included in the first developed casemix model.
   Illness prognosis, continence, dressing, washing/showering, medication use.

2.  Characteristics that were (additionally) found relevant in the Delphi-study.
   Mental functioning, memory, resilience, learning ability, social network, multimorbidity, need for technical nursing care.

3. Other characteristics there were considered as potentially relevant by the majority of the research team.
   Eating and drinking, self-management and self-direction, informal care, skin problems.

Developing CM-SF version 2.0

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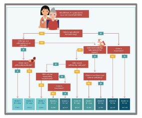
1. 

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   Illness prognosis, continence, dressing, washing/showering, medication use.

2. Characteristics th ... elevant in the Delphi-study.
   Mental functioni ... g ability, social network, multimorbidity, n...

   Challenge: to objectively measure these characteristics

3. Other characteristics there were considered as potentially relevant by the majority of the research team.
   Eating and drinking, self-management and self-direction, informal care, skin problems.

Development CM-SF version 2.0

Formulating a **concept CM-SF version 2.0**, based on (parts of) existing validated questionnaires

Examples of sources:

- **Mental functioning →** based on one item of the BelRAI screener
- **Memory →** based on one item of the Groningen Frailty Index
- **Resilience →** based on the definition of resilience according to a study from Tugade & Fredrickson (2007)

Development CM-SF version 2.0

Formulating a **concept CM-SF version 2.0**, based on (parts of) existing validated questionnaires

Ask for feedback from several stakeholders

- Think-aloud **interviews with 6 district nurses**
- Written feedback from **6 homecare providers** who will implement the CM-SF version 2.0
- Written feedback from the **Dutch Nurses' Association**

"This new version of the CM-SF has greatly improved compared to the first version. The new items make it a better representation of the broad client needs in homecare." (*district nurse*)

Development CM-SF version 2.0

Formulating a **concept CM-SF version 2.0**, based on (parts of) existing validated questionnaires

Ask for feedback from several stakeholders

- Think-aloud **interviews with 6 district nurses**
- Written feedback from **6 homecare providers** who will implement the CM-SF version 2.0
- Written feedback from the **Dutch Nurses' Association**

Process the feedback and define the **final CM-SF version 2.0**

Collecting data for casemix classification

The **Case-Mix Short Form questionnaire version 2.0**

Other

1. Illness prognosis
2. Need for technical nursing care

Physical health status

3. Multimorbidity

Daily functioning

4. Continence
5. Eating and drinking
6. Dressing
7. Washing/showering
8. Medication use

Social environment and network

9. Social network
10. Informal care

Mental health status and behavior

11. Mental functioning and behavior
12. Memory
13. Resilience
14. Self-direction

Health literacy

15. Learning ability

Improving the casemix model

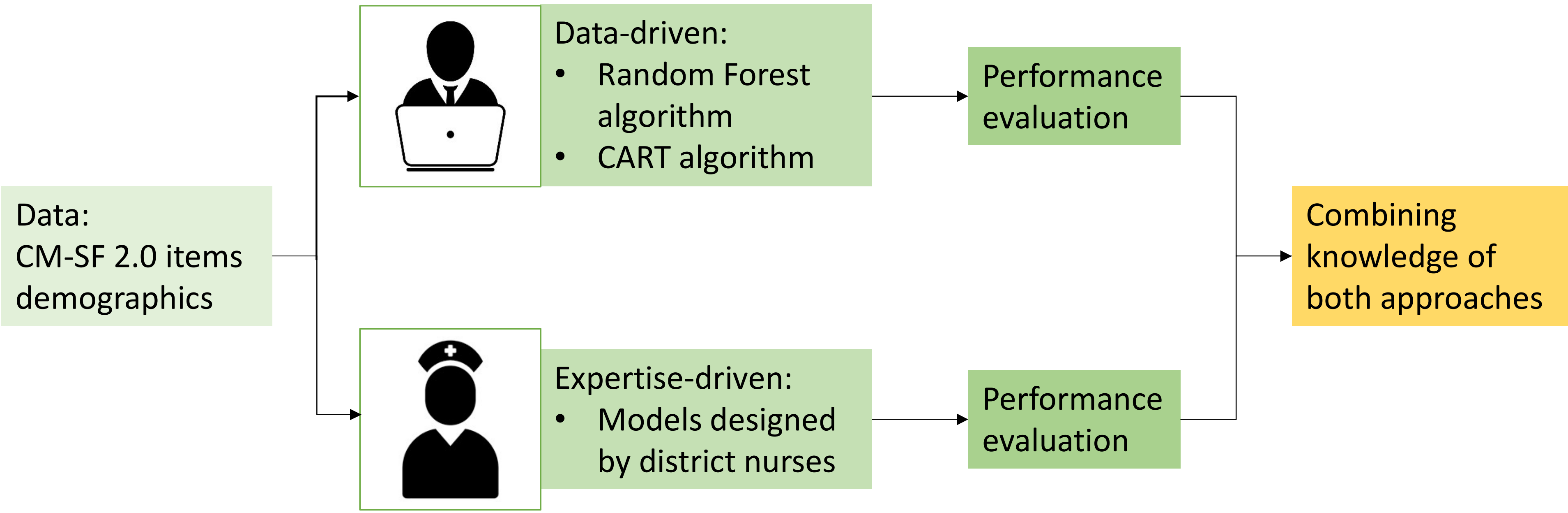
What was our goal?

We want to **optimize** the current case-mix model.

- Higher **predictive power**
- More relevant to **clinical practice**
- But without getting too **complex**

What did we learn from previous research?

- In previous research: solely data-driven.
- New approach: data- and expertise-driven.

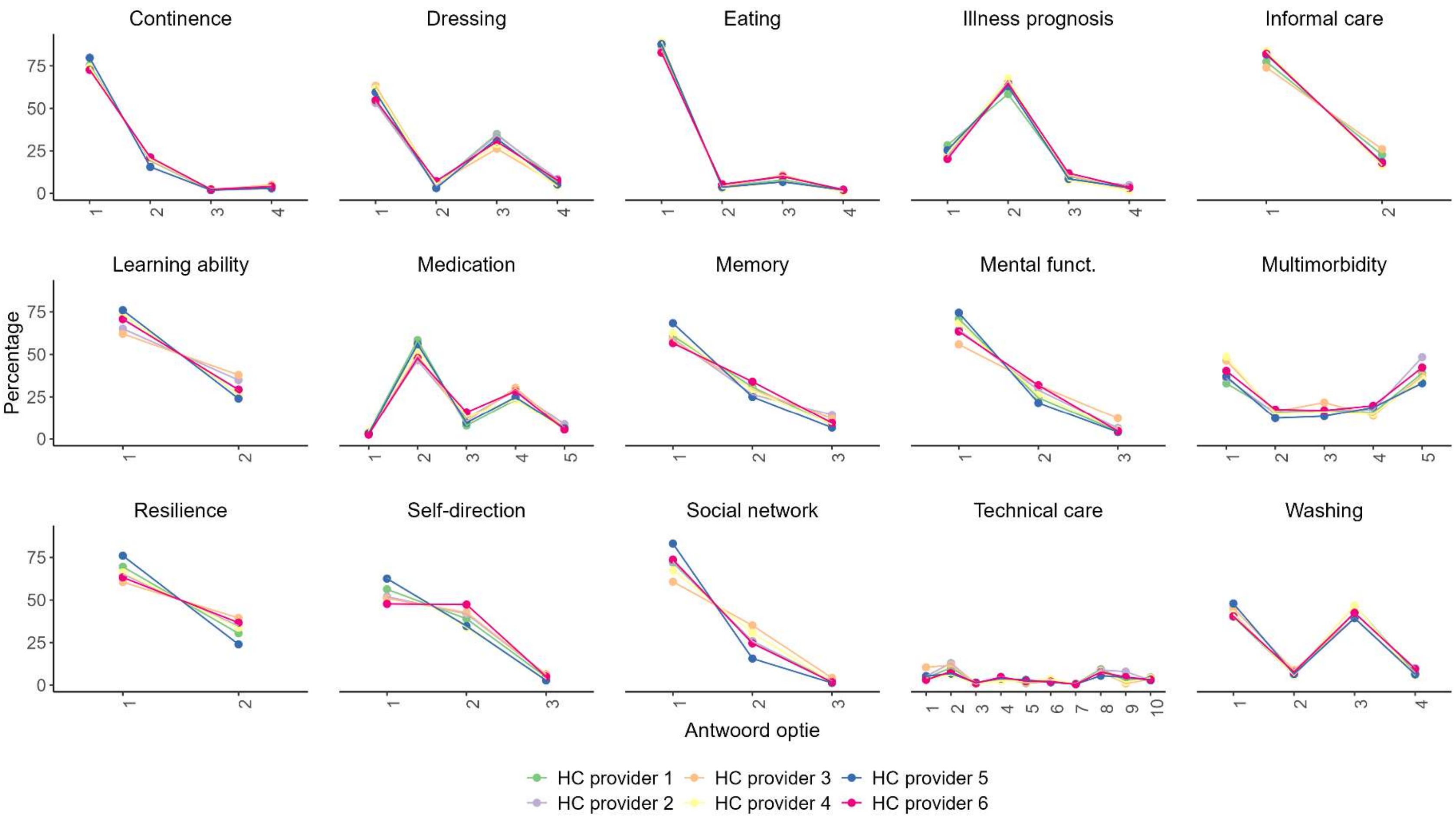


From instrument to data collection

- Data collection took place at **6 homecare providers**
  - From November 2021 until April 2022
  - After each (re)assessment
  - **23.335 CM-SF questionnaires** filled out by **830 district nurses**

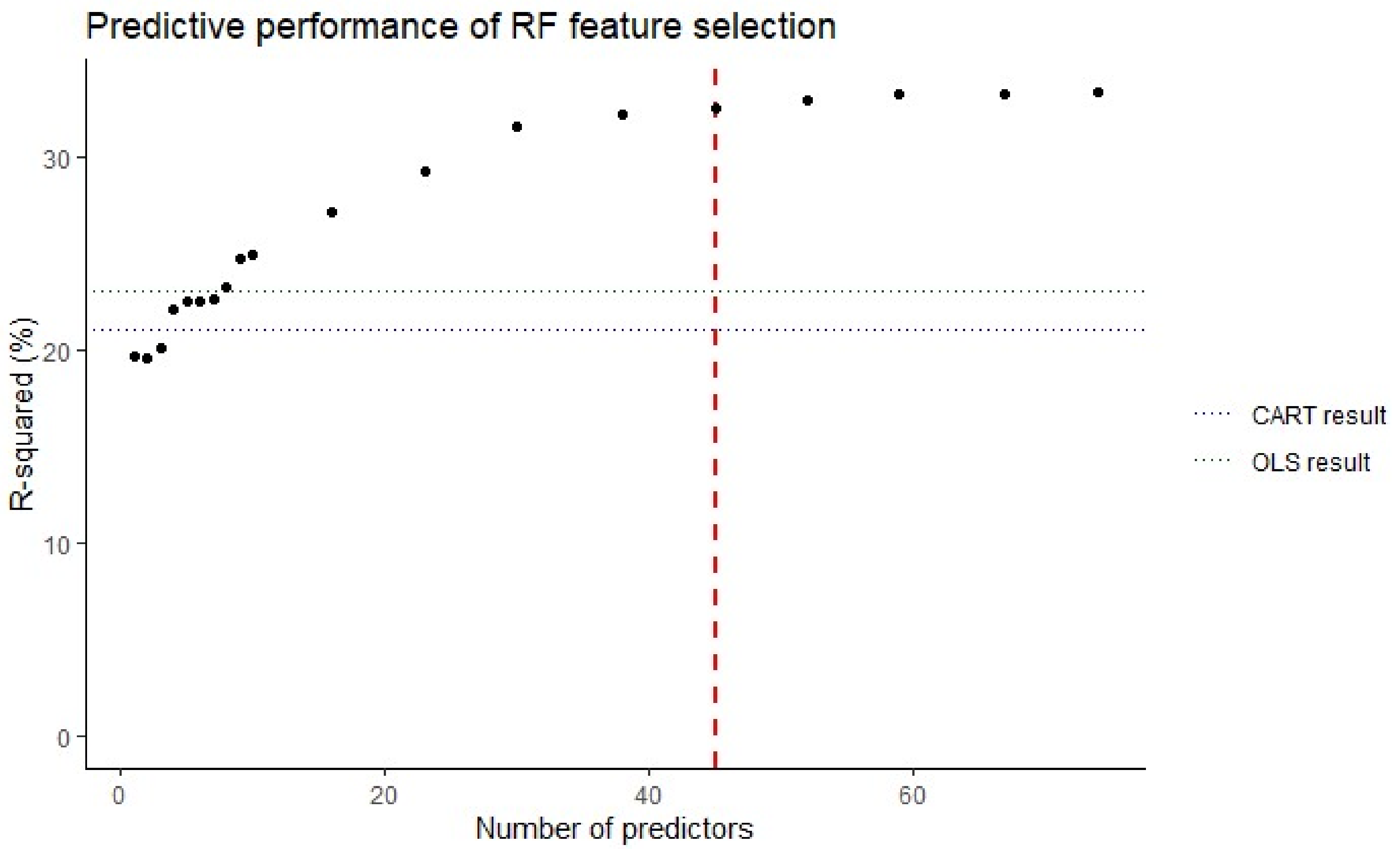
- Dependent variables: all items from CM-SF + age/gender
- Independent variable: weighted hours of homecare over 4 week time frames after scoring CM-SF

What do the data look like?

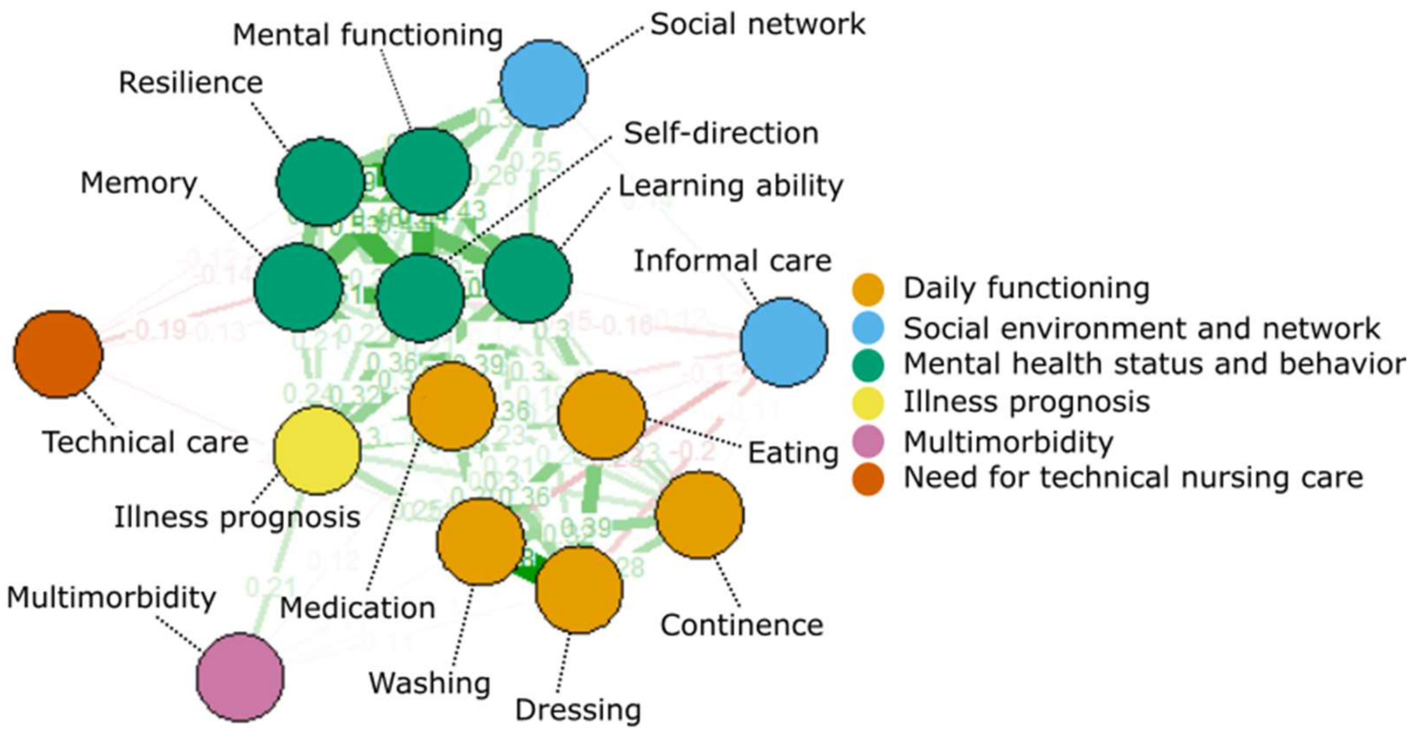


Results from the data-driven approach

Maximum predictive power: 33% R-squared



Correlation between predictors



Predictive power: mostly in items that directly imply care activity

1. Continence
2. Eating and drinking
3. Dressing
4. Washing/showering
5. Medication use
6. Need for technical nursing care
7. Informal care
8. Illness prognosis (palliative care)

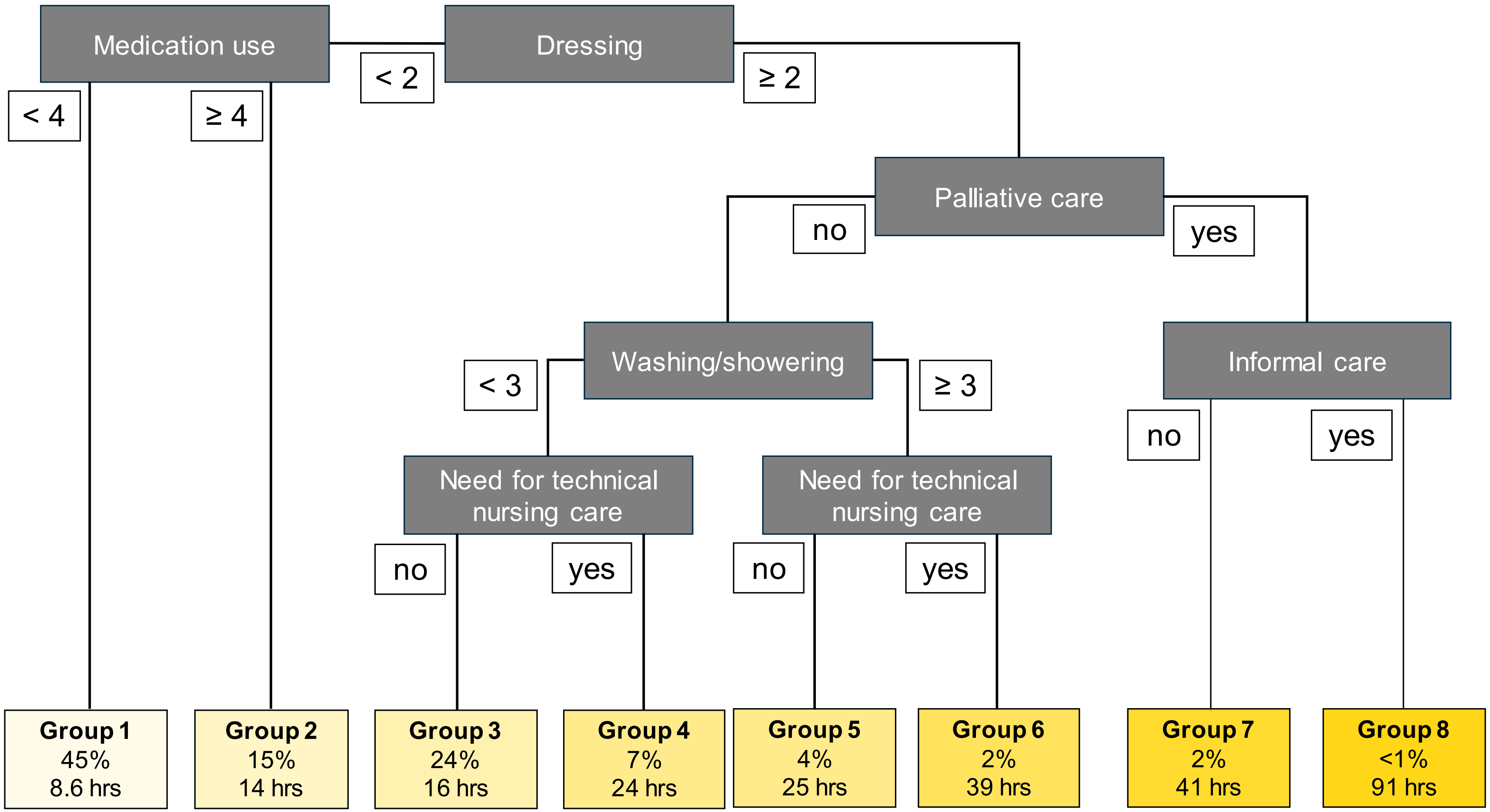
R-squared: 27%

1. Multimorbidity
2. Social network
3. Mental functioning and behavior
4. Memory
5. Resilience
6. Self-direction
7. Learning ability

R-squared: 9%

Data-driven, interpretable model (CART algorithm)

R-squared: 21%



Results from the expertise-driven approach

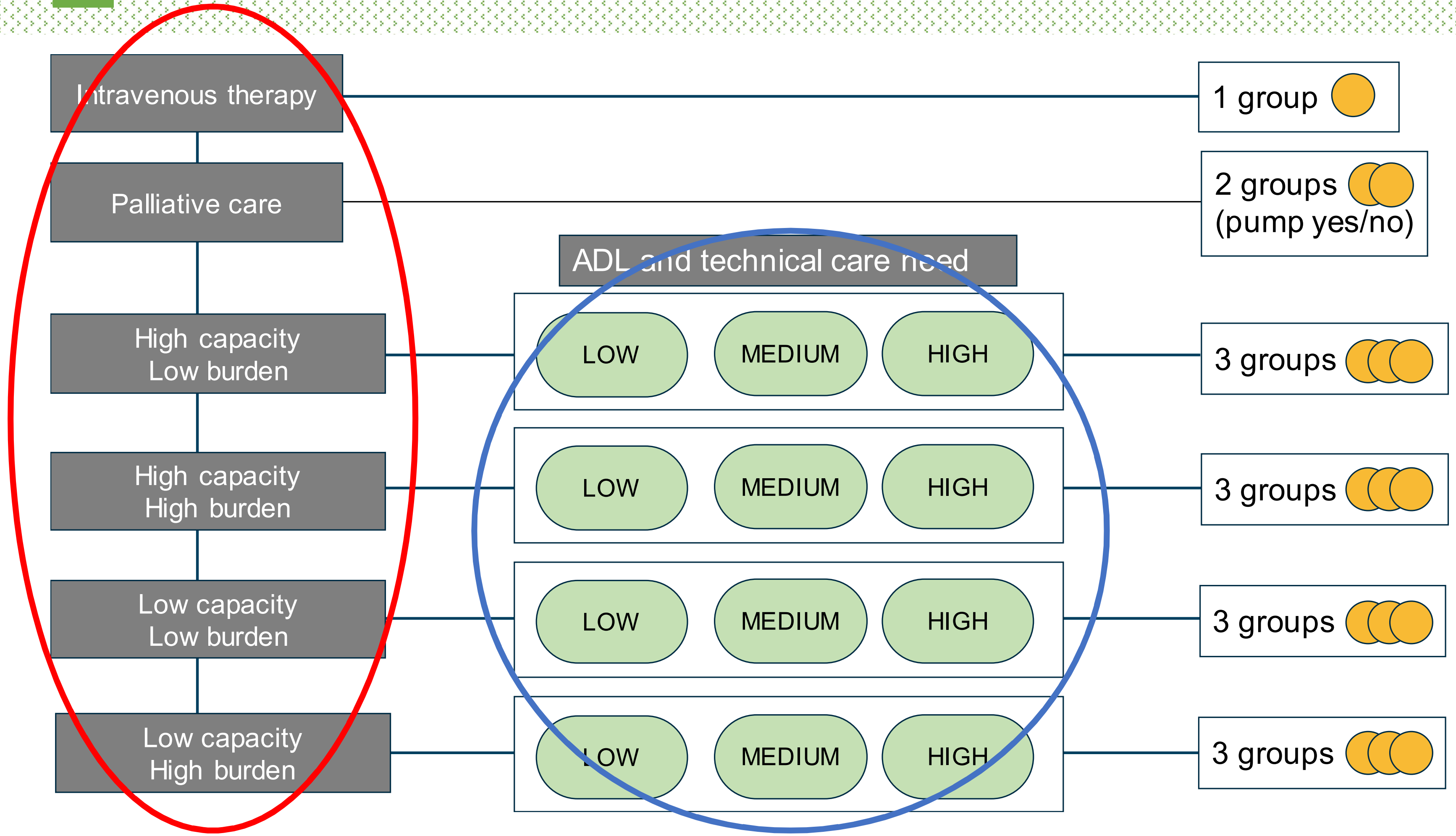
“Rules” for the expertise-driven approach

“Draft a model that you think has the most added value in your daily work”

Examples of some ‘rules’:

- You can only use the CM-SF items.
- You are allowed to combine items or create a sum score of items.
- Number of items and casemix groups are not limited.

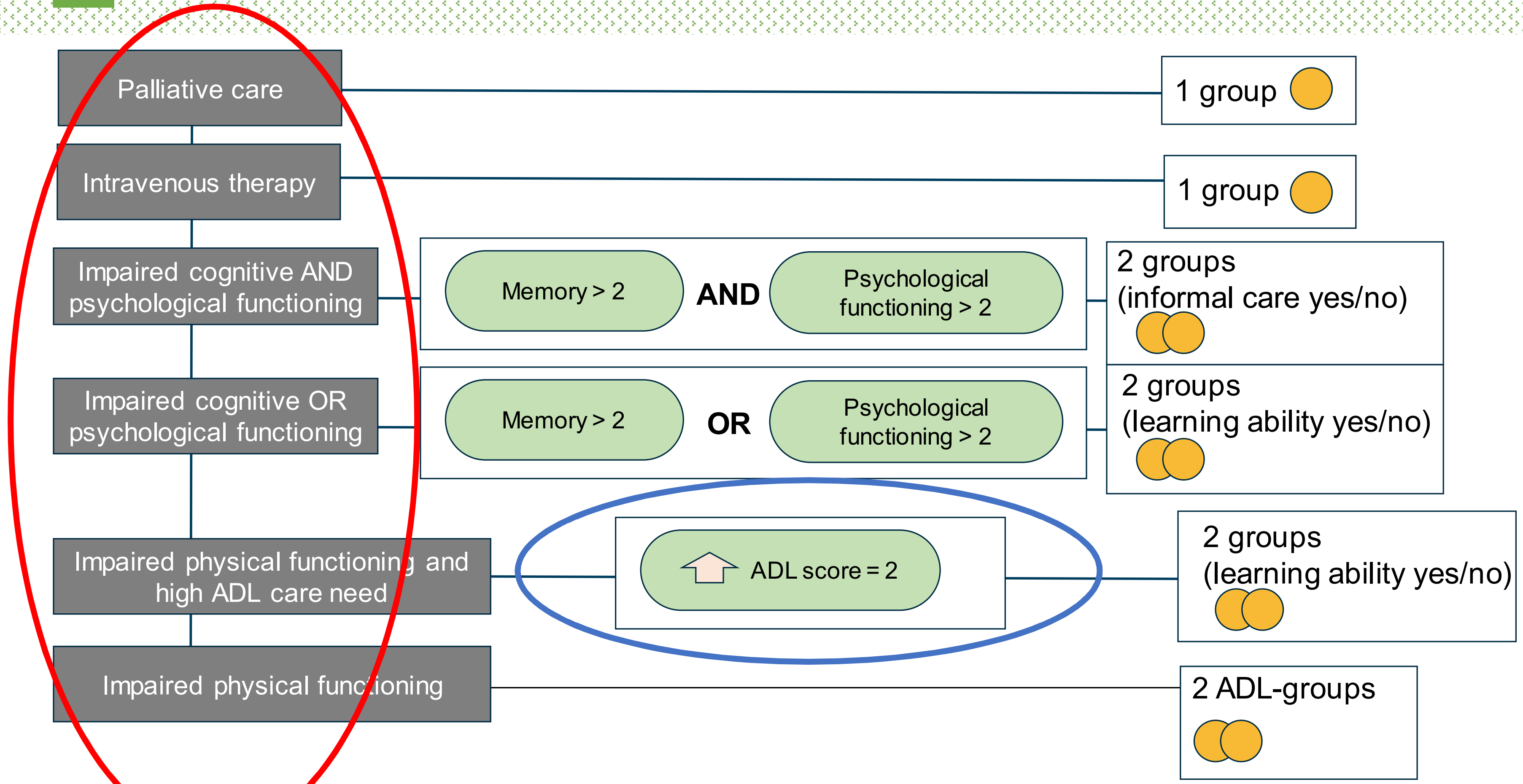
Model designed by district nurses (I)



R-squared: 19.3%

Model designed by district nurses (II)

R-squared: 11.2%



* **ADL score** (0, 1, 2): based on items ‘Dressing’, ‘Washing’ and ‘Continence’

What did we learn?

- More data and more CM items result in more **predictive accuracy**. But not within an interpretable model.
- ADL need, palliative care need and technical care need add most to predictive power.
- It is possible to improve **clinical relevance/recognizability** without losing (too much) predictive power
  - Adding an extra level with more general client groups
  - Isolating high care need clients (palliative, complex technical care)
  - Sum scores of correlated items, e.g. ADL need
- However: **complexity** increases.

Closing remarks

Closing remarks

- Developing casemix classification for homecare remains challenging.

- The model choice requires policy consideration: does better clinical relevance/recognizability outweigh additional registration?

- Connecting the case-mix model with outcome information is crucial for meaningful use of the case-mix model in e.g. procurement practice or payment system.

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A selection of articles about our project:

- Van den Bulck AOE, et al. Identifying client characteristics to predict homecare use more accurately: A Delphi-study involving nurses and homecare purchasing specialists. *BMC Health Serv Res*. 2022;22:394
- Elissen AMJ, et al. Development of a casemix classification to predict costs of home care in the Netherlands: a study protocol. *BMJ Open*. 2020;10(2):035683.
- De Korte MH, et al. Using machine learning to assess the predictive potential of standardized nursing data for home healthcare case-mix classification. *Eur J Health Econ*. 2020;21:1121-9.