Improving Judgment Performance by Examining the Relationship Between Task Properties and Cognitive Mode

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Introduction

• Purpose of this research is to illuminate the degree to which task structure influences cognitive mode and task performance in judgment tasks.
• Underlying basis for research is Hammond’s Cognitive Continuum Theory (CCT)
  • Cognition runs in a continuum from intuitive to analytical
  • Task properties run in a parallel continuum, and when task properties match cognitive mode, achievement is improved
• Previous research in CCT has seen mixed empirical support.
  • Hammond et al. experiment in 1987; showed some support
  • Dunwoody et al. experiment in 2000; showed mixed results
• Previous experiments used different metrics and had different, and unexpected, results
• We developed a new metric that did demonstrate empirical support for CCT
Why Is This Important to C²?

• An empirically-supportable theory relating task structure to human cognition can result in higher task achievement for judgment tasks
• Matching task properties with the corresponding cognitive mode (e.g., intuitive or analytical cognition) can improve efficiency by predicting improved achievement
• These benefits can improve the design of command and control systems by incorporating elements of cognitive systems engineering
Hammond et al. Experiment (1987)

- Tested relationship between task properties and cognitive mode for highway engineers
- Tested three *task surface* characteristics (film strips, bar graphs and formulas) against three *task depth* characteristics (judging highway aesthetics, safety and capacity)
- Five hypotheses, of which three are relevant to this discussion:
  - $H_1$: Surface and depth task properties induced corresponding cognitive mode
    - Supported in most cases but not all
  - $H_2$: Intuitive cognition could outperform analytical cognition
    - Supported, demonstrating that one cognitive mode is not always best
  - $H_3$: Knowledge of the congruence between surface and depth task characteristics would be necessary and sufficient to predict achievement
    - Not supported in their results
Dunwoody et al. Experiment (2000)
Our Issues with Previous Experiments

• Construction of TCI and CCI indices differed between Hammond et al. and Dunwoody et al.
  – Hammond et al. describes eleven relevant task properties, but only used eight in their experiment
  – Dunwoody et al. used four of the eight in their task index
  – Similar issue with both CCI indices of cognitive mode
  – Selection of task properties to include in their respective indices seems arbitrary in both cases
• Hammond et al. results are relatively weak, preserving order but not precise location on the continuums
• Dunwoody et al. results were unexpected, with cognitive mode on analytical task very similar to cognitive mode on intuitive task
An Example

\[ \beta_e = [0.8 \ 0.4 \ 0.2 \ 0.1] \]

\[
R = \begin{bmatrix}
1 & 0.8 & 0.2 & 0.1 \\
0.8 & 1 & 0.2 & 0.2 \\
0.2 & 0.2 & 1 & 0.1 \\
0.1 & 0.2 & 0.1 & 1 \\
\end{bmatrix}
\]
Research Question

Does an index based on a formulation of vicarious mediation and vicarious functioning outperform Dunwoody et al.'s index in an empirical demonstration of Cognitive Continuum Theory?
VMI Index Construction

• Before an experiment could be devised, some preliminary work had to be accomplished:
  – what is a good operational definition of variability in matrix product?
  – what values of ecological validity weights ($\beta_e$) are operationally meaningful?
  – How should one rank order a set of matrices of non-uniform $\mathbf{R}$?

• We chose the *mean deviation* of the matrix product of $\beta_e\mathbf{R}$

$$\text{Mean deviation} = \frac{\sum |X_i - \overline{X}|}{n}$$

  – a more robust estimator of variability than range alone

• We chose common heuristics seen in judgment research as choices for ecological validity ($\beta_e$) values
  – Take the Best heuristic: $\beta_{e1} > \Sigma (\beta_{e2} + \beta_{e3} + \beta_{e4})$
  – Tally heuristic: $\beta_{e1} = \beta_{e2} = \beta_{e3} = \beta_{e4}$

• We chose $(1 - \text{det}[\mathbf{R}])$ as a scalar way to rank a set of matrices
## Task Packages

<table>
<thead>
<tr>
<th>Variable</th>
<th>Task Package 1 (Intuition)</th>
<th>Task Package 2 (Quasi-rational)</th>
<th>Task Package 3 (Analytical)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ecological Validities</td>
<td>Tally (0.25 for all)</td>
<td>Take the Best (0.8, 0.4, 0.2, 0.1)</td>
<td>Take the Best (-0.8, 0.4, 0.2, 0.1)</td>
</tr>
<tr>
<td>Cue Intercorrelations</td>
<td>$R$ uniform (0.1)</td>
<td>$R$ non-uniform (0.8, 0.2, 0.1)</td>
<td>$R$ non-uniform (-0.7, 0.2, 0.1)</td>
</tr>
<tr>
<td>VMI score</td>
<td>0</td>
<td>0.385</td>
<td>0.625</td>
</tr>
<tr>
<td>average $r_{ij}$ (used in TCI_D)</td>
<td>0.1</td>
<td>0.267</td>
<td>-0.060</td>
</tr>
<tr>
<td>Std Dev of $\beta_e$ (used in TCI_D)</td>
<td>0</td>
<td>0.310</td>
<td>0.532</td>
</tr>
<tr>
<td>Task Predictability</td>
<td>$R^2_e = 0.55$</td>
<td>$R^2_e = 0.59$</td>
<td>$R^2_e = 0.94$</td>
</tr>
<tr>
<td>Overall TCI_D score</td>
<td>0.51</td>
<td>0.56</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Methodology (1)

• We performed an experiment using both the VMI index and Dunwoody et al.’s TCI index and compared the results
• The experiment used a double system lens model design with four cues
• We controlled environment side of the lens through task properties as Dunwoody et al. did.
• We created three task packages (inducing intuition, quasi-rationality and analysis) presented to participants
• Participants made judgments based on the four cues
• We used a within-subjects design (as in Hammond et al.) vice between-subjects design (as in Dunwoody et al.)
  – cognitive shift across tasks better observed with a within-subjects design
  – Analysis done both within-subjects and between-subjects
Methodology (2)

- Participants were experienced teachers performing a student placement task on hypothetical student profiles (60 student profiles for each of the three tasks)
  - Demographics: 43 females, 9 males, average 17.3 years experience teaching
- Student profile information was created by varying the task properties of $\beta_e$ and $[R]$ in the three cases described above
  - We used examples drawn from the Scales for Rating the Behavioral Characteristics for Superior Students, familiar to the subjects
  - Tasks were labeled as judgments on students creativity, academic performance and learning potential
  - Tasks were presented to teachers as either bar graphs or tables of values
- A pilot test was done to be sure tasks were familiar to the subjects; no issues arose in pilot test
- Participants volunteered for the study and were awarded continuing education points based on their participation
- Participants performed the judgments, recorded their times and demographic information, then returned the packages via mail
Dependent Variables

• We used two dependent variables, a CCI value for cognitive mode and achievement ($r_a$)

• We utilized two different methods to create indices of cognitive mode
  – Dunwoody et al. used a linear additive model for CCI_D of five cognitive properties which we emulated
    • judgment control ($R_s$)
    • kurtosis of error distribution
    • response rate of subjects while making judgments
    • subject self-insight into his judgment policy (subjective)
    • difference in subject confidence in method versus confidence in answer (subjective)
  – We also created a VFI index as an alternate CCI value, in a parallel structure to the VMI index
    • the mean deviation of the matrix product of the cue utilization weights ($\beta s$) with $[R]$
Hypotheses

• $H_1$: The means of the VFI scores will increase as VMI scores increase, reflecting significant shifts in cognitive mode based on task properties. The $CCID_D$ index of cognitive mode will not show similar increases.

• $H_2$: Achievement will be highest when there is close correspondence between the VMI index and the VFI index (i.e., when task properties match cognitive mode). The $TCID_D$ and $CCID_D$ indices will not show a similar relationship.
H₁: VFI Scores by Task Package

- Between subjects analysis
- VFI scores show significant differences and increase as VMI increases, as predicted
- CCID scores do not vary as TCID increases; no significant difference between them
- This result provides support for CCT because it indicate that as task property index (VMI) increases, cognitive mode index (VFI) also increases
H$_2$: Achievement Scores ($r_a$) and Correspondence Score

- VMI-VFI construct shows predicted relationship ($r^2 = 0.22$ (significant at 0.05 level), slope significantly different than zero ($t = -6.64, p < 0.001$)) when all tasks considered collectively.
- TCI$_D$-CC$_D$ construct shows predicted relationship at a lower coefficient of determination ($r^2 = 0.10$ (significant at 0.05 level), slope significantly different than zero ($t = -4.06, p < 0.001$)), when all tasks considered collectively.
- VMI-VFI predicted relationship demonstrated in all individual tasks as well as in the aggregate.
- TCI$_D$-CC$_D$ construct fails to demonstrate the predicted relationship in individual tasks except for TP2.

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Summary of Experimental Results

• $H_1$: Task properties induce shift in cognitive mode when measured by VMI-VFI methodology
  – Supported by VFI increases corresponding to VMI increases
  – Not supported by $CC_ID$ metric, which remained unchanged while $TC_ID$ increased

• $H_2$: Achievement will improve when there is close correspondence between task properties and cognitive mode
  – Supported by VMI-VFI methodology in each task package and in total
  – Only supported by $TC_ID$-$CC_ID$ methodology in TP2
    • Weakly supported in aggregate for all task packages, but due to bimodal clustering of task package data
Discussion

• Two major facets of CCT were empirically demonstrated in this experiment in contrast to the Dunwoody et al. methodology
  – Support was shown for the relationship between task properties and cognitive mode
  – Support was shown for the relationship between achievement and correspondence between task properties and cognitive mode
• Negatively correlated cues present difficulties for some subjects
  – The impact of negatively correlated cues (and the corresponding cue utilization weight) was seen in the VMI-VFI methodology
  – This effect is masked in the Hammond et al. and Dunwoody et al. methodologies that depend upon average $r_{ij}$ and the standard deviation of $\beta_e$.
• Further research into the full impact of negatively correlated cues is warranted in light of these experimental results
Implications of These Results

• These experimental results support the CCT precepts that judgment task properties influence cognitive mode and that close correspondence between the two can result improve judgment performance
  – Using experienced teachers
  – Doing representative tasks

• The result that VMI scores can be predictive of VFI scores can serve to identify optimal cognitive modes for given tasks
  – Which can then serve to identify $\beta_s$ weighting to maximize achievement potential
  – Knowing the $\beta_s$ weights can be exploited though cue salience in presentation or by choosing the best heuristic for cue utilization weights

• Identifying negatively correlated cues can have significant impact
  – Transforming a negatively correlated cue into a positively correlated one could serve as a mechanism to increase achievement by itself; this hypothesis should be further examined

• The knowledge of task properties from actual case data could serve to accurately predict and therefore improve judgment performance

• If actual case data is lacking then task properties (lens model parameters) can be estimated from other, similar tasks
  – Similar in the sense of similar cue ecological weights and cue inter-correlations
  – Which can then be refined through an iterative process
Next Steps

• Research into CCT has been largely dormant in recent years due to the previous mixed empirical results; this research should revitalize interest in CCT

• The cases presented do not represent the full spectrum of possible cases; further research is warranted into more diverse cases

• Further research is required in the central region of quasi-rationality
  – The poles are easier to define
  – What is the impact of different combinations of intuitive task properties and analytical task properties on achievement?

• Other premises of CCT can now be examined using our methodology
  – Such as dynamic cognition and oscillation between pattern recognition and functional relationships
  – Our metric is a more sensitive tool than the Dunwoody et al. metric