A Motivation-based Cognitive Diagnostic Model for Disengaged Responses Detection

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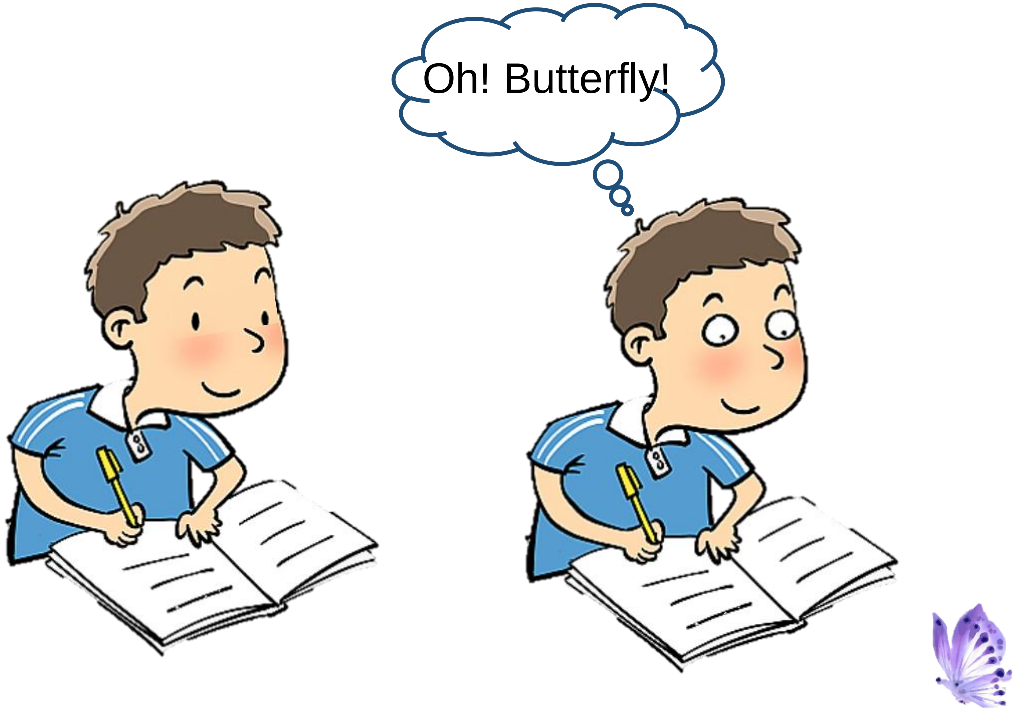
Have you encountered such data?



	response
item 1	C
item 2	C
item 3	C
item 4	C
item 5	C
item 6	C

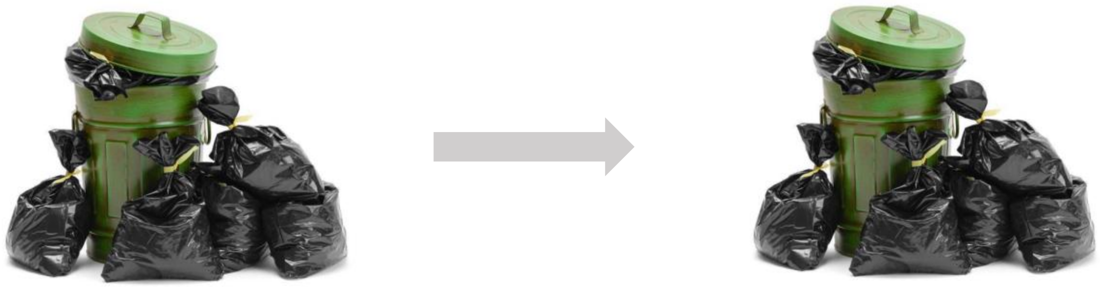
	response
item 1	C
item 2	C
item 3	C
item 4	NA
item 5	NA
item 6	NA

The current challenges

- Disengaged responses (low test-taking motivation):
  - rapid guessing and item omission

- Low-stakes testing:
  - one typical scenario is cognitive diagnostic testing (CDT) which aims to provide feedback to help students to improve
  - students will have no consequence for poor performances
  - a more significant proportion of disengaged responses

- Low-quality data would damage the quality of decision-making



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- Purpose:
  - formulate a new motivation-based cognitive diagnostic model (MCDM) to detect disengaged responses

Existing solutions

- **Rapid guessing:** mixture hierarchical model (Wang & Xu, 2015)
  - define a latent variable indicator Δ_{ij} (1 = rapid guessing, 0 = normal response)
  - response accuracy: $P(Y_{ij}=1|\Delta_{ij}) = (1-\Delta_{ij})P(Y_{ij}=1|\Delta_{ij}=0) + \Delta_{ij}P(Y_{ij}=1|\Delta_{ij}=1)$
  - response time: $f(t_{ij}|\Delta_{ij}) = (1-\Delta_{ij})f(t_{ij}|\Delta_{ij}=0) + \Delta_{ij}f(t_{ij}|\Delta_{ij}=1)$

- **Both rapid guessing and omission:** hierarchical latent response model (Ulitzsch et al., 2020)
  - define a latent variable indicator Δ_{ij} (1 = engaged behavior, 0 = disengaged behavior)
  - engagement: $\text{logit}\left(P(\Delta_{ij}=1)\right) = \phi_i - \iota_j$

    ϕ_i represents engagement tendency
  - omission: $\text{logit}\left(P(O_{ij}=1|\Delta_{ij}=0)\right) = \gamma_0 + \gamma_1\theta_i + \gamma_2\tau_i$

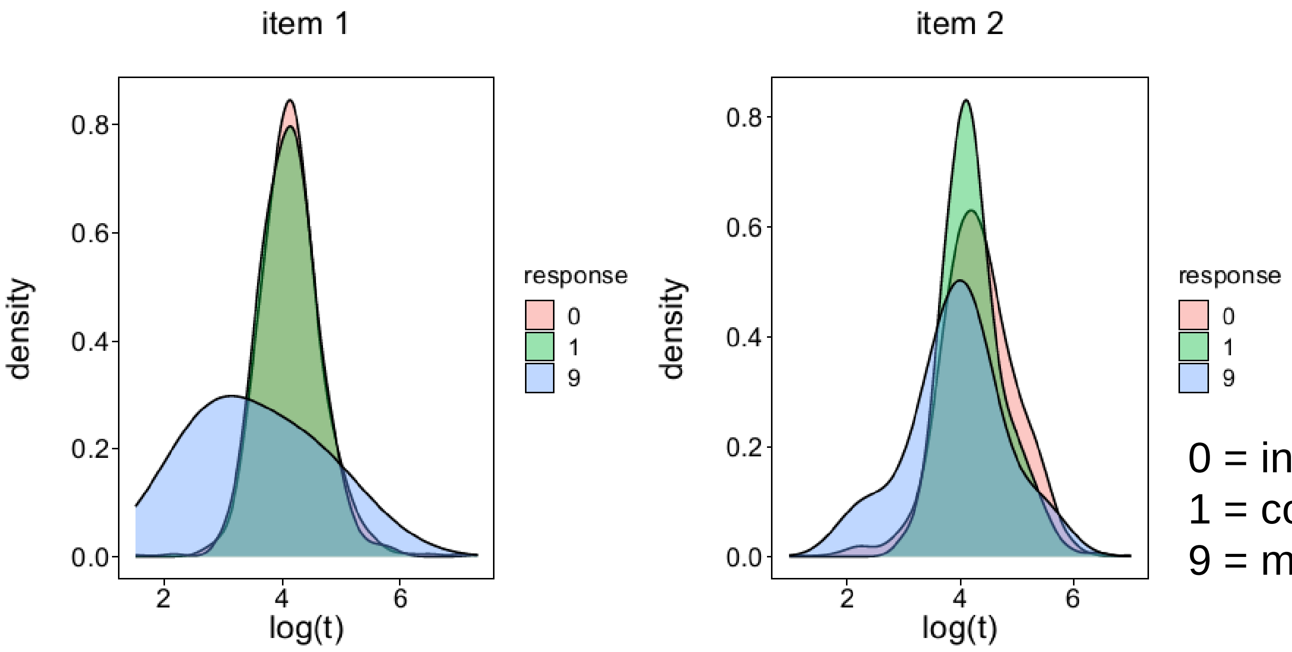
Remaining questions

- **How to detect disengaged responses for CDT?**
  - Hsu et al. (2020) extended the mixture model with G-DINA for rapid guessing detection
  - Chen et al. (2022) modeled response time with G-DINA and define $\alpha_{ik}^{\mathrm{RT}}$ to represent whether a student spends less response times on the items related to a specific attribute

- Little attentions are placed on the item omission

Remaining questions

- **How to distinguish missing caused by low ability level or low motivation?**
  - bimodal distribution
  - overlap between omission and correct response



0 = incorrect
1 = correct
9 = missing

Our solution: Motivation-based CDM (MCDM)

- Engaged responding
  - respondents must have invested at least some effort into reading the item and retrieving relevant information
  - active status: attribute(s) can be reflective by responses

- Disengaged responding
  - do not include information processing
  - non-active status: attribute(s) that contains noises caused by disengaged behaviors

- Aiming to label the specific attribute(s) affected by disengagement:
  - highest level: actively engage & master $\alpha_{ik} = 1$
  - medium level: actively engage & not master $\alpha_{ik} = 0$
  - lowest level: problematic attribute $\alpha_{ik} = -1$

Our solution: Motivation-based CDM (MCDM)

- The ideal response function
  - $\eta_{ij} = I\left(\sum_{k=1}^{K}(\alpha_{ik})^{q_{jk}} = \sum_{k=1}^{K} q_{jk}\right) - I\left(\sum_{k=1}^{K}(\alpha_{ik})^{q_{jk}} < \sum_{k=1}^{K}|\alpha_{ik}|^{q_{jk}}\right)$
- A plug-and-play framework
  - response accuracy: $P(Y_{ij} = 1) = \begin{cases} 1 - s_j, & \text{if } \eta_{ij} = 1 \\ g_{1j}, & \text{if } \eta_{ij} = 0 \\ g_{2j}, & \text{if } \eta_{ij} = -1 \end{cases}$ $\quad (0 < g_{2j} < g_{1j} < 1 - s_j < 1)$
  - response time: $\ln(t_{ij}) \sim \begin{cases} N(\beta_{Mj} - \tau_i, \sigma_{Mj}^2), & \text{if } \eta_{ij} = 0 \text{ or } 1 \\ N(\beta_D, \sigma_D^2), & \text{if } \eta_{ij} = -1 \end{cases}$ $\quad \beta_{Mj} = \beta_j^* + \beta_D \; (\beta_j^* \geq 0)$
  - item omission: $P(O_{ij} = 1) = (1 - r_j)^{\{1 - I(\eta_{ij} = -1)\}} o_j^{I(\eta_{ij} = -1)}$ $\quad (0 < 1 - r_j < o_j < 1)$

Simulation study

- Purpose:
  - examine the estimation accuracy of the new model

- Experimental design:
  - sample size: 1,000 and 1,500
  - item omission rate: 0%, 5%, and 10%
  - disengaged response rate: 30% and 50%

  - three attributes (16 items):
    space and shape (α_1)
    quantity (α_2)
    uncertainty and data (α_3)

Item	α_1	α_2	α_3
1	1	0	0
2	0	1	0
3	0	1	0
4	0	0	1
5	0	0	1
6	0	1	0
7	1	0	0
8	1	0	0
9	0	1	0
10	0	1	0
11	0	0	1
12	1	0	0
13	1	0	0
14	0	1	0
15	0	1	0
16	0	0	1

Simulation study

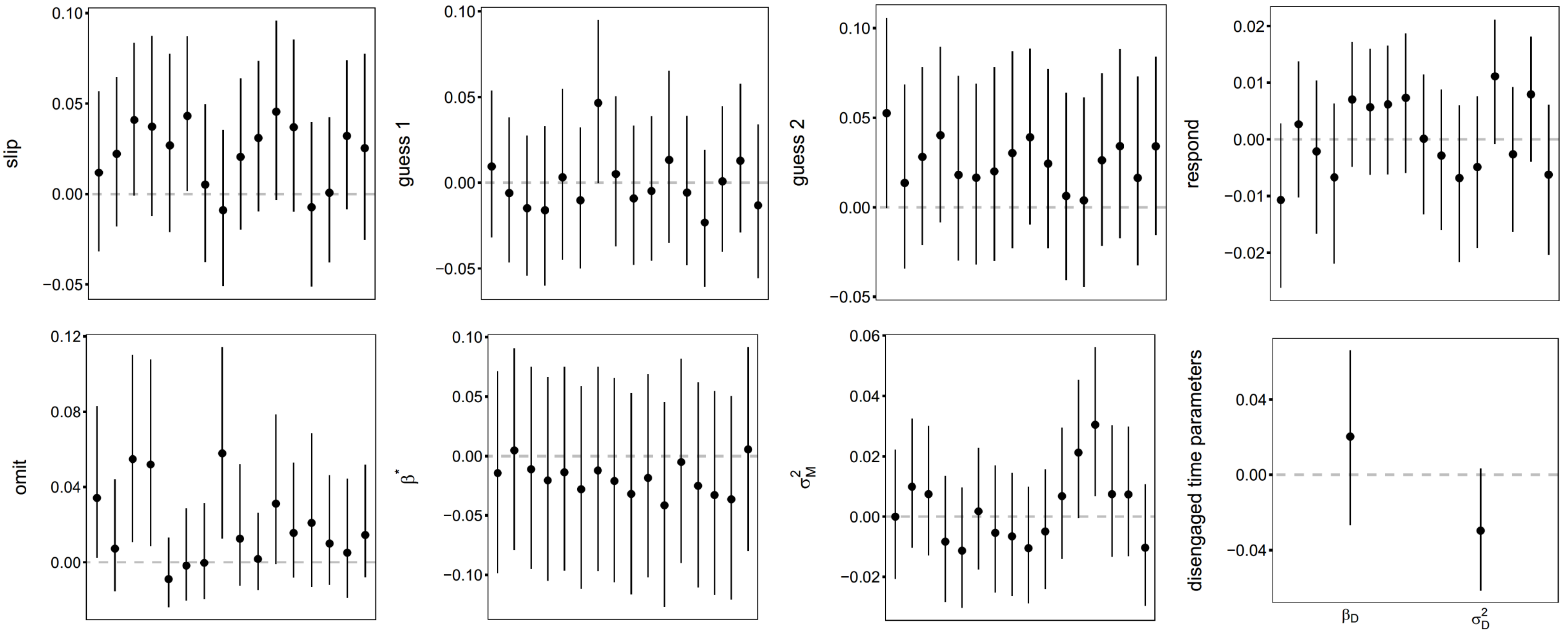
- Evaluation criteria:
  - for parameter recovery:
    - attribute-wise agreement rate (AAR), true positive rate (TPR), true negative rate (TNR)
    - discrepancy / correlation between estimates and true values

- Bayesian estimation:
  - use Stan with Hamiltonian Monte Carlo sampling
  - four chains with 5,000 iterations each
  - first 2,500 were discarded as warm-up

Results: MCDM achieved precise accuracy for attribute patterns and the speed parameter

missing (%)	sample size	disengaged (%)	AAR	TPR	TNR	$\rho_{\tau\hat{\tau}}$
0	1000	30	0.929	0.993	0.928	0.945
		50	0.921	0.986	0.945	0.935
	1500	30	0.924	0.991	0.927	0.958
		50	0.929	0.990	0.958	0.941
5	1000	30	0.922	0.993	0.900	0.935
		50	0.912	0.988	0.929	0.935
	1500	30	0.919	0.993	0.940	0.963
		50	0.914	0.983	0.944	0.943
10	1000	30	0.916	0.992	0.928	0.949
		50	0.914	0.979	0.929	0.939
	1500	30	0.913	0.991	0.914	0.955
		50	0.917	0.988	0.939	0.938

Results: MCDM achieved precise accuracy for item parameters



(1,000 respondents, 0.05 omission rate, 0.3 disengaged rate)

Empirical study

- Purpose:
  - examine model fit of the full model and reduced model, and investigate whether the new model can reveal novel messages for educators
    1. baseline model: DINA
    2. full model: MCDM
    3. response accuracy + omission: MCDM-O
    4. response accuracy + response time: MCDM-RT

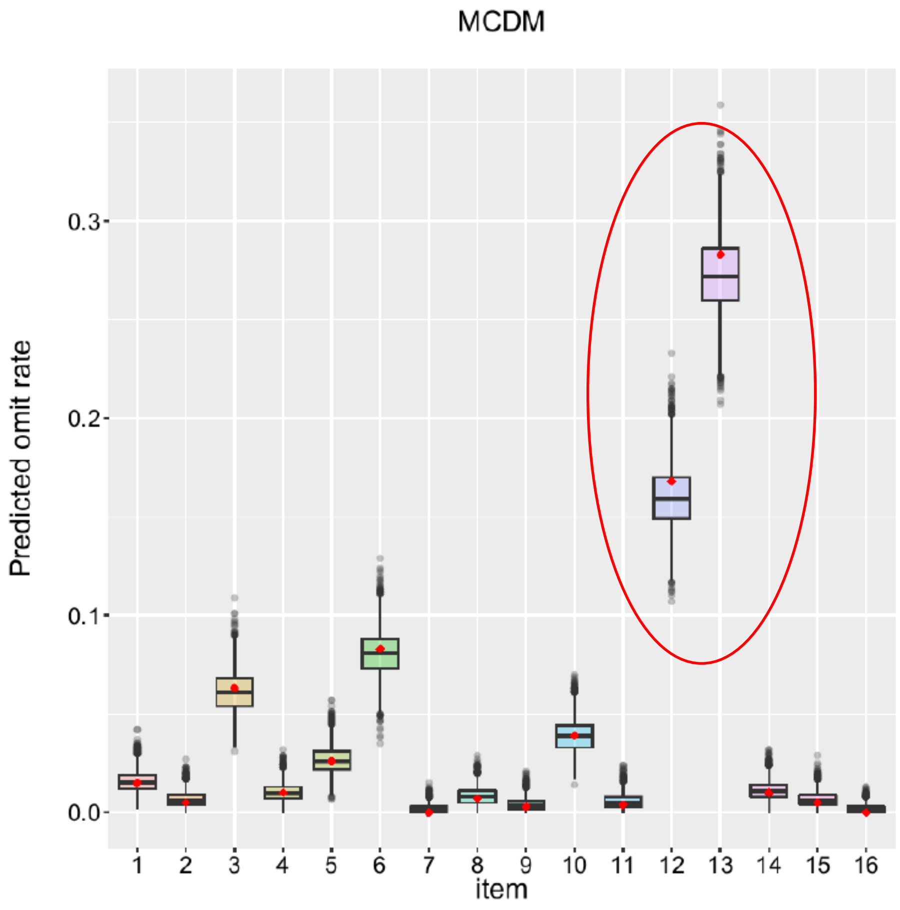
- Dataset:
  - PISA 2015 Math, 16 items from two forms (M01 and M02)
  - randomly select 1,000 examinees (omission rate ≈ 5%)

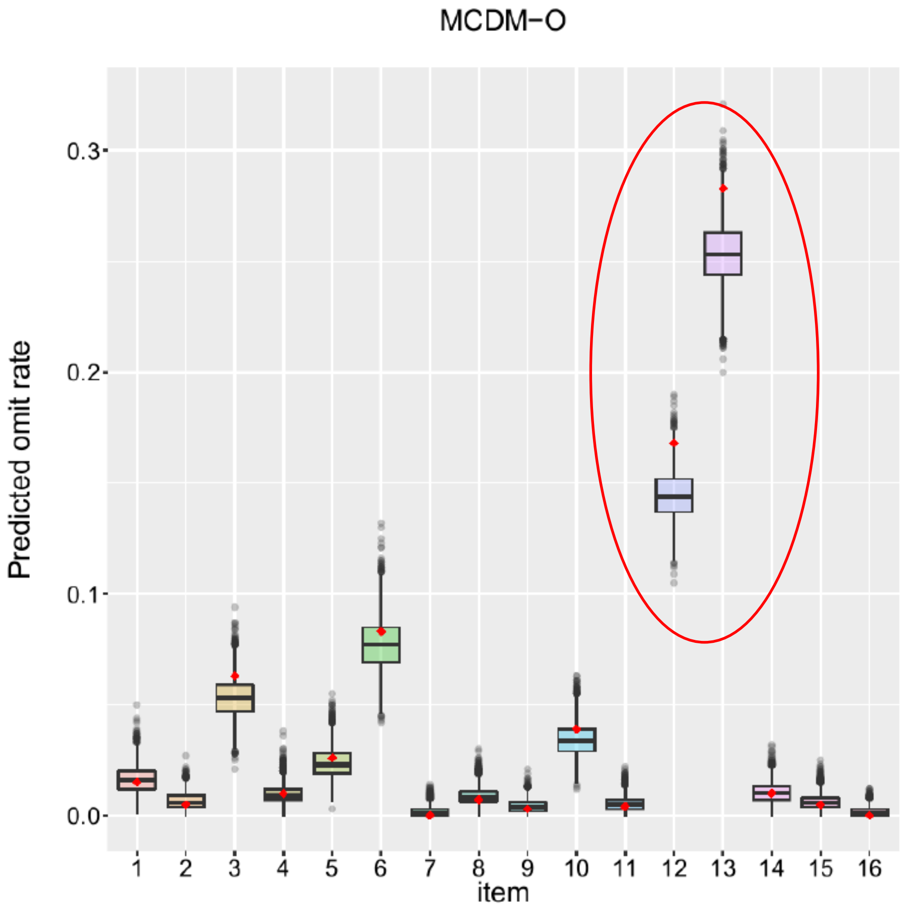
- Evaluation criteria:
  - the Gelman-Rubin $\hat{R}$ and effective sample sizes (ESSs)
  - the adjusted leave-one-out cross-validation information criterion (LOOIC_adjusted)
  - posterior predictive checking

Results: full MCDM and MCDM-O fitted well while MCDM-RT was inferior to DINA

	$\mathrm{LOOIC_{adjusted}}$	$\hat{R}$<1.1 (%)	ESSs>5,000 (%)
DINA	18.007	1	1
MCDM	17.413	1	0.928
MCDM-O	10.571	1	1
MCDM-RT	23.671	1	0.915

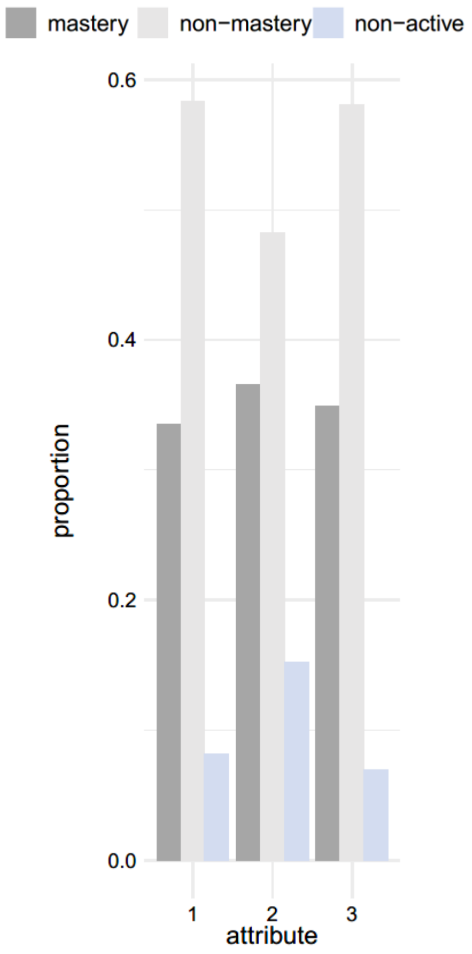
Results: MCDM covered the true missing rate better than MCDM-O





The red diamond represents the proportion of missing calculated from the raw data.

Results: ignoring disengaged responses might lead to improper conclusions



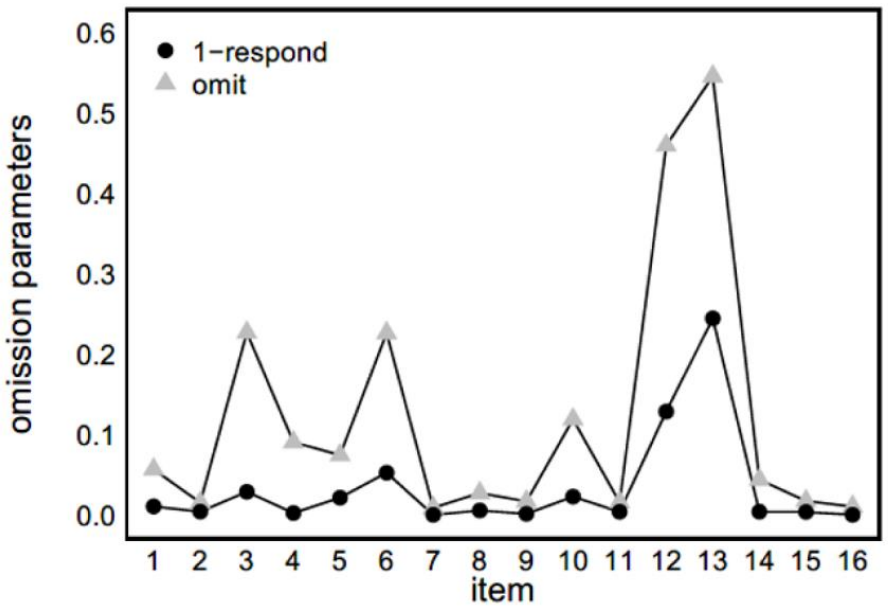
	α_1	α_2	α_3
mastery	0.335	0.366	0.349
non-mastery	0.583	0.482	0.581

Students master α_2 the best?
Not sure!

1. non-active α_2 = 0.152
2. if all these students do not master α_2,
   then non-mastery α_2 = 0.482 + 0.152 = 0.634

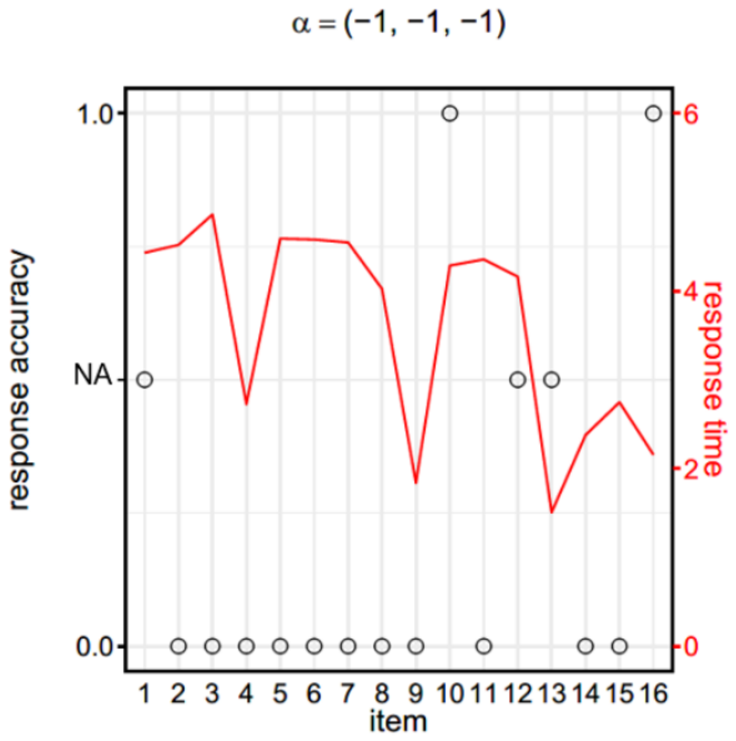
Results: it is unfair to simply consider all omissions are caused by disengaged responses

Attribute	Item format	Disengaged omission	Engaged omission
α_1	MC	26.67	73.33
	OR	-	-
	MC	28.57	71.43
	OR	25.60	74.40
	OR	17.67	82.33
α_2	MC	40.00	60.00
	OR	63.49	36.51
	MC	46.99	53.01
	MC	66.67	33.33
	OR	48.72	51.28
	MC	70.00	30.00
	MC	40.00	60.00
α_3	MC	80.00	20.00
	OR	23.08	76.92
	MC	0.00	100.00
	MC	-	-

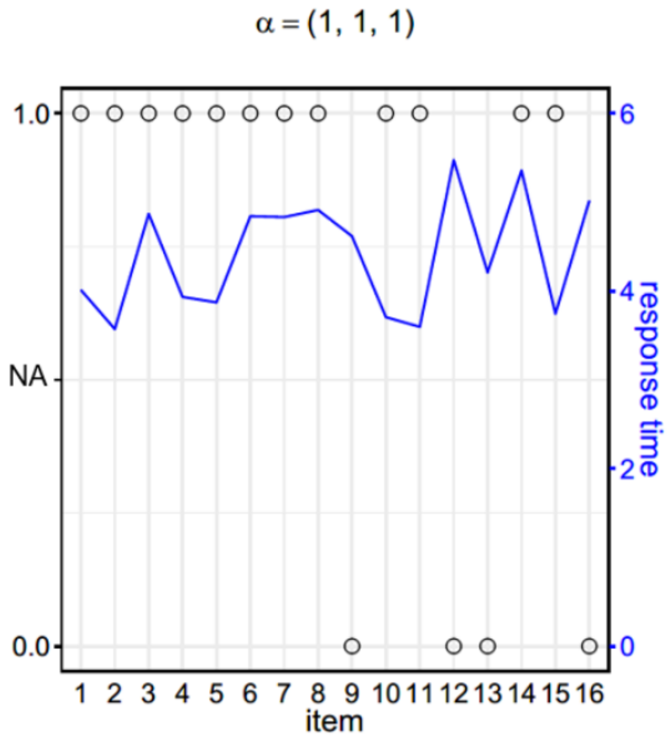


MC = Multiple choice
OR = Open Response

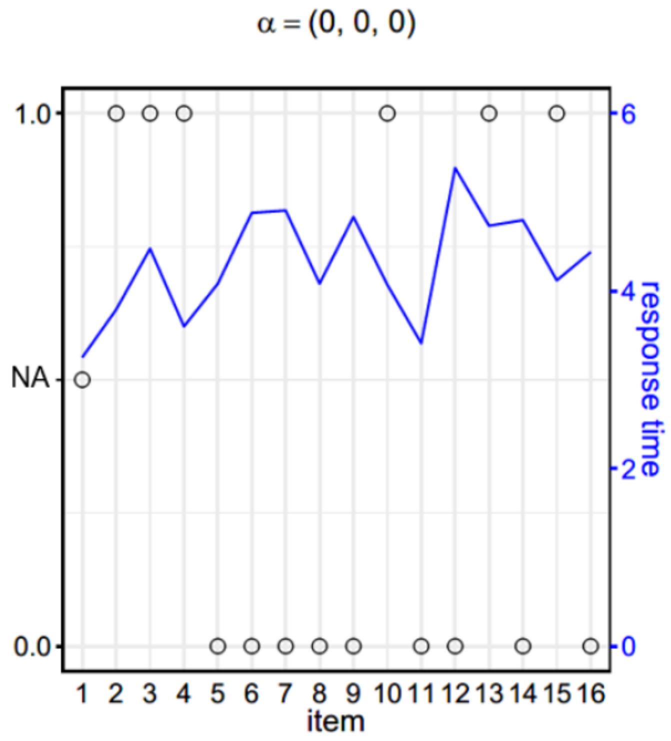
Results: students with low motivation showed unstable response time, high missing and incorrect proportion



Disengaged responding



Engaged responding (mastery)



Engaged responding (non-mastery)

Discussion

- Summary:
  - MCDM allows researchers to pinpoint the specific attribute(s) affected by disengaged responses and refine the inference of students' knowledge profiles, enhancing the quality of decision-making

- Practical implications:
  - MCDM can be flexibly adjusted for specific research purposes and data structures (with G-DINA, reduce to MCDM-RT, etc.)
  - parameters obtained from MCDM can provide important insights into potential factors that cause disengaged behaviors or omissions of engaged responding (e.g., whether the word count of the item would increase the probability of disengaged responding)

Thank you for listening!

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