Which combinations of behavior change techniques are effective? Assessing interaction effects in meta-analysis

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Examples are:

- Intention formation & Provide info on behavior-health link
- Barrier identification & Set graded tasks

Dusseldorp et al. (2014)

Which kind of data?

- Part of a meta-analytic data set Michie et al. (2009):

	effect size	se	n	BCT1	BCT2	BCT3	BCT4	BCT5	BCT6	BCT7	BCT8	BCT9
1	0.60751	0.15715	170	1	1	0	1	0	1	0	1	1
2	0.74651	0.22619	66	0	0	0	1	0	0	0	0	0
3	0.73090	0.25874	58	0	0	0	1	0	0	0	0	0
4	0.65716	0.27659	24	0	0	0	0	0	0	0	0	0
5	0.88197	0.31482	41	0	0	0	1	0	0	0	1	0

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- Moderators (e.g. BCTs) are the study characteristics that explain the heterogeneity of the study effect sizes.
- Two standard types: subgroup analysis (for categorical) and meta-regression (for continuous).

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- has difficulty to investigate higher-order interaction effects (e.g., $m_1 * m_2 * m_3$)

Solution? Meta-CART

This method is a combination of subgroup meta-analysis and CART, Breiman et al. (1984), and

- can identify interaction(s) easily;
- can detect higher-order interaction(s);
- presents results in a parsimonious tree structure.

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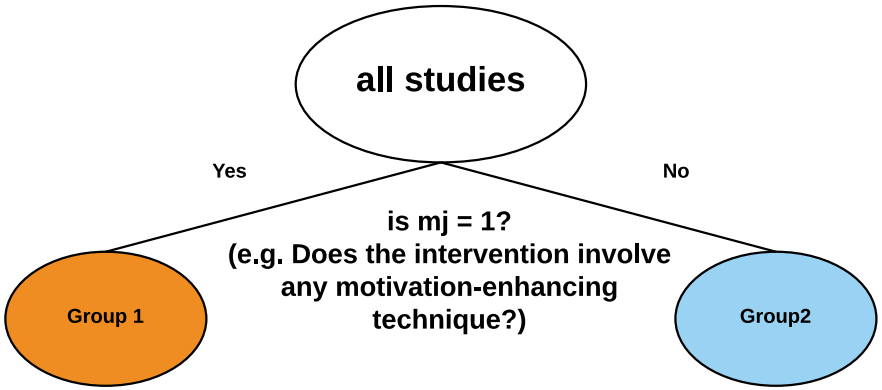
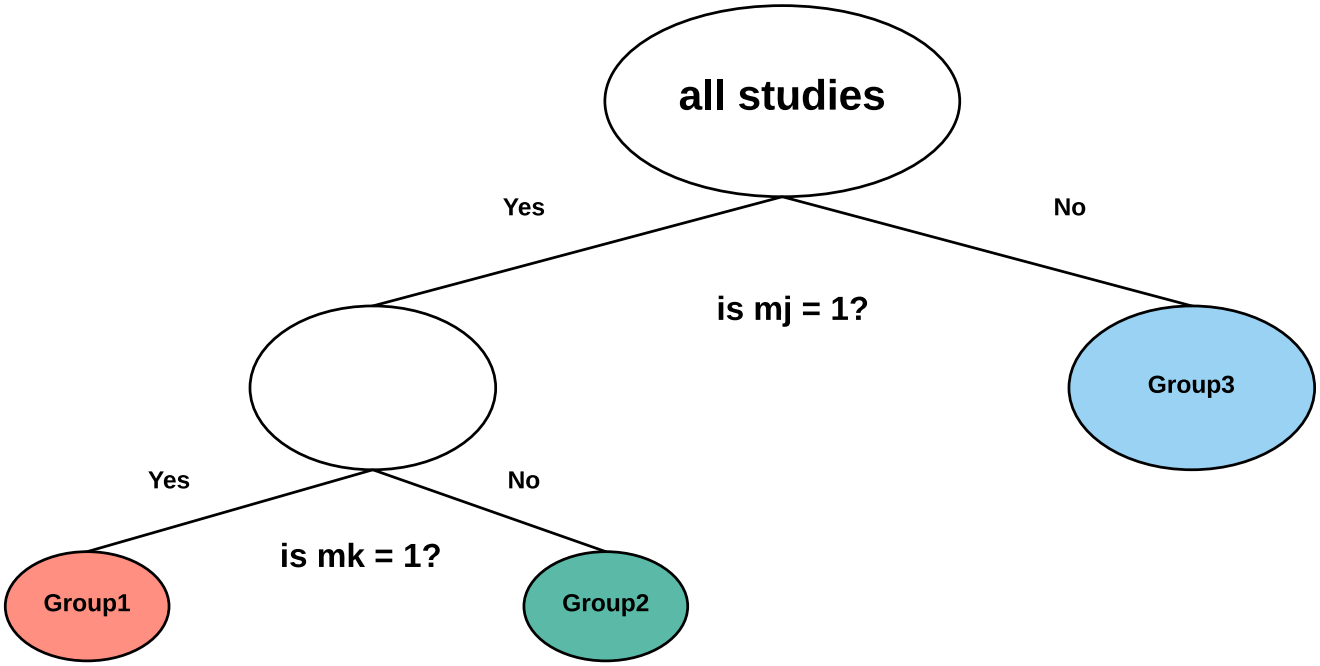
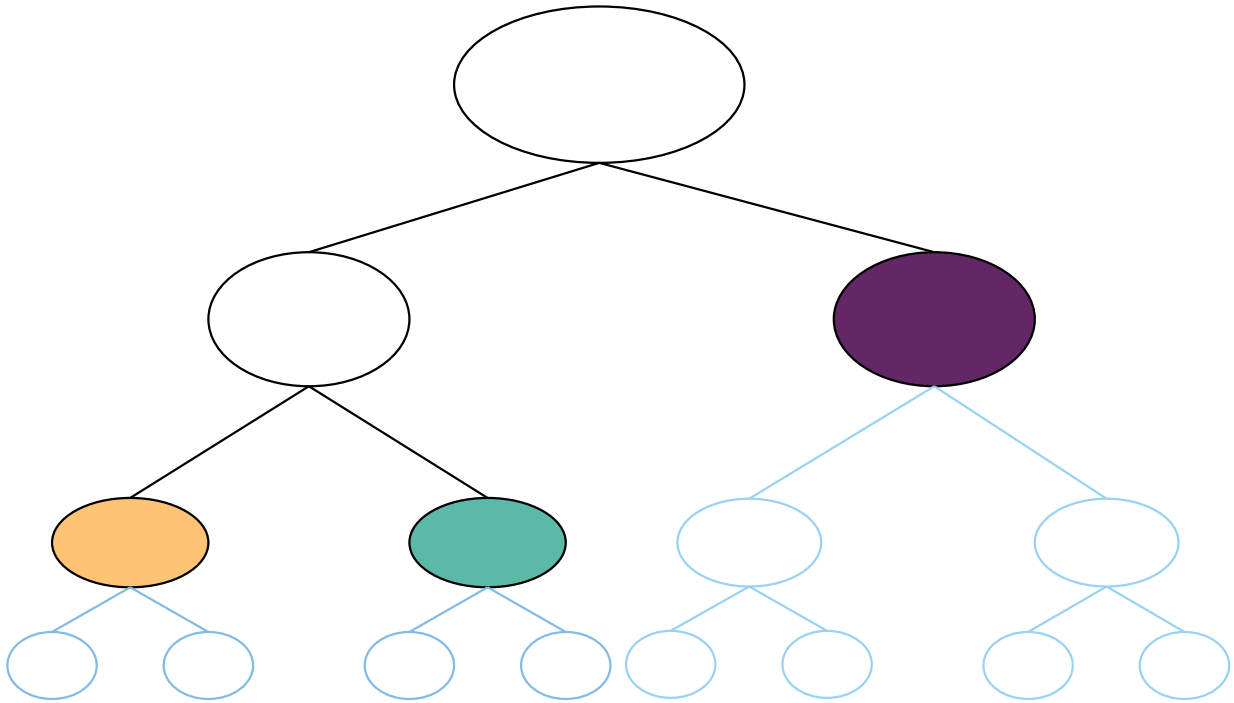
- Step 2: perform a standard subgroup meta-analysis using the leaves of the tree as a new subgroup variable.

Step 1: fitting a tree

- Grow the tree: the tree starts from a root node with all studies.
  The tree algorithm searches the study characteristic (splitting variable) that can best discriminate between the two groups.

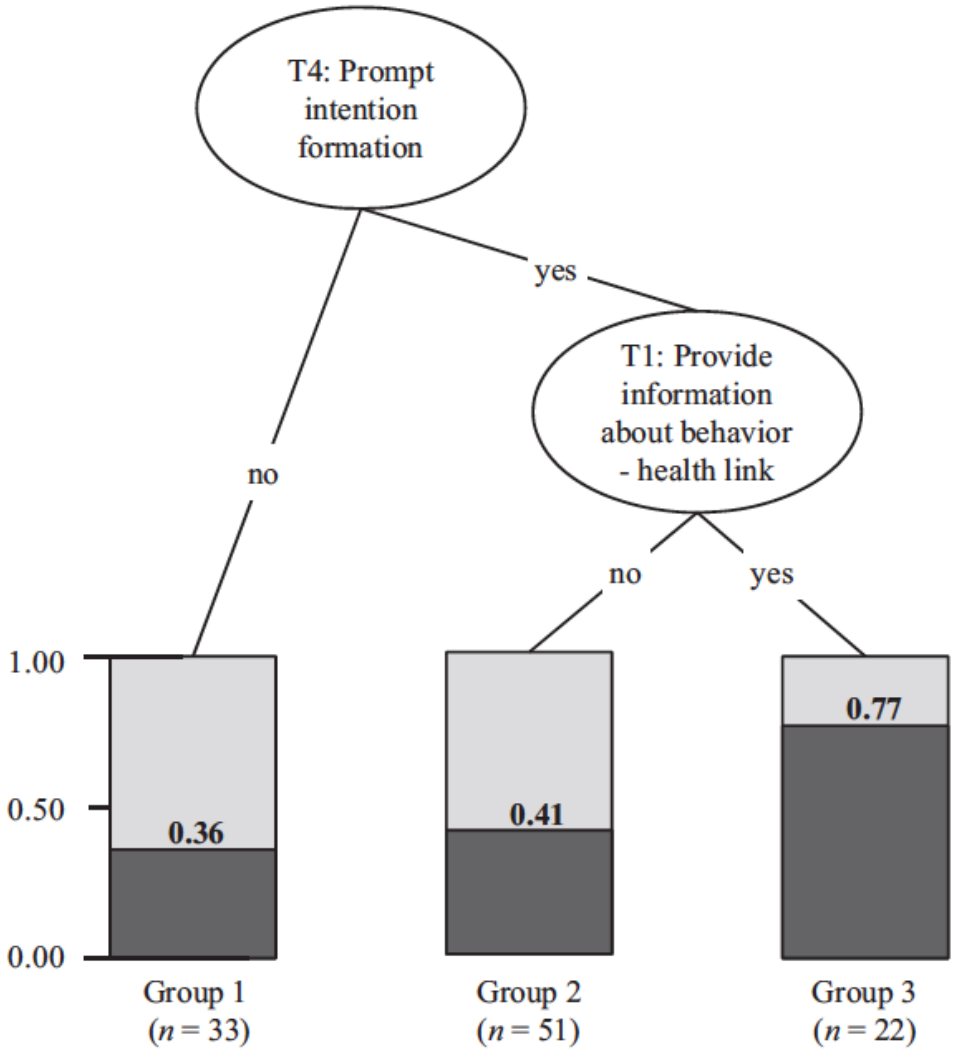



all studies
Yes
No
is mj = 1?
Group3
Yes
No
is mk = 1?
Group1
Group2



Prune the tree: to prevent overfitting, the prediction accuracy for differently sized trees is estimated by cross-validation. Then the initial tree is reduced to a smaller size by “cutting off" splits that decrease the prediction accuracy.

Example of result Step 1: the final meta-classification tree



Step 2: Standard subgroup analysis

An example:

Table : Results of Subgroup Analysis Using a Mixed Effects Model

Group	# interv.	$\bar{g}$	95% CI	$Q(df)$	p value
Grouping variable of tree					
Group 1	33	0.26	0.16,0.35		
Group 2	51	0.24	0.18,0.29		
Group 3	22	0.46	0.39,0.59		
				25.2(2)	<0.001

Possible versions of meta-CART

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- Options for the weights: no weights, fixed effects weights, and random effects weights.
- Options for the pruning rules ($c \cdot SE$ rule): Small amount ($c = 0$), medium amount ($c = 0.5$), and large amount ($c = 1$).
- In total $3 \times 3 = 9$ options for each type of tree.

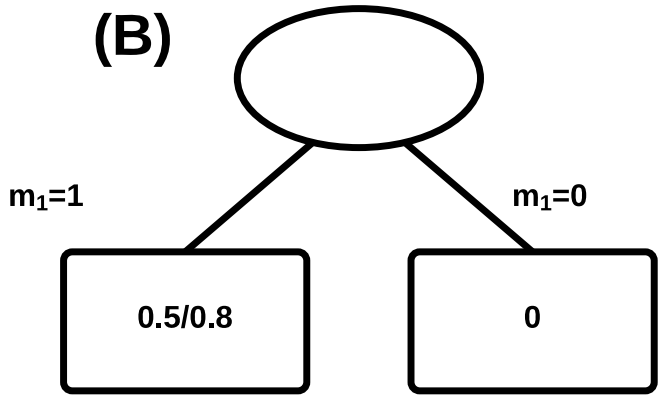
A simulation study was carried out to answer:

- Which options of meta-CART have the best performance?
- Which characteristics influence the performance of meta-CART?

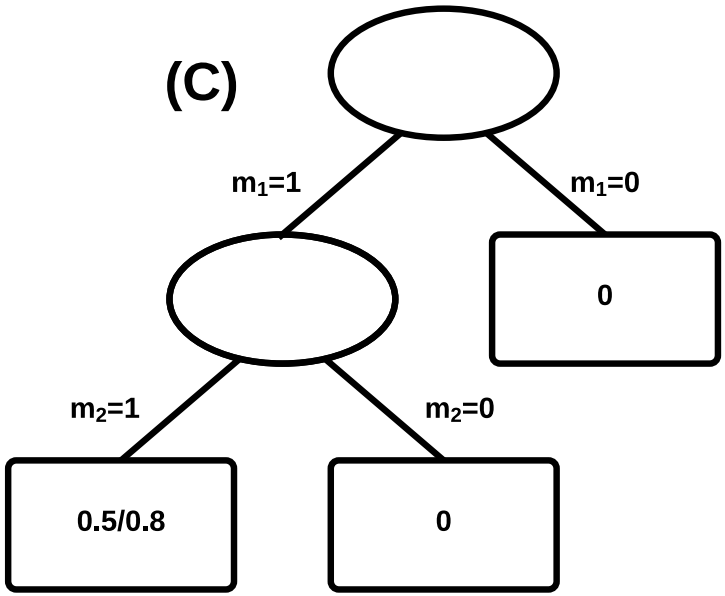
For details, see Li et al. (2016).

Five true scenarios, varying in complexity:

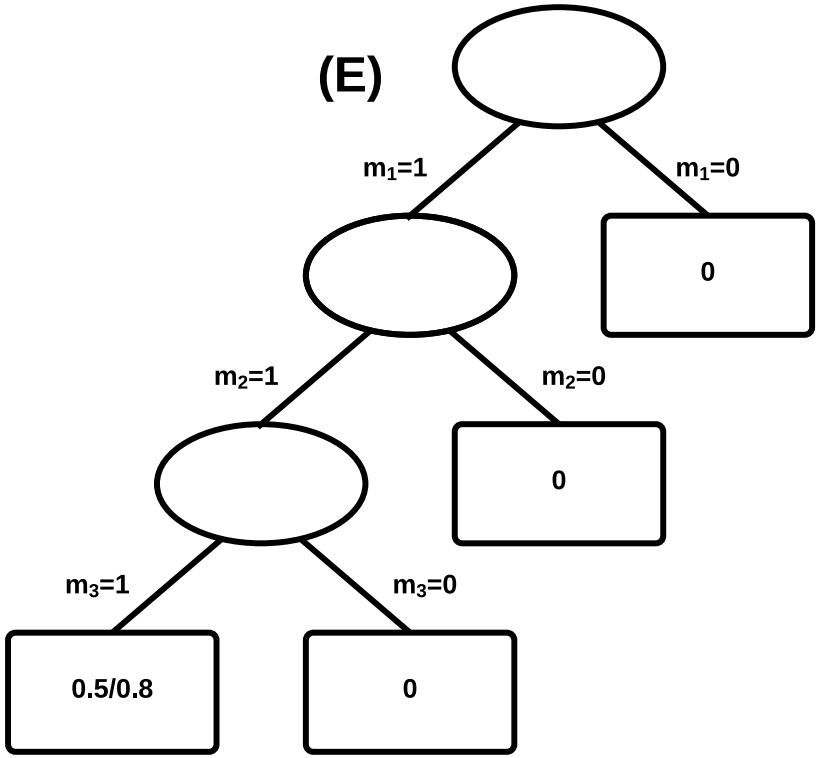
One main effect:



One two-way interaction effect:

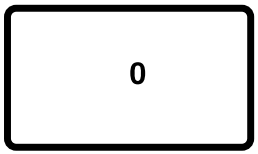


Three-way interaction



No moderator effect at all:

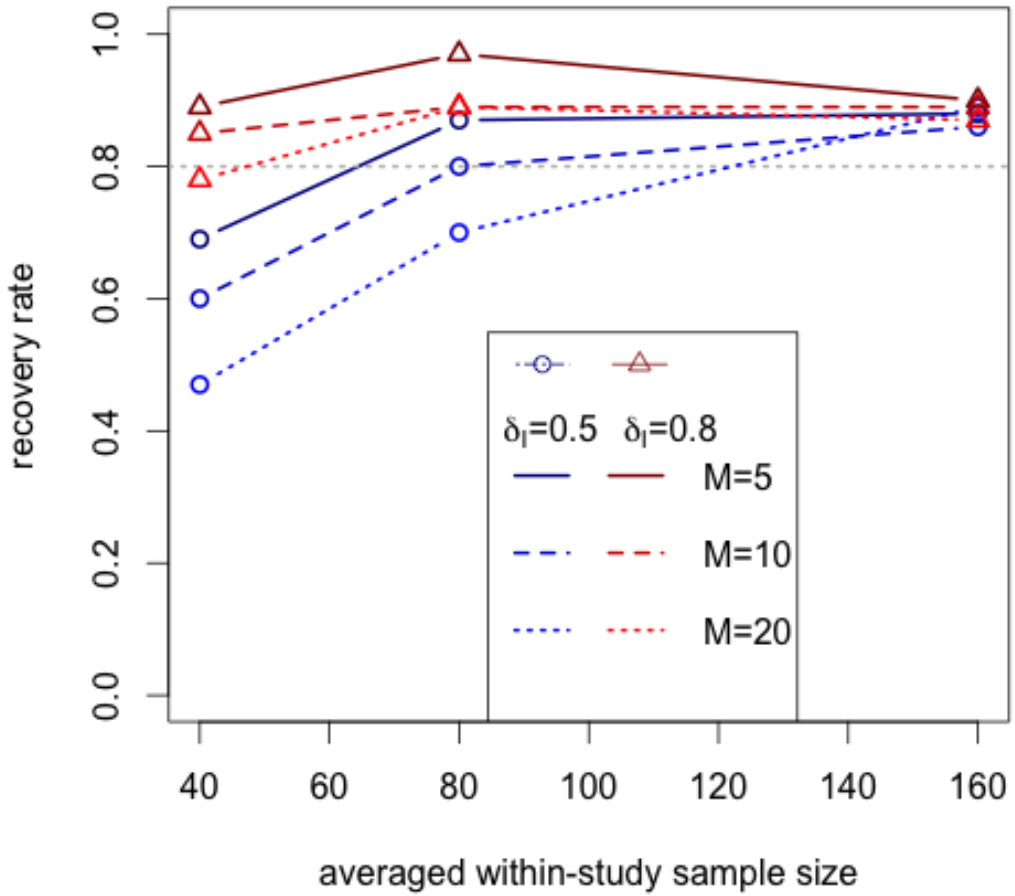
(A)



Results: Type I error rates of meta-CART

	Meta-regression tree		Meta-classification tree	
c	$\mathcal{W}_0$	$\mathcal{W}_2$	$\mathcal{W}_0$	$\mathcal{W}_2$
0.0	**0.114 (0.029)**	**0.117 (0.029)**	**0.485 (0.179)**	**0.477 (0.189)**
0.5	0.041 (0.021)	0.042 (0.022)	**0.447 (0.156)**	**0.432 (0.159)**
1.0	0.014 (0.013)	0.014 (0.013)	**0.391 (0.130)**	**0.380 (0.132)**

Results: Recovery rates K=40, one two-way interaction



Recommendations based on simulation results

- Best options: A meta-regression tree with random effects weights and a pruning rule with $c = 0.5$.
- At least 40 studies in a meta-analysis is required for meta-CART to achieve a satisfactory performance (detection rate ≥ 0.80). A large number of studies ($K = 80$) is needed to detect complex interactions.
- Many moderators (20) is not a problem.

Future

- Development of software: R-package metacart (available on request)
- Applications of meta-CART: contact elise.dusseldorp@fsw.leidenuniv.nl

References: check www.elisedusseldorp.nl

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