Modeling mental workload via rule-based expert system: a comparison with NASA-TLX & Workload Profile

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September, 2016

Research question

- *Can implementations of* **rule-based expert systems**, *compared to state-of-the-art* **MWL inference techniques**, *enhance the modelling of* **mental workload** *according to* **sensitivity** *and* **validity***?*

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- Mental workload (MWL) is a multi-faceted phenomenon with no clear and widely accepted definition
- All studied measures of MWL do not take into consideration conflicts between pieces of evidence which might lead to contraction and loss of information.

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  - Based on 8 dimensions: perceptual/central processing, response selection and execution, spatial processing, verbal processing, visual processing, auditory processing, manual output and speech output
  - The operator is asked to provide the proportion of attentional resources, in the range 0 to 1, for each dimension. The overall workload is a sum of these scores

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- The knowledge base was developed for the inference of MWL in the field of human computer interaction. It comprises 21 different attributes all quantified, through a subjective question, in the range $[0, 100] \in \mathbb{R}$.

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- At the end of the process, from the set of forecast rules, there will be a resulting set of **surviving** rules

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  - $\boldsymbol{h_4}$: to give equal importance to all point of views.

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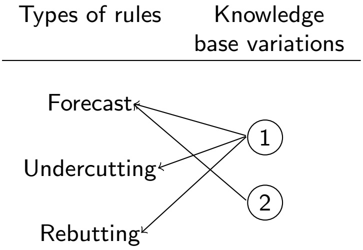
    - **Convergent validity**: determine to what extent a model correlate with other model of MWL
    - **Concurrent validity**: determine the extent to which a model correlate with task completion time
  - **Sensitivity**: investigate how many pairs of tasks each measure is capable of differentiating. Technique: *One way analysis of variance + post hoc*

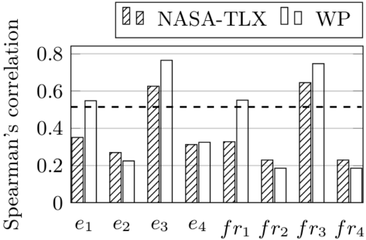
Design and methodology

Table: Experiments set up: types of rules employed by two variations of the same knowledge base (left) and name of each model, variation used, heuristic adopted (right).

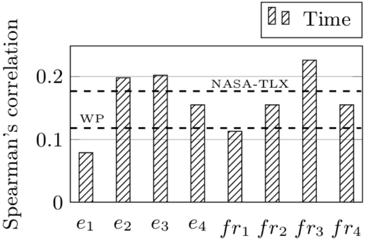


Model	KB variation		Heuristics			
	1	2	h_1	h_2	h_3	h_4
e_1	✓		✓			
e_2	✓			✓		
e_3	✓				✓	
e_4	✓					✓
fr_1		✓	✓			
fr_2		✓		✓		
fr_3		✓			✓	
fr_4		✓				✓

Results: validity



Convergent validity: $p < 0.05$.



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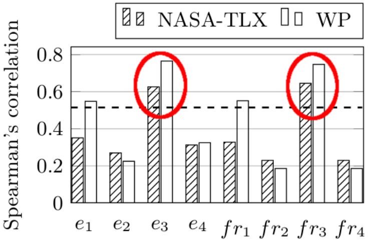

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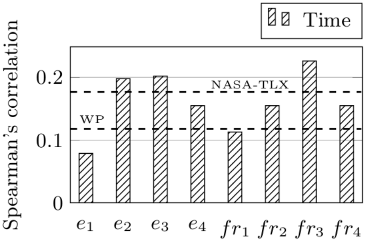

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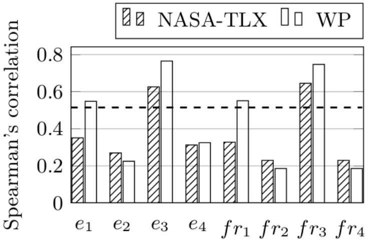

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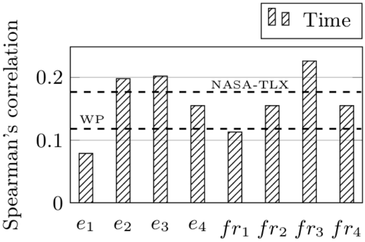

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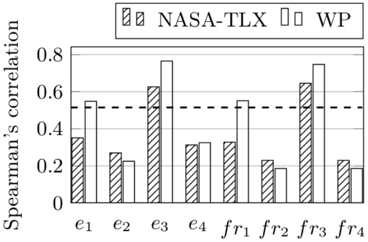

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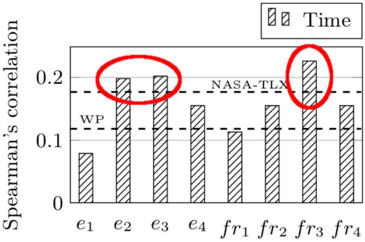

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Results: sensitivity

Table: Sensitivity of MWL models with Games-Howell post hoc analysis. The maximum pairwise comparisons of 9 tasks is $\binom{9}{2} = 36$).

Model	$p < 0.05$	$p < 0.01$
NASA-TLX	18	12
WP	9	4
e_1	2	1
e_2	5	3
e_3	13	10
e_4	0	0

Model	$p < 0.05$	$p < 0.01$
NASA-TLX	18	12
WP	9	4
fr_1	2	0
fr_2	4	1
fr_3	17	10
fr_4	4	1

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  - Heuristics for aggregating rules with a better capacity of handling uncertainty and conflicting pieces of information compared to fixed formulas.
  - Easier comparison of knowledge-bases and beliefs of different MWL designers.

Conclusions and future work

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- Rule-based expert systems demonstrated to be a flexible approach for translating knowledge-bases and thus enhancing the understanding of the construct of mental workload itself.
- Future works include the use of different knowledge-bases, incorporation of fuzzy representation of rules and incorporation of acceptability semantics from argumentation theory.

Thank you!

Questions?

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NASA-TLX

Table: Questionnaire - Part 1

Dimension	Question
Mental demand	How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
Physical demand	How much physical activity was required (e.g.,pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal demand	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

NASA-TLX

Table: Questionnaire - Part 2

Dimension	**Question**
Effort	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Performance	How successful do you think you were in accomplishing the goals, of the task set by the experimenter (or yourself)?
Frustration	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?