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The small effects of non-hierarchical complexity variables on performance

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ABSTRACT

Even when the results show that most of the difficulty in solving problems is explained by the hierarchical complexity of the item, there are still variables that help in small ways in predicting how well items measure difficulty. One must understand what these variables are and take them into consideration when analyzing data from instruments designed to measure the impact of the order of hierarchical complexity of items.

This study was designed to test the effect of small variables on task performance. The variables tested were hierarchical complexity, place in order, the number of calculations needs, the size of the numbers, and the causal variable position.

Participants were asked to solve problems from task sequences from the logic/mathematics/physical science subdomains. The four instruments used were the algebra, balance beam, infinity and laundry instruments. These instruments were based on the model of hierarchical complexity (MHC). Participants were asked to first complete the laundry task sequence and move to the next task sequence. Items from each instrument were analyzed individually and as a group. A Rasch analysis was performed on all the items from all the instruments. The variables thought to have an effect were coded. The coded variables were then analyzed using stepwise regression.

A stepwise regression was used and the small variables were tested with and without hierarchical complexity as a factor. The variables were regressed against the stage score of the items. For all four instruments stepwise regression with hierarchical complexity as one of the variable accounted for about 95% of the variance and the β was greater than 0.9. Stepwise regression with all the other variables except hierarchical complexity accounted for relatively lower variance and β.

The results showed that order of hierarchical complexity has a very strong predictive role and accounts for most of the variance. The other variables only made very small contributions.

KEYWORDS: model of hierarchical complexity, difficulty of items, small effect variables

Even when the results show that most of the difficulty in solving problems is explained by the hierarchical complexity of the item, there are still variables that help in small ways in predicting how well items measure difficulty. One must understand what these variables are and take them into consideration when analyzing data from instruments designed to measure order the impact of the order of hierarchical complexity of items. Some of these variables change depending on the instrument.

Results from the one domain paper showed that problem solving difficulty of instruments from logic/mathematics/physical sciences subdomain is explained by the order of hierarchical complexity of the item. Other instrument variables may help better predict how well items measure difficulty. These variables should be taken into consideration when analyzing data. This study was designed to test the effect of small variables on task performance. The variables tested were hierarchical complexity, place in order, the number of calculations needed, the size of the numbers, and the causal variable position.

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» THE MODEL OF HIERARCHICAL COMPLEXITY

The four instruments used in the study were from logic/mathematics/physical sciences subdomain. The four instruments used were the algebra, balance beam, infinity and laundry instruments. These instruments were based on the model of hierarchical complexity. The model of hierarchical complexity (MHC) is a non mentalistic, neo Piagetian mathematical model (Krantz, Luce, Suppes, & Tversky, 1971; Luce & Tukey, 1964). MHC allows for the measurement of stage performance. It deconstructs tasks into the actions that must be done at each order. This is to build the behavior needed to successfully complete a task.

MHC provides an analytic *a priori* measurement of the difficulty of task actions. The difficulty is represented by the orders of hierarchical complexity (OHC) (Commons & Pekker, 2008). There are 17 known orders of hierarchical complexity. This is shown in Table 1

Hierarchical complexity describes a form of information that is different from traditional information theory (Shannon & Weaver, 1948) in which information is coded as bits that increase quantitatively with the amount of information. Theorem 4 of the model (Commons, et al, 1998) shows that every task action has an order of hierarchical complexity associated with it. The ideal correct task actions may be classified as to their order of hierarchical complexity. The tasks actions may address every experimental task, every clinical test item that has a difficulty associated with it, every behavior, developmental task, survey item, and statement made by people regardless of the content or context. Each task action will have a difficulty of performance associated with it.

A task action is defined as more hierarchically complex when 1) A higher-order task is defined in terms of two or more tasks at the next lower order of hierarchical complexity, 2) Higher-order tasks organize the lower order actions and 3) The lower order tasks are coordinated non-arbitrarily, not just put together as an arbitrary chain. This is illustrated schematically in Figure 1.

Table 1. the 17 known orders of hierarchical complexity

order	
number	name
0	computational
1	automatic
2	sensory or motor
3	circular sensory motor
4	sensory-motor
5	nominal
6	sentential
7	preoperational
8	primary
9	concrete
10	abstract
11	formal
12	systematic
13	metasystematic
14	paradigmatic
15	crossparadigmatic
16	meta-crossparadigmatic

» THE RASCH MODEL

Whereas they are well-known in psychometric circles, Rasch's (1980), models for measurement have been employed by developmental psychologists only recently (Andrich & Constable, 1984; Bond, 1994; Dawson, 1998, 2000, 2002; Draney, 1996; Muller, Sokol, & Overton, 1999; Wilson, 1984). These models are designed specifically to examine hierarchies of person and item performance, displaying both person proficiency and item difficulty estimates along a single interval scale (logit scale) under a probabilistic function. In addition, they can be employed to test the extent to which items or scores conform to a theoretically specified hierarchical sequence. A central tenet of stage theory is that cognitive abilities develop in a specified sequence, making the statistical tests implemented in a Rasch analysis especially relevant to understanding stage data. The Rasch model permits researchers to address questions like, "Are all single abstractions items more difficult than all representational systems level and less difficult than all abstract mappings items?" Moreover, the detailed information about item functioning and individual performances provided by the software makes it possible to simultaneously examine group and individual effects. These properties make Rasch models uniquely suitable for the investigation of many developmental phenomena.

The Rasch (1980) model uses logistic regression to minimize person and item error simultaneously. The model allows researchers to convert raw scores into equal interval linear scales. The item scores on the right represent how difficult the item was. The person scores on the left represent how good a person was at dealing with the item difficulty. The model also produces an objective, additive, and one dimensional scale. These are some of its advantages over other scaling techniques in measuring stage.

It is beyond the scope of this paper to provide a comprehensive account of the Rasch model, though we do attempt to provide enough information to allow readers who are unfamiliar with the model to follow the results of the analysis. For an introduction to the Rasch model, see Bond and Fox (2001), Rasch (1980), Smith (2004), and Wilson (2005).

» METHOD

Participants

The convenience sample of 309 participants was obtained from various ListServ's. There were 232 (77.3%) men and 77 (22.7%) women ranging in age from 12 to 87 (M = 24.02, SD = 8.86) with education varying from elementary school to graduate degree (M = 4, SD = 1.01)

Instruments

A number of task sequences were used. The task sequences were categorized as either belonging to the mathematical (algebra & infinity), logical (laundry version of the Inhelder and Piaget's (1958) pendulum problem), or physical science (balance beam) subdomains.

Task sequences from the mathematics, logic and physical science subdomains were used. Participants were asked to solve problems from a task sequence with a given content. There were a total of 250 items.

Table 2. number of participants for each instrument of the social subdomain and mathematical/logical/physical science subdomain

instrument	number of participants
laundry	109
algebra	37
balance beam	46
infinity	50

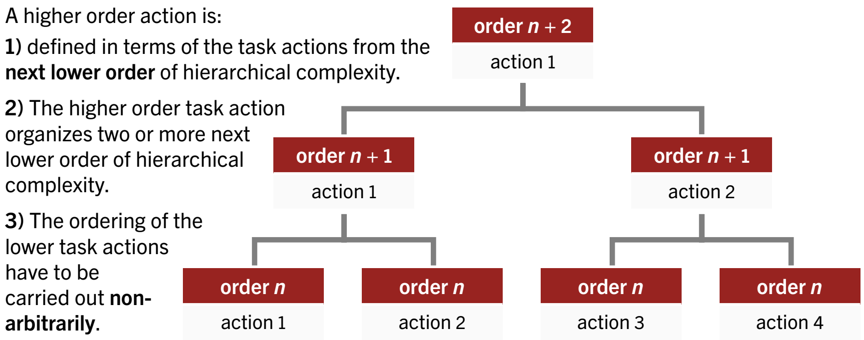

Figure 1. This figure schematically shows the three axioms of the model of hierarchical complexity

Each task sequence was at a different order of hierarchical complexity. These included:

1. Preoperational
2. Primary
3. Concrete
4. Abstract
5. Formal
6. Systematic
7. Metasystematic

Instrument description for logic/mathematics/ physical sciences subdomain

Algebra (mathematics): This instrument sequence asked participants solve standard algebraic problems

Balance beam (physics): This instrument sequence was derived from Inhelder and Piaget (1958) balance beam task

Infinity (mathematics): This instrument sequence asked participants to solve problems that dealt with conceptualizing infinity

Laundry (logic and mathematics): This instrument sequence was a version of Inhelder & Piaget (1958) pendulum task. It asked participants to detect causal relationships from various systems and then compare the systems using logic (Bernholt, Parchmann, & Commons, 2009; Commons, Miller, & Kuhn, 1982).

An example of logic/mathematics/physical sciences subdomain problem sequence is shown in Appendix A.

Procedure

Participants were asked to solve problems from a task sequences from the logic/mathematics/physical science subdomains. Participants were asked to first complete the laundry task sequence and move to the next task sequence. Items from each instrument were analyzed individually and as a group. A Rasch analysis was performed on all the items from all the instruments. The variables thought to have an effect were coded. The coded variables were then analyzed using stepwise regression.

Instrument variables affecting performance

Number of calculations required to solve the task: This was coded by counting each calculation required to solve the task and putting down the actual number. No shortcuts were taken so each number represented the maximum amount of steps a person had to take in order to correctly solve the task.

Size of numbers in the task: This was coded by counting the digits of the numbers in the problem and the answer choices. The number of digits in the largest number was used.

Where problem is within an order: This variable is determined by the order in which the problems were asked. For example, if in the primary order (8) there were five questions then the first question was coded as 1 and the last question was coded as 5. It is expected that the questions towards the end of an order would be easier because of the practice effect. With all the instruments, within each order of hierarchical complexity, an item presented became progressively more difficult as the regular complexity of the expressions representing a variable increased

Where the item is within a problem: Some of these variables change depending on the instrument. The last variable only occurred in the laundry instrument. It was used in place of the number size variable as the laundry instrument did now have numbers. This variable was coded based on the position of the causal variable. The variable which operates on the outcome is known as the operative variable. This is the variable which must be known in order to answer the question correctly. In the four variable laundry instrument the difficulty of the item changed depending on the position of the causal variable of the outcome within the episode. When first it was second easiest (primacy), when in the middle it was the most difficult and when right before the outcome the easiest (recency.)

What is the position of the causal variable: The variable which operates on the outcome is known as the operative variable. This is the variable which must be known in order to answer the question correctly. The laundry problem in Appendix B demonstrates this clearly.

Table 3. stepwise regression for all instruments *without* hierarchical complexity

model 1						
balance beam		**algebra**		**laundry**		**infinity**
size of numbers	$\beta = .906$ $p \leq .001$ $n = 46$	place in order	$\beta = .366$ $p = .047$ $n = 37$	calc. needed	$\beta = .829$ $p \leq .001$ $n = 109$	n/a
model 2						
balance beam		**algebra**		**laundry**		**infinity**
calc. needed added	$\beta = .926$ $\Delta R^2 = .037$ $n = 46$	size of numbers added	$\beta = .545$ $\Delta R^2 = .163$ $n = 37$	variable position added	$\beta = .855$ $\Delta R^2 \leq .001$ $n = 109$	n/a
size of numbers	$\beta = .702$ $p \leq .001$ $n = 42$	place in order	$\beta = .436$ $p = .013$ $n = 37$	calc. needed	$\beta = .739$ $p \leq .001$ $n = 109$	n/a
calc. needed	$\beta = .279$ $p = .016$ $n = 46$	size of numbers	$\beta = -.410$ $p = .019$ $n = 37$	variable position	$\beta = .228$ $p \leq .001$ $n = 109$	n/a

Table 4. stepwise regression for all instruments *with* hierarchical complexity

model 1							
balance beam		algebra		laundry		infinity	
OHC	$\beta = .977$ $p \le .001$ $n = 46$	OHC	$\beta = .953$ $p \le .001$ $n = 37$	OHC	$\beta = .964$ $p \le .001$ $n = 109$	OHC	$\beta = .912$ $p \le .001$ $n = 50$
model 2							
balance beam		algebra		laundry		infinity	
size of numbers added	$\beta = .991$ $\Delta R^2 = .003$ $n = 46$	calc. needed added	$\beta = .968$ $\Delta R^2 \le .001$ n = 37	calc. needed added	$\beta = .969$ $\Delta R^2 = .010$ n = 109	calc. needed added	$\beta = .969$ $\Delta R^2 = .010$ n = 50
OHC	$\beta = .735$ $p \le .001$ $n = 46$	OHC	$\beta = .943$ $p \le .001$ $n = 37$	OHC	$\beta = .830$ $p \le .001$ $n = 109$	OHC	$\beta = .830$ $p \le .001$ $n = 50$
size of numbers	$\beta = .128$ $p = .035$ $n = 46$	calc. needed	$\beta = .117$ $p = .024$ $n = 37$	calc. needed	$\beta = .168$ $p \le .001$ $n = 109$	calc. needed	$\beta = .168$ $p \le .001$ $n = 50$

» RESULTS

Variables combined

A stepwise regression was used and the small variables were tested with and without hierarchical complexity as a factor. The variables were regressed against the stage score of the items.

Stepwise regression without OHC

For the balance beam instrument without hierarchical complexity in the stepwise regression outputted two models. In the first model, size of numbers accounted for about 91% of the variance ($r(46) = .906$, $p \le .001$). In the second model size of numbers and calculations needed accounted for about 93% of the variance ($r(46) = .926$, r^2 change = .037). Size of numbers was responsible for about 70% ($r(46) = .702$, $p \le .001$) of the variance and calculations needed was responsible for about 28% of the variance ($r(46) = .279$, $p = .016$). Please refer to Table 3.

The algebra instrument without hierarchical complexity in the stepwise regression outputted two models. In the first model, the place of the problem within the order of hierarchical complexity accounted for about 37% of the variance ($r(37) = .366$, $p = .047$). The second added size of the numbers to the previous model. This addition accounted for about 55% of the variance ($r(37) = .545$, r^2 change = .163). The place in the order was responsible for about 44% ($r(37) = .436$, $p = .013$) of the variance and the size of the numbers was responsible for about 41% of the variance ($r(37) = -.410$, $p = .019$). Please refer to Table 3.

The laundry instrument without hierarchical complexity in the stepwise regression outputted two models. In the first model, the number of calculations required accounted for about 83% of the variance ($r(109) = .829$, $p \le .001$). The second model added the position of causal variable to the previous model. This addition accounted for about 86% of the variance ($r(109) = .855$, r^2 change = .044). The number of calculations needed was responsible for about 74% ($r(109) = .739$, $p \le .001$) of the variance and the position of causal variable was responsible for about 23% of the variance ($r(109) = .228$, $p \le .001$). Please refer to Table 3.

The infinity instrument without hierarchical complexity included in the stepwise regression could not be computed because the effect of the small variables was not large enough.

Stepwise regression with OHC

For the balance beam instrument with hierarchical complexity as a variable in the stepwise regression, there were two models and the numbers change drastically. In first model, hierarchical complexity alone, accounted for about 98% of the variance ($r(46) = .982$, $p \le .001$). The second model added the size of numbers to the previous model. This addition accounted for just over 99% of the ($r(46) = .991$, r^2 change = .003). Hierarchical complexity accounted for about 74% ($r(46) = .735$, $p \le .001$) of the variance, and the size of the numbers accounted for about 13% of the variance ($r(46) = .128$, $p = .035$). Please refer to Table 4.

The algebra instrument with hierarchical complexity in the stepwise regression outputted two models. In the first model, hierarchical complexity alone accounted for about 95% of the variance ($r(37) = .953$, $p \le .001$). The second model added the number of calculations needed to the previous model. This addition accounted for about 97% of the variance ($r(37) = .968$, r^2 change = .013). Hierarchical complexity accounted for about 94% ($r(37) = .943$, $p \le .001$) of the variance and the number of calculations needed accounted for about 12% of the variance ($r(37) = .117$, $p = .024$). Please refer to Table 4.

The laundry instrument with hierarchical complexity in the stepwise regression outputted two models. In the first model, hierarchical complexity alone accounted for about 97% of the variance ($r(109) = .964$, $p \le .001$). The second model added the number of calculations to the previous model. This addition accounted for 97% of the variance ($r(109) = .969$, r^2 change = .010). Hierarchical complexity accounted for 83% ($r(109) = .830$, $p \le .001$) of the variance and the number of calculations required accounted for about 17% of the variance ($r(109) = .168$, $p \le .001$). Please refer to Table 4.

The infinity instrument with hierarchical complexity as a variable in the stepwise regression outputted two models. In the first model, hierarchical complexity alone accounted for 91% of the variance ($r(50) = .912$, $p \le .001$). The second model added the number of calculations needed to the previous model. This addition accounted for 97% of the variance ($r(50) = .969$, r^2 change = .010.) Hierarchical complexity accounted for 83% ($r(50) = .830$, $p \le .001$) of the variance and the number of calculations required accounted for about 17% of the variance ($r(50) = .168$, $p \le .001$). Please refer to Table 4.

Table 5. Pearson correlations with the major variables that affected performance

hierarchical complexity and stage score	$r = 0.955$
calculations required and hierarchical complexity	$r = 0.542$
calculations required and stage score	$r = 0.571$
calculations required and causal variable position	$r = 0.395$
causal variable and stage score	$r = 0.520$
causal variable and hierarchical complexity	$r = 0.527$

Table 6. stepwise regression for all instruments without hierarchical complexity

calculations needed	$\beta = .592$	$p \leq .001$
excluded variables		
place in order	$\beta = .094$	$p = .268$
size of numbers	$\beta = -.011$	$p = .894$

Collinearity

Some of the small variables correlated with the major variables that affected performance. The order of hierarchical complexity was correlated with the number of calculations required ($r = .542$) and the position of the causal variable ($r = .527$). The stage score of the items also correlated with the number of calculations required ($r = .571$) and the position of the causal variable ($r = .520$.) The number of calculations required and the position of the causal variable had a correlation of $r = .395$ and the order of hierarchical complexity and the stage score had a correlation of $r = .955$.

Overall regression analysis

An overall stepwise regression analysis was conducted across all instruments and the small variables were tested with and without hierarchical complexity as a factor. The variables were regressed against the stage score of the items. Without hierarchical complexity, the number of calculations accounted for 59% of the variance ($r(242) = .592$, $p \leq .001$). The place of the problem within the order of hierarchical complexity and size of numbers were excluded from the regression because of the effect of these variables were not large enough. Place in the order accounted for 9% of the variance ($r(242) = .094$, $p = .268$) and size of numbers accounted for 1.1% of the variance ($r(242) = -.011$, $p = .894$).

With hierarchical complexity as a variable in the stepwise regression there were two models. In the first model, hierarchical complexity alone as predictor accounted for about 96% of the variance ($r(242) = .955$, $p \leq .001$). In the first model, place of the problem within the order of hierarchical complexity, number of calculations needed and size of numbers were excluded from the regression because of the effect of these variables were not large enough. The second model added number of calculations needed to the previous model. This addition accounted for 96% of the variance ($r(242) = .957$, r^2 change = .004). Hierarchical complexity accounted for 91% ($r(242) = .914$, $p \leq .001$) of the variance and the number of calculations required accounted for about 7% of the variance ($r(242) = .075$, $p = .037$). In the second model, place of the problem within the order of hierarchical complexity, and size of numbers were excluded from the regression because of the effect of these variables were not large enough.

Table 7. stepwise regression for all instruments with hierarchical complexity

model 1		
hierarchical complexity	$\beta = .955$	$p \leq .001$
excluded variables		
place in order	$\beta = .020$	$p = .506$
calculations needed	$\beta = .075$	$p = .037$
size of numbers	$\beta = .029$	$p = .343$
model 2		
number of calculations needed added	$\beta = .957$	$\Delta R^2 = .004$
hierarchical complexity	$\beta = .914$	$p \leq .001$
calculations needed	$\beta = .075$	$p = .037$
excluded variables		
place in order	$\beta = .029$	$p = .339$
size of numbers	$\beta = .024$	$p = .422$

» DISCUSSION

Order of hierarchical complexity has a very strong predictive role and accounts for most of the variance. The other variables only made very small contributions. In the case of Balance Beam, the following small variables accounted for .991 Of the variance: hierarchical complexity, size of numbers in the task, number of calculations needed and place of the problem within the order of hierarchical complexity.

The small variables each would make a contribution when analyzed alone. When hierarchical complexity is used in the overall stepwise regression it wipes out almost all of the effect of the small variables. Number of calculations needed is the only variable with an effect. This variable had a β of only .075. The reason it had such a small effect was ***a)*** hierarchical complexity already accounted for most of the variance and ***b)*** calculations required was highly collinear with hierarchical complexity, $r = .542$. ■

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APPENDIX

» APPENDIX A: *logic/mathematics/physical sciences subdomain problem sequence*

Balance beam metasystematic problem sequence example

Subsystem A: In one class, $x + 6$ students each received a rating of 1. The other 5 students received a rating of x.

ratings	1	x
number of students	$x + 6$	5

Subsystem B: In one class, $y + 6$ students each received a rating of 500. The other 5 students received a rating of 500y.

ratings	500	500y
number of students	$y + 6$	5

» APPENDIX B: *laundry problem*

Read the six examples. Each example tells what was done to the cloth and how the cloth turned out. Give the answer to the questions that follow the examples.

A cloth was stained with red lipstick. There are six ways the cloth can be washed. Sometimes the cloth will be clean after being washed and sometimes the cloth will be dirty.

A bleach	powder soap	blue booster	cold water	⟶	dirty
B bleach	liquid soap	pink booster	hot water	⟶	clean
A bleach	powder soap	pink booster	hot water	⟶	dirty
B bleach	powder soap	pink booster	cold water	⟶	dirty
A bleach	liquid soap	blue booster	hot water	⟶	clean
B bleach	liquid soap	blue booster	cold water	⟶	clean

Question

Look back at the examples. After being washed, will the cloth be clean or dirty?

B bleach	powder soap	blue booster	hot water	clean?	dirty?
A bleach	liquid soap	blue booster	cold water		
A bleach	powder soap	pink booster	cold water		
B bleach	liquid soap	blue booster	hot water		
B bleach	powder soap	blue booster	cold water		
B bleach	powder soap	pink booster	hot water		
A bleach	liquid soap	pink booster	hot water		
A bleach	powder soap	blue booster	hot water		
B bleach	liquid soap	pink booster	cold water		
A bleach	liquid soap	pink booster	cold water		