On the impact of decision rule assumptions in experimental designs on preference recovery

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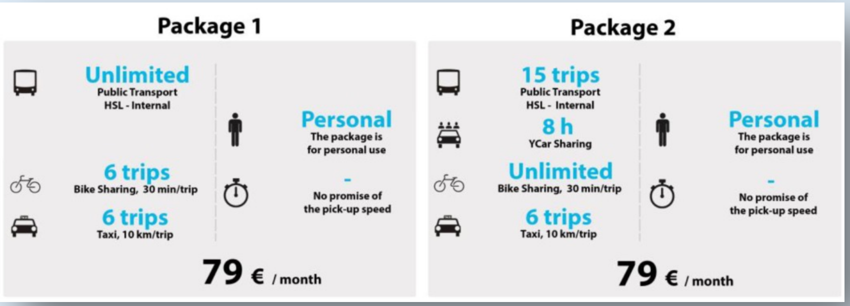
Background

- **Optimal experimental designs in choice modelling field:**
  - are widely used for designing Stated Choice (SC) experiments
  - aim to maximise the information to statistically efficiently estimate the choice model's parameters

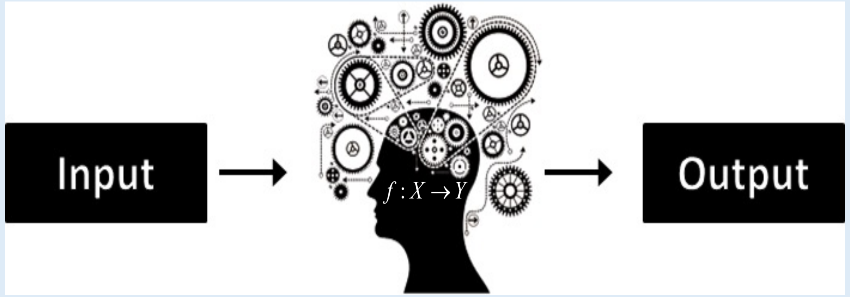


- Almost all experimental designs are optimised for the **assumption** that decision makers use **linear-additive Random Utility Maximisation (RUM)** as the **decision rule**

$$U_i = \sum_{m=1..M} \beta_m x_{im} + \varepsilon_i$$

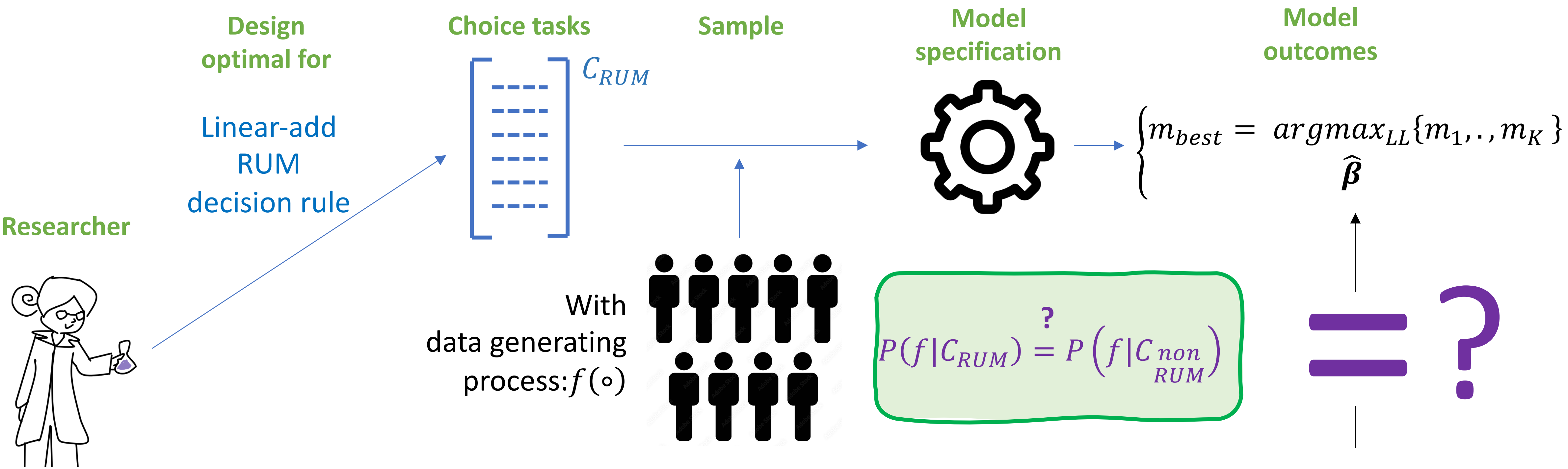
$$y_{ni} = \begin{cases} 1 & if \quad U_{ni} > U_{nj} \quad \forall j \neq i \\ 0 & otherwise \end{cases}$$

- Compelling evidence that people use various **non-RUM decision rules**, including:
  - Satisficing [Simon, 1955]
  - Elimination-by-aspects [Tversky, 1972]
  - Regret minimization [Loomes & Sugden 1982]



Background

- When using experimental designs optimised for RUM, **researchers** (implicitly) **assume** that the **decision rule used to optimise** the design **does not affect** the **choice behaviour**



Research Goals & approach

<u>Research Goals</u> **(RGs) To examine whether:**

1. The **decision rule assumption** underlying the **experimental design** affects respondents' **choice behaviour** (i.e. making a particular model more likely)

$$P(f|C_{RUM}) \stackrel{?}{=} P\left(f|C_{\substack{non\\RUM}}\right)$$

2. Some **choice tasks** invoke a particular RUM or non-RUM decisions rule

   (i.e. making a RUM or a non-RUM model more likely)

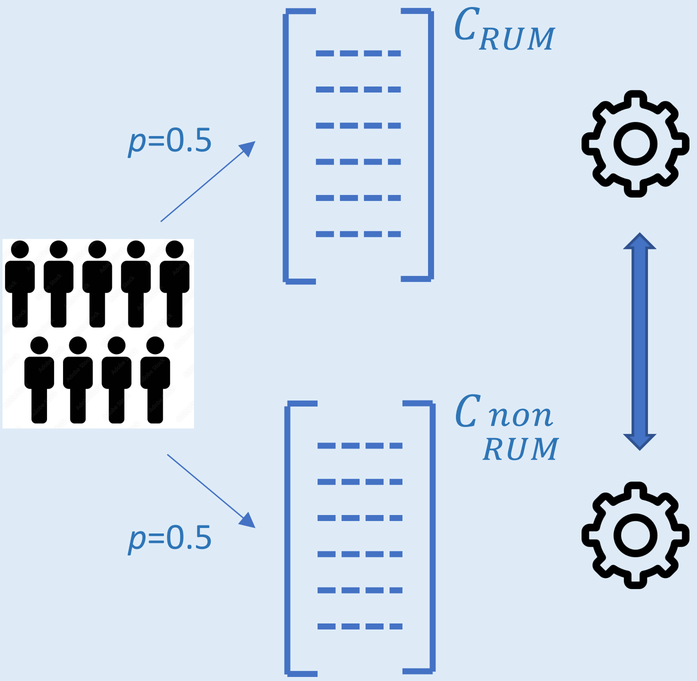
$$P(f|C) \stackrel{?}{=} P(f)$$

Approach RG1

1. Create two experimental designs, one optimised for linear-additive **RUM decision rule** and optimized for **non-RUM decision rule***

2. Randomly assign respondents to the RUM or to the non-RUM design

3. Examine the impact of the design decision rule on the likelihood of competing models*



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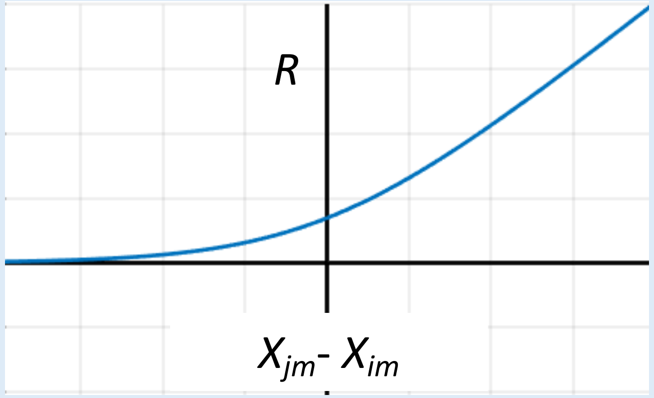
Non-RUM decision rule

- We use **regret minimisation** as the non-RUM decision rule

$$RR_i = \sum_{m=1}^{M} \sum_{j \neq i} \mu \ln\left(1 + \exp\left(\frac{\beta_m}{\mu}\left[x_{jm} - x_{im}\right]\right)\right) + \varepsilon_i$$



- Experimental design theory for RRM models has been developed by (Van Cranenburgh et al., 2018) and implemented in Ngene software

- Also allows to optimise designs for a **combination** of RUM and RRM

Data collection

Context

- Coastal **adaptation to climate change** at **North Sea** and **Baltic Sea** coasts, Germany

- Adaptation strategies were described by 6 attributes: *beach nourishment*, *dyke height*, *planting of the dykes*, *shoreline conditions*, *local relocations of dykes*, *individual payment*

- Respondents had to choose between three alternatives, two hypothetical adaptation scenarios and the status quo

Data collection

Beach nourishment

Dyke heightening

Planting of dykes

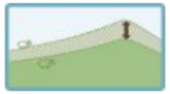
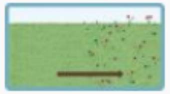
Soft shore

Realignment of dykes and dunes

My payment

Wenn nur die folgenden Alternativen für die Nordseeküste zur Auswahl stehen würden: Welche Alternative bevorzugen Sie?

Bitte wählen Sie eine Alternative aus. Liegt die Zahlung über dem Betrag, den Sie tatsächlich zahlen würden, dann überdenken Sie bitte Ihre Auswahl noch einmal.

		Anpassung A	Anpassung B	Heute
Sandvorspülung (auf 60 km Länge)		20 m	40 m	40 m
Deicherhöhung (auf 950 km Länge)		100 cm	150 cm	50 cm
Bepflanzung von Deichen		5 km	30 km	5 km
Weiche Ufer		0 km	0 km	0 km
Rückverlegung von Deichen und Dünen		9 Stellen	6 Stellen	1 Stelle
Meine Zahlungen pro Jahr (für die nächsten 10 Jahren)		20 €	110 €	0 €
Ich wähle		○	○	○

weiter ...

Data collection

Context

- Two designs (48 sets, 12 within 4 blocks) :
  - ➢ Design 1: Bayesian D-eff design **optimised for RUM-only** with weak priors
  - ➢ Design 2: Bayesian D-eff design **optimised for mixture of RUM and RRM** (50:50) with weak priors
- Two coastlines: Baltic Sea, North Sea → **4 data set**

		Coastline	
		Baltic Sea	North Sea
Experimental design optimised for:	RUM	T1	T3
	Mixture of RUM and RRM	T2	T4

← Each data set contain between 800 - 1000 respondents

← 9,500 – 12,000 observations per data set

Results RG1

Research Goal 1: examine whether the **decision rule assumption** underlying the **experimental design** affects respondents’ **choice behaviour** (i.e. making a particular model more likely)

Final Log-likelihood	T1 RUM Baltic Sea	T2 RUM_RRM Baltic Sea	T3 RUM North Sea	T4 RUM_RRM North Sea
1: lin-add RUM	-10,183	-10,145	-11,932	-12,435
2: µRRM	-10,183	-10,141	-11,931	-12,437

- Overall small model fit differences (µRRM model collapses to lin-add RUM)

→ **The design decision rule does not seem to impact the relative likelihood of competing models**

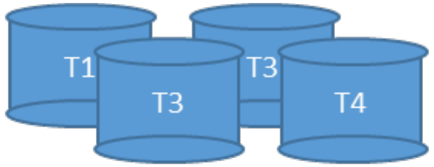
Approach RG2

Research Goal 2: examine whether some **choice tasks** invoke a particular RUM or non-RUM decisions rule

$$P(f|C) \stackrel{?}{=} P(f)$$

How?

[1] Pick data set



Resp	Block	Choice tasks
1	1	1,6,9,11,15,17,27,32,34,38,39,40
2	3	2,3,8,12,18,26,35,41,42,45,47,48
…	…	…
N	4	10,13,19,20,23,24,25,28,33,36,37,46

[2] Randomly assign half the choice tasks to a RUM subset and the half the choice tasks to a RRM subset

Resp	Block	Choice tasks RUM	Choice tasks RRM
1	1	1,11,15,17,32,39	6,9,27,34,38,40
2	3	8,12,18,35,45,48	2,3,26,41,42,47
…	…	…	
N	4	10,19,24,28,36,46	13,20,23,25,33,37

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How?

Resp	Block	Choice tasks RUM	Choice tasks RRM
1	1	1,11,15,17,32,39	6,9,27,34,38,40
2	3	8,12,18,35,45,48	2,3,26,41,42,47
…	…	…	
N	4	10,19,24,28,36,46	13,20,23,25,33,37

[3A] Count the occurrences of choice tasks

$$\sum$$

Choice task	'1'	'2'	'3'	…	'48'
Count	107	86	98		102

Choice task	'1'	'2'	'3'	…	'48'
Count	97	105	103		111

[3B] Estimate a RUM model on the RUM subset and a P-RRM model on the RRM subset

LL_{RUM} = -5108

LL_{PRRM} = -5157

[4] Repeat steps 1 to 3B numerous times, do for each data set, and store results.

Compute ALL: the deviation from

T1

Approach RG2

Research Goal 2: examine whether some **choice tasks** invoke a particular RUM or non-RUM decisions rule

$$P(f|C) \overset{?}{=} P(f)$$

How?

on the RUM subset and a P-RRM model on the RRM subset

LL_{RUM} = -5108 LL_{PRRM} = -5157

[4] Repeat steps 1 to 3B numerous times, do for each data set, and store results. Compute ΔLL: the deviation from the mean LL.

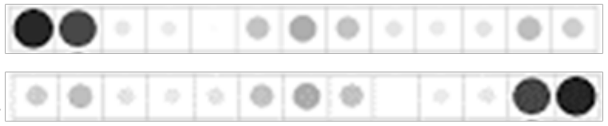
T1 T2 T3 T4

	'1'	'2'	'3'	…	'48'	LL_{RUM}	LL_{PRRM}	∑ LL	ΔLL
1	107	86	98		102	-5,108	-5,167	-10,275	-27
2	101	95	88		105	-5,069	-5,197	-10,196	52
3	99	102	99		95	-5,160	-5,102	-10,262	-14
…									
S	88	97	105		113	-5,134	-5,124	-10,258	-10
							E[∑LL]	-10,248	

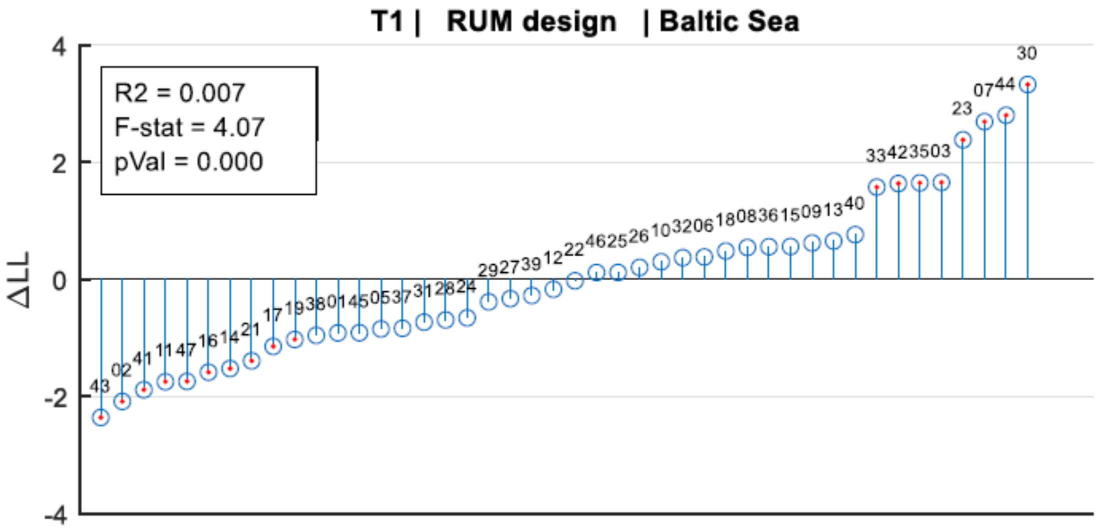
[5] Compute correlation, corr('1','2',…,ΔLL). Identify, for all except 1 block, the task with the lowest correlation with ΔLL.

T1&T3

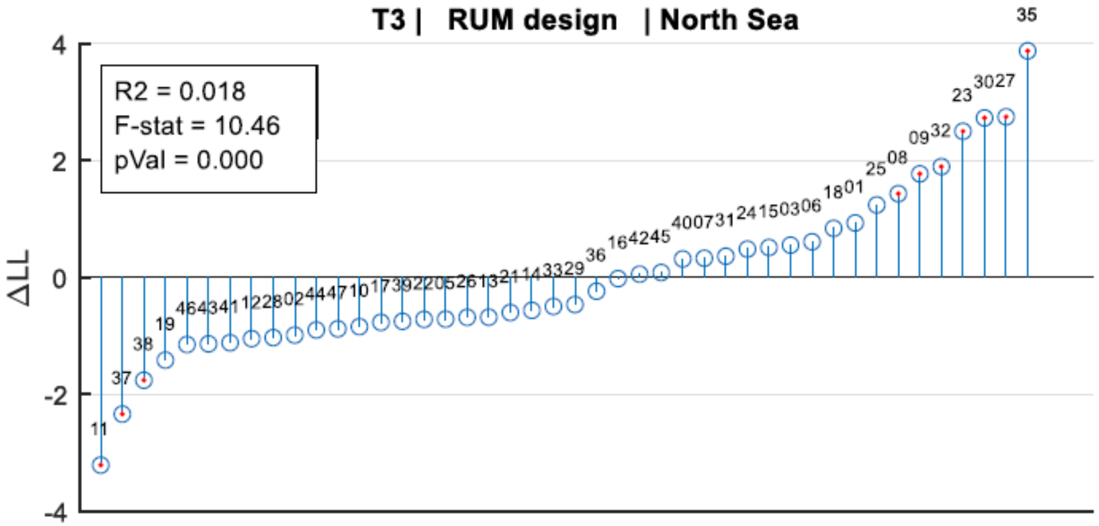
T2&T4



Results RG2

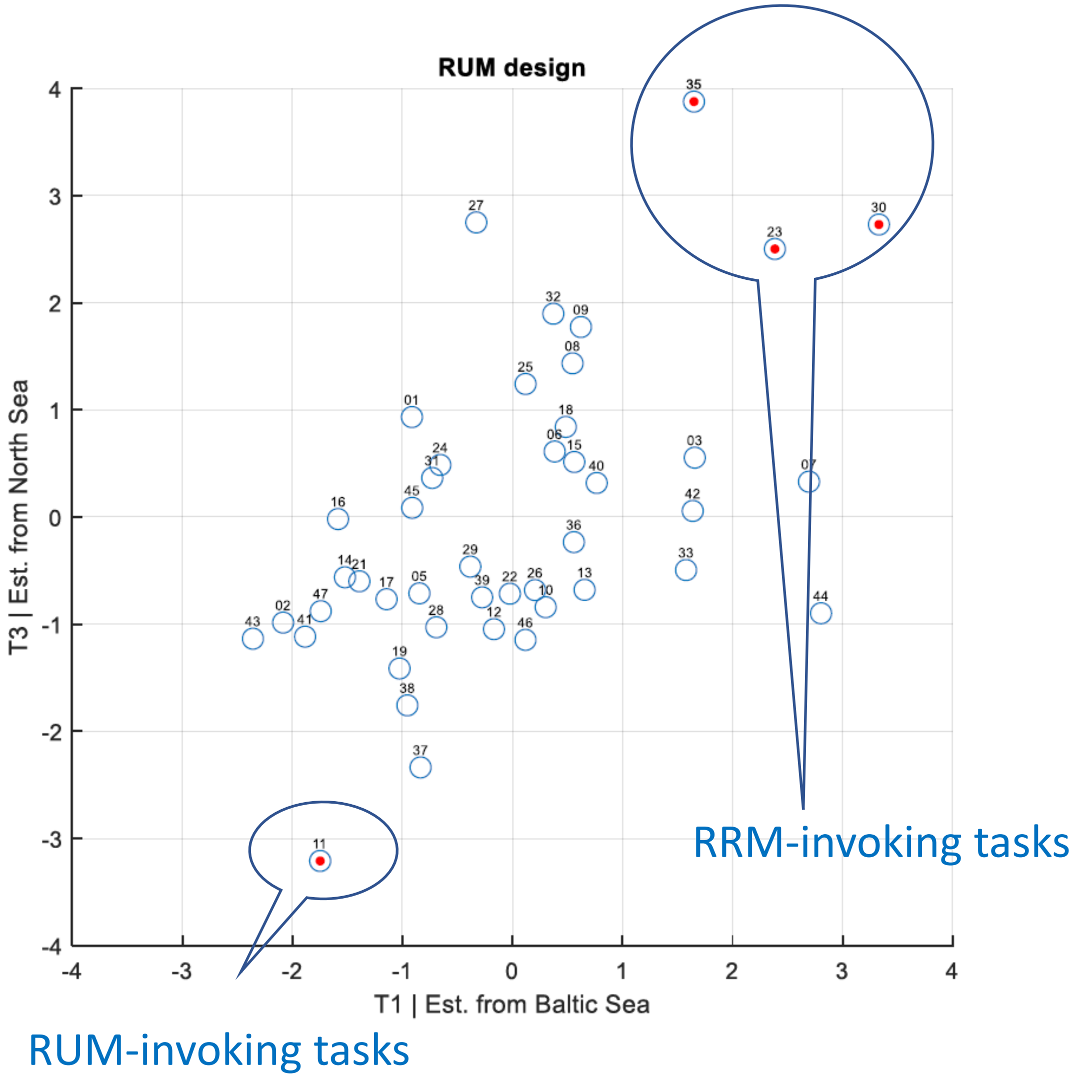

T1 | RUM design | Baltic Sea
R2 = 0.007
F-stat = 4.07
pVal = 0.000
ΔLL

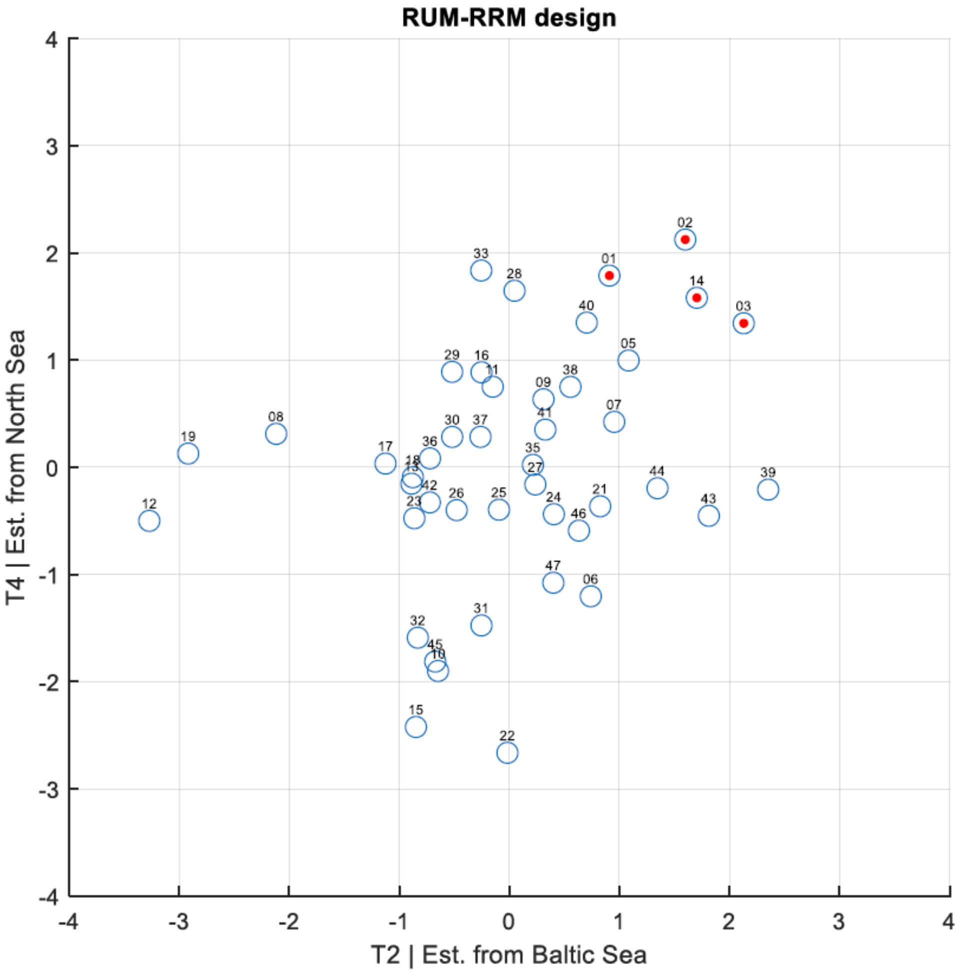
T2 | RUM-RRM design | Baltic Sea
R2 = 0.014
F-stat = 7.78
pVal = 0.000
ΔLL


T3 | RUM design | North Sea
R2 = 0.018
F-stat = 10.46
pVal = 0.000
ΔLL

T4 | RUM-RRM design | North Sea
R2 = 0.016
F-stat = 9.11
pVal = 0.000
ΔLL

Results RG2





- **Some choice tasks seem to invoke a particular decision rule**
- **Choice tasks optimised for RUM seem to produce stronger decision rule invocations.**

Conclusions

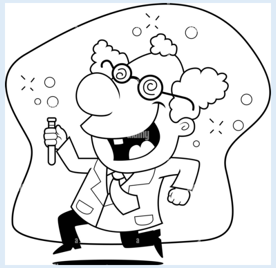
1. The decision rule assumption underlying optimal experimental design do not seem to affect respondents' choice behaviour (i.e. making a particular model/decision rule more likely)

$$P(f|C_{RUM}) = P\left(f|C_{\substack{non\\RUM}}\right)$$

2. Some choice tasks **do invoke a particular decision rule** – violating the assumption that the data generating process of decision makers is **invariant** to the choice tasks design

   → In theory, this opens up the possibility to engineer desired outcomes using the design (which is highly undesirable!)

$$P(f|C) \neq P(f)$$



3. Unclear what properties drive that some choice tasks invoke a linear-additive RUM decision rule while others invoke an RRM decision rule, and yet others seem neutral

Further research

To deepen understanding of the impact of choice tasks on choice behaviour, we need to:

1. Improve data collection and experimental design:
   - Use designs optimised for RUM and RRM only (instead of a combination of RUM and RRM)
   - Use designs with fewer attributes
2. Extend analysis towards more than 2 decision rules (at least in the modelling)
3. Deepen investigation into what properties drive that some choice tasks invoke a particular decision rule

Questions?

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