



optimization

Forecast Adjustment in Multicriteria Analysis Using Parameterisable Functions



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Prospect Theory and TODIM

Prospect Theory

Outcomes are evaluated as **gains or losses** relative to a reference point.

Losses usually have a stronger psychological impact than equivalent gains.



TODIM

TODIM incorporates the behavioural principles of Prospect Theory, developed by Daniel Kahneman and Amos Tversky, into multicriteria decision analysis.

Alternatives are compared pairwise and aggregated through a global dominance measure.

For more information, visit [ScienceDirect](#).

Kahneman & Tversky (1979); Gomes & Lima (1992)

Which holiday destination would you choose?

Why do people choose differently?



Different choices Same information.

In Prospect Theory, human behaviour matters

The decision maker is the protagonist, not the algorithm.

Same information

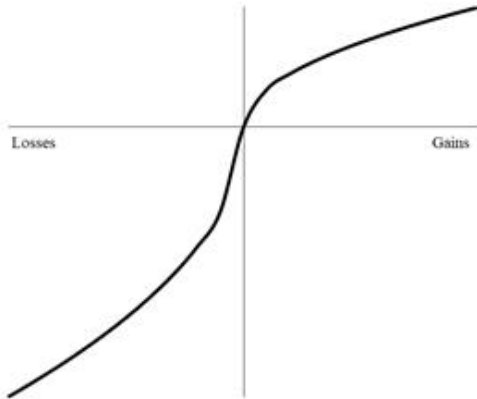
Different perceptions

Different preferences



**The decision maker is
not noise but the
object of modelling.**

Prospect Theory changed decision modelling



Reference point

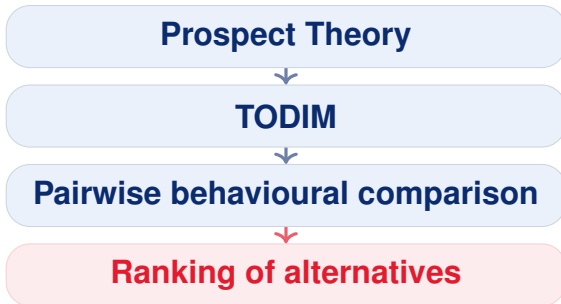
choices are relative

Loss aversion

losses weigh more

In Prospect Theory decisions are evaluated relative to a reference point. Losses have a greater psychological impact than equivalent gains.

TODIM: behaviour before optimisation



**TODIM does not only rank alternatives.
It models how alternatives are compared.**

Gomes and Lima (1991, 1992): TODIM applies Prospect Theory principles within multicriteria analysis.

Building the bridge

Behavioural Economics



Mathematical Modelling



- TODIM
- TODIMAdp

PARAMETERIZATION

Case study: choosing a holiday destination

As input data, an experiment previously presented in Leoneti [2016] was used, involving twenty students from different years and degree programs at the School of Economics, Business Administration and Accounting at Ribeirão Preto (São Paulo, Brazil). For more information, visit USP repository.



Destination A



Destination B



Destination C



Destination D



Destination E



Hotel classification



Travel distance / time



Length of stay



Cost



Shopping



Cultural attractions



Natural landscapes



Safety

20 decision makers · 8 criteria · individual weights and initial rankings

Empirical validation uses the holiday-destination example and the preference/weighting data from Leoneti (2016).

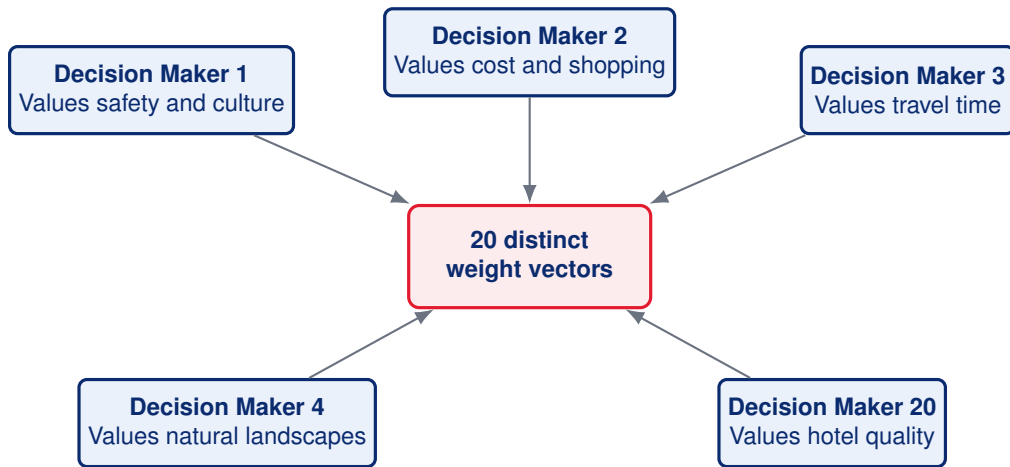
Decision Matrix

	HC	TT	LS	Cost	Shop.	Cult.	Nature	Safety
Destination A	5.0	2.5 h	4	2839.68	5	3	9	8
Destination B	3.5	12 h	6	3700.00	9	7	3	6
Destination C	2.5	4 h	5	2683.00	4	5	7	7.5
Destination D	3.0	13 h	7	4150.00	6	9	6	7
Destination E	4.0	18 h	9	4500.00	3	8	5	4

HC: Hotel classification **TT:** Travel time **LS:** Length of stay

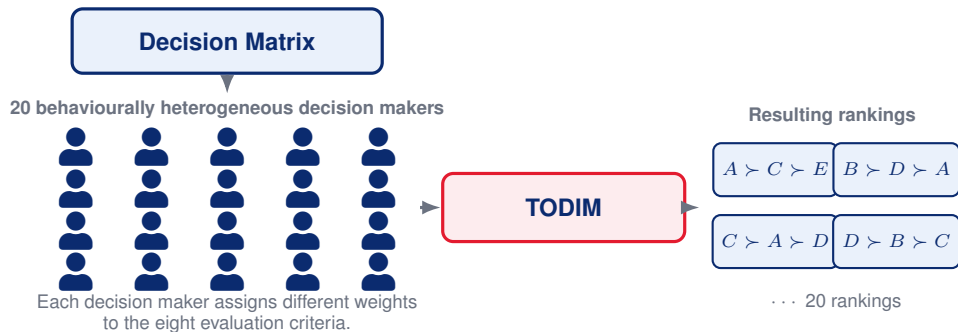
Five destinations are evaluated according to eight criteria.

Behaviourally Heterogeneous Decision Makers



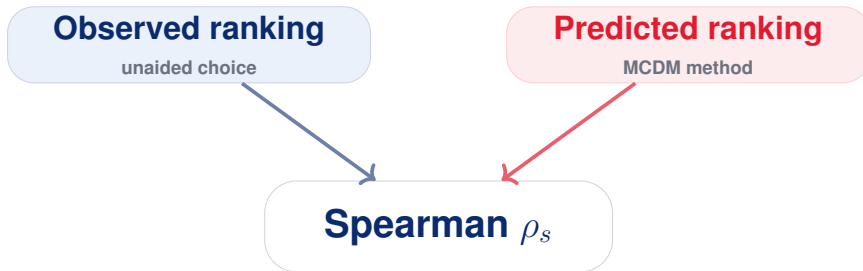
Each vector represents a different preference structure.

From Heterogeneous Preferences to Rankings



The same decision matrix may produce different rankings when decision makers assign different importance to the criteria.

What does forecasting mean here?

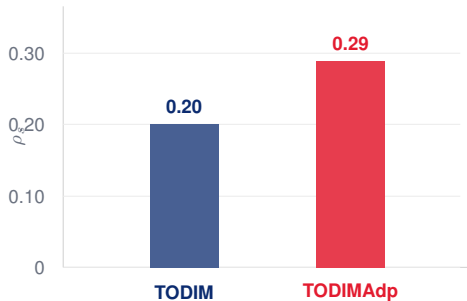


Forecasting = predicting human choices, not future events.

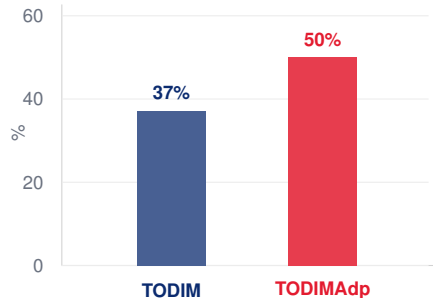
The method is evaluated by how closely its ranking reproduces the initial ranking expressed by the decision maker.

Does parameterization improve predictive performance?

Average Spearman correlation



Top-ranked alternative correctly predicted



Parameterization improves behavioural realism $\Rightarrow$ stronger predictive performance

Results: average Spearman correlation improves from 0.20 to 0.29; top-alternative prediction improves from 37% to 50%.

Conclusions

1. MCDM ranking methods can be evaluated by their ability to reproduce initial preferences;
2. TODIMAdp's additional parameters increase modelling flexibility and predictive capacity;
3. The results suggest that further exploration of parameter combinations may strengthen TODIM's descriptive and forecasting performance in applied multicriteria decision contexts.

Thank you so much for your PPA!¹

¹Participation, Patience & Attention

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