Development of Executive Function in Childhood: Implications for Learning and LD

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Executive Function

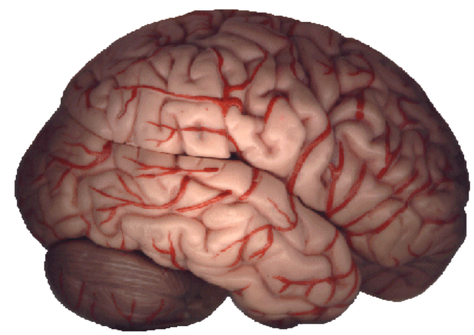
- A set of attentional skills (ways of using attention) involved in the goal-directed control of thought, emotion, motivation, and action
- Processes related to, but different from, "intelligence"
  - Using knowledge in service of goals
- EF skills invoked when we notice problem, go off autopilot
- Develop as a result of reflection

- Reflection changes one's perspective, providing "psychological distance" from a situation
- Just as physical distance provides a panorama, psychological distance
  - shows us the range of possible responses
  - allows us to select among them

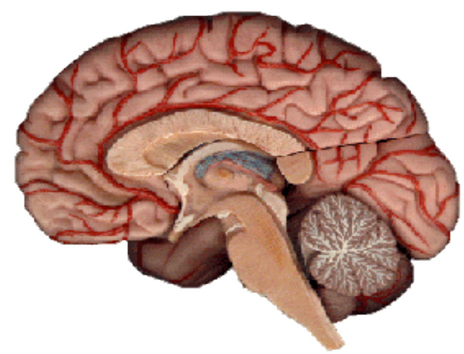
- EF skills as 3 ways of using attention–
  - Flexibly, Selectively, & Sustained over time
  - *(1) Cognitive flexibility*
    - Shifting task sets or perspectives
  - *(2) Inhibitory control*
    - Ignoring distractions, suppressing responses
  - *(3) Working memory*
    - Holding info in mind and working with it

“Hot” vs. “Cool” EF

- Cool EF
  - Assessed via abstract, decontextualized problems
  - Control processes required for affectively neutral problems



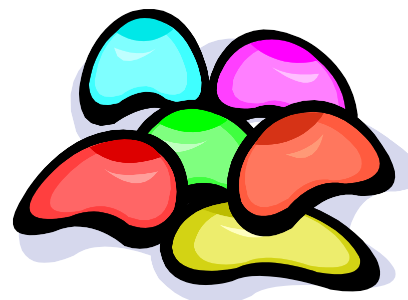
- Hot EF
  - Needed for problems w/ affective or motivational significance (meaningful consequences)
  - Flexible reappraisal of whether to approach/withdraw concrete stimulus



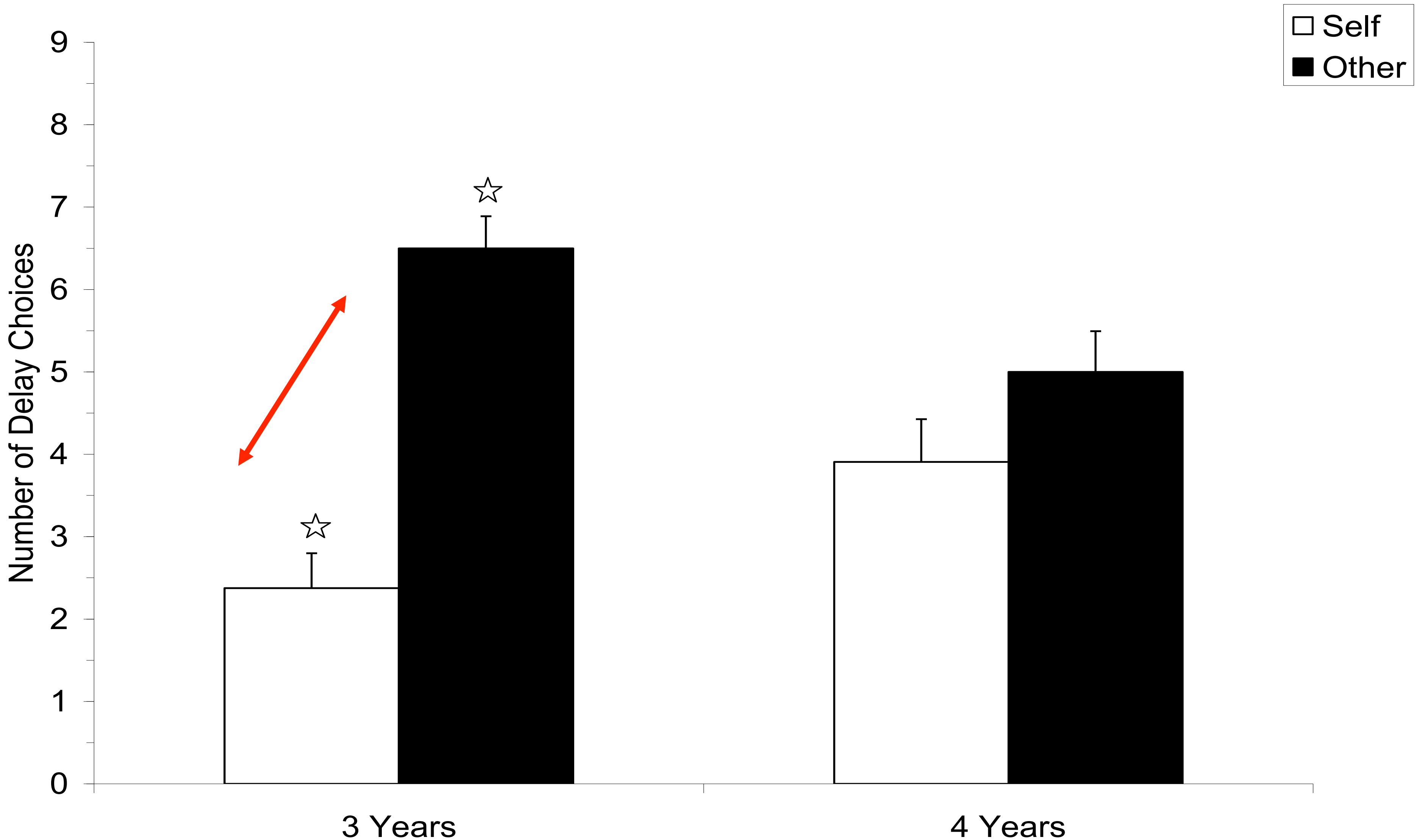
Zelazo & Müller (2002)

Delay of Gratification (Prencipe & Zelazo, 2005)

- Choice
  - Smaller immediate vs. larger delayed reward?
- 3- and 4-year-olds
- Self & Other versions



Would you like to have <u>one</u> candy now or <u>two</u> candies at the end of the game?



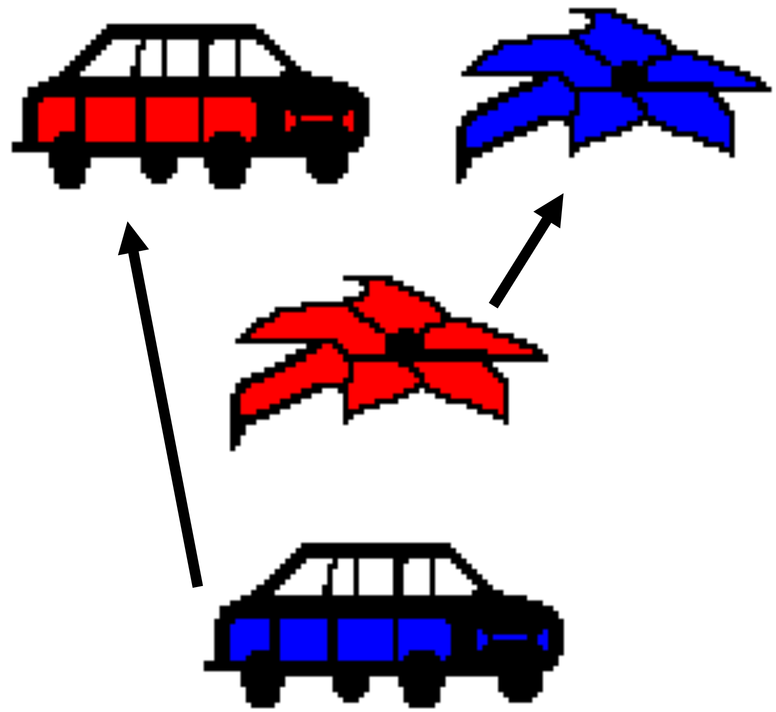
Prencipe & Zelazo (2005). *Psychological Science.*

Dimensional Change Card Sort (DCCS)

Zelazo, 2006, *Nature Protocols*

Target Cards

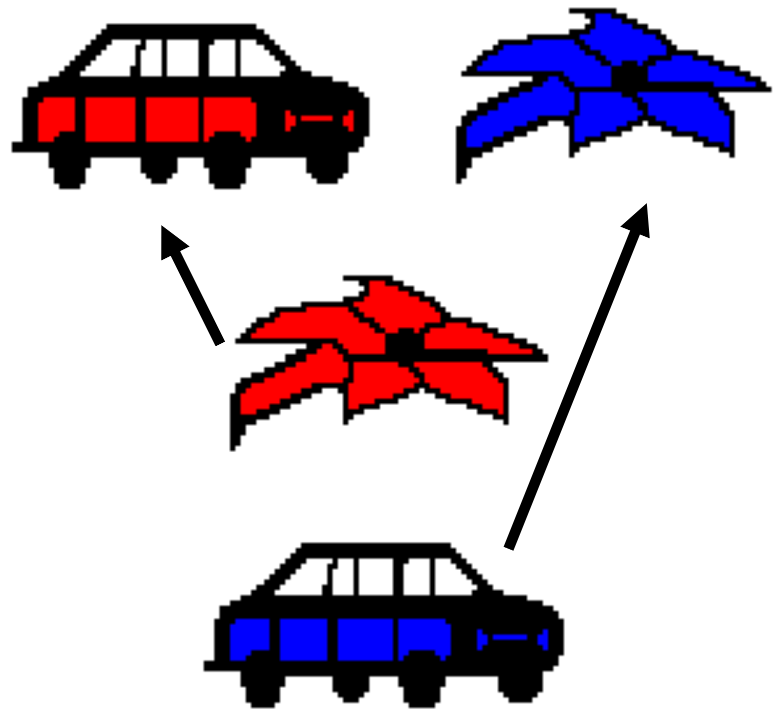
Test Cards



Told to sort by shape

Target Cards

Test Cards



Told to switch and sort by color
Told rules on every trial

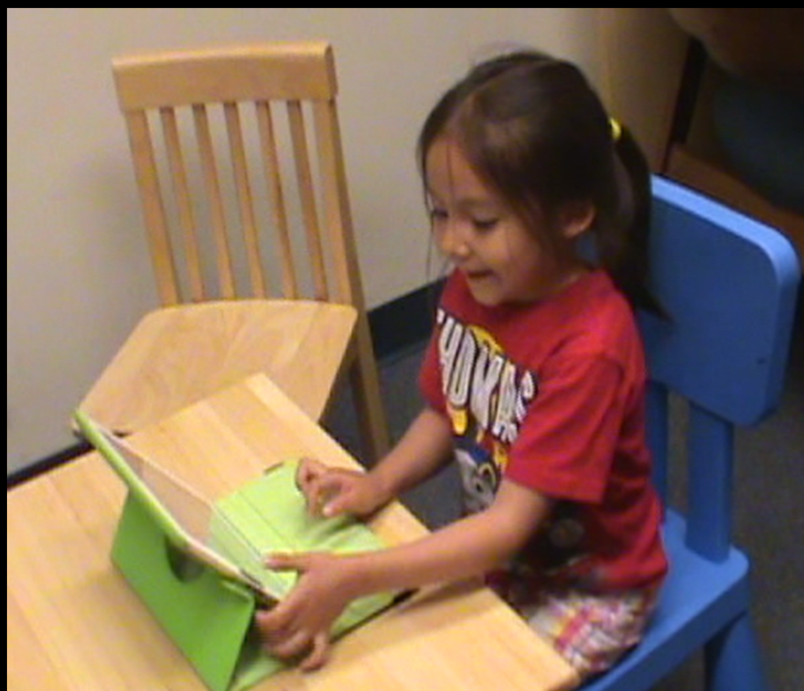
Basic Results

- Regardless of dimension order, 3-year-olds:
  - Continue to sort by the first dimension (e.g., shape)

- Despite:
  - Demonstrating knowledge of the new rules
  - When asked, “Where do the red ones go?” they’re correct
  - “Where does this red one go?” they *perseverate*, and sort by shape....

Minnesota EF Scale (MEFS™)

Carlson and Zelazo, 2014

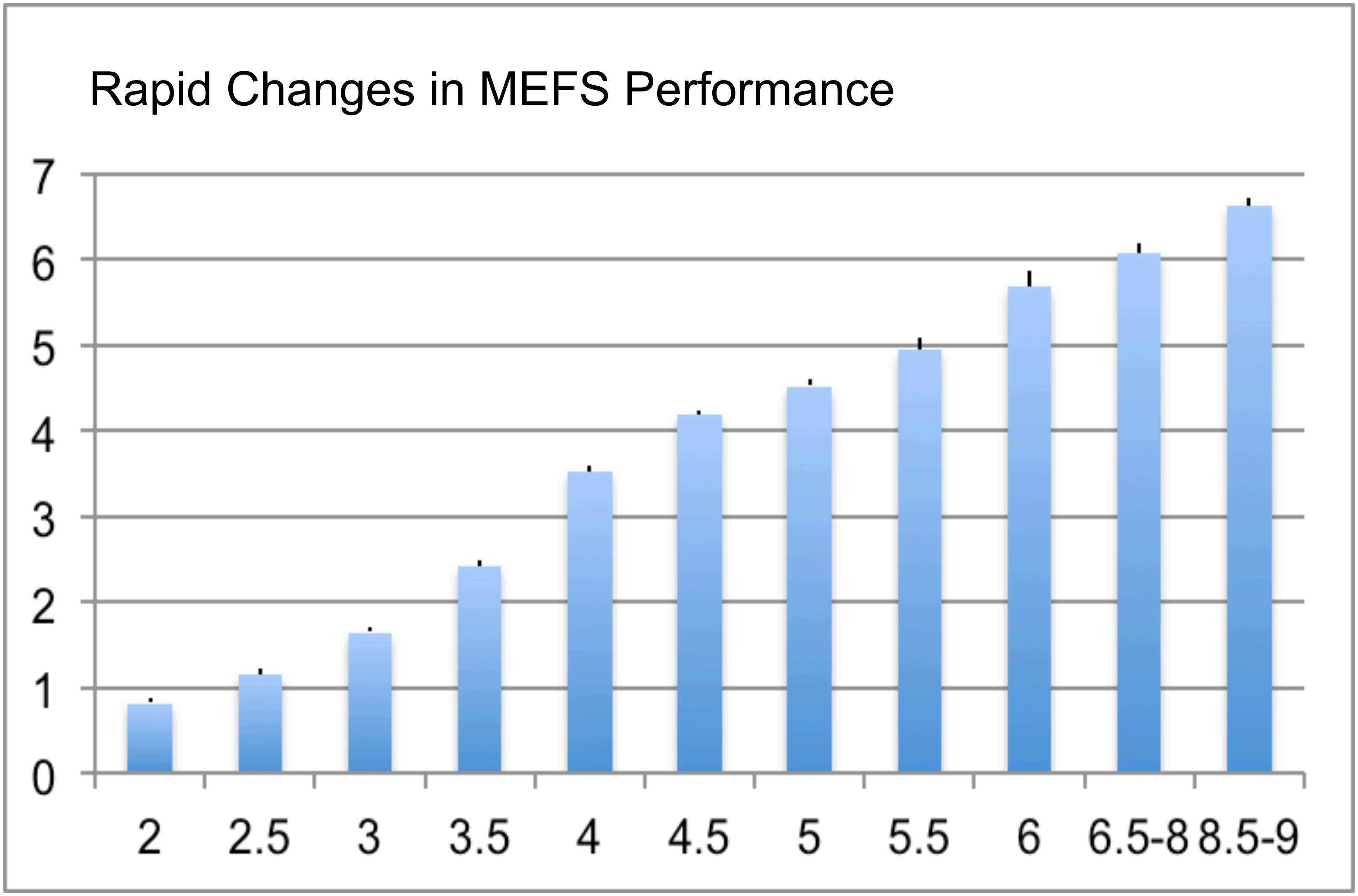


Version designed as computer-adaptive tablet game for convenient school use, ~4 min

REFLECTION SCIENCES™

- *Disclaimer*: Stephanie Carlson, Philip Zelazo, and the University of Minnesota are entitled to royalties from the sale of the Minnesota Executive Function Scale by Reflection Sciences, Inc.

Administered to over 20K individuals, 8 countries, 7 languages



Interest in Development of EF

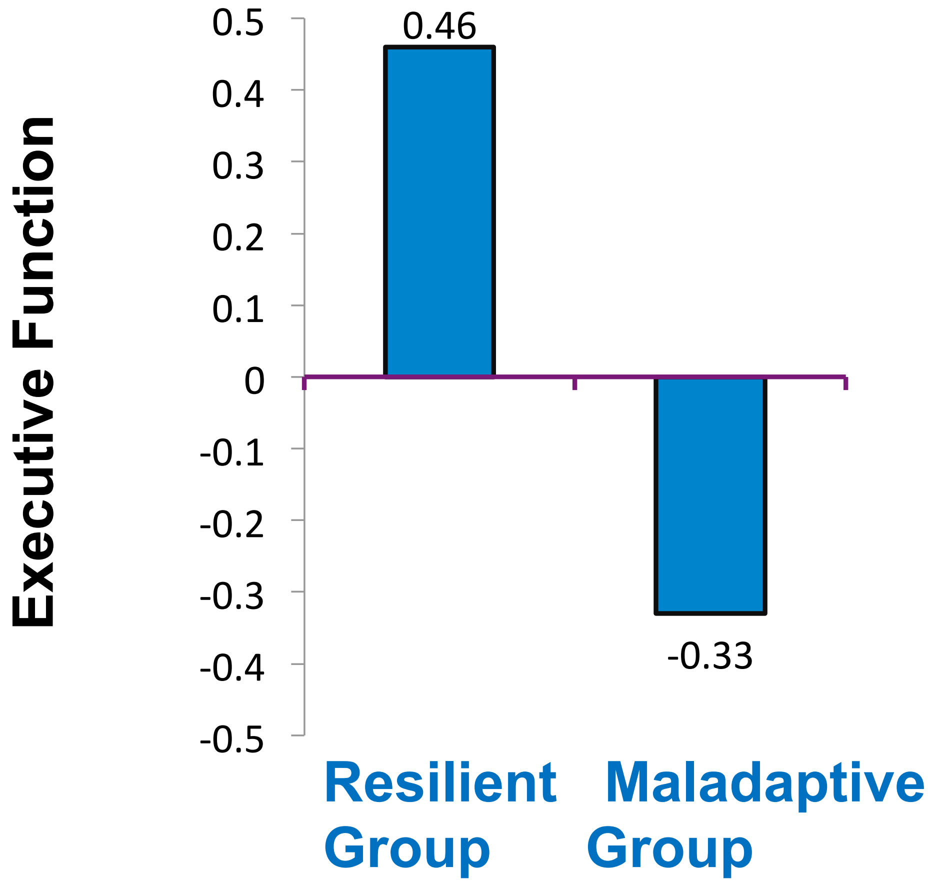
- EF skills predict learning, achievement, adaptation
  - Better than IQ and across decades

- Problems with EF are associated with clinical conditions w/ child onset
  - ADHD, autism, Conduct Disorder, others

- Evidence that EF skills can be improved with practice

- EF skills protect against risks associated with poverty

EF Skills Predict School Success in Homeless & Highly Mobile (HHM) Children



Obradovic 2010
Masten et al 2012

Why does EF Predict Key Outcomes?

- EF skills provide a foundation for *learning* and *adaptation* across a wide range of situations

- Essential for learning in classroom environment
  - Paying attention, avoiding distractions
  - Remembering rules
  - Resisting impulsive responses
  - Managing emotional reactions, including motivation and boredom

Children with Better EF…

- Learn more efficiently (e.g., Benson et al., 2013)
- Show > gains in math, K-1st grade (Hassinger-Das et al., 2014)

- Children with poor EF skills
  - Distracted, fail to remember rules
  - Act out in class
- Learn less effectively
- Get in trouble, suspended, even expelled

Training and Neuroplasticity

- EF skills are modified by experience
- The brain is an inherently adaptive organ: We grow our brains in particular ways by using them in particular ways
- When we activate brain networks, they adapt
  - Synaptic pruning and myelination
- True across lifespan, but periods of relative plasticity associated with rapid behavioral change

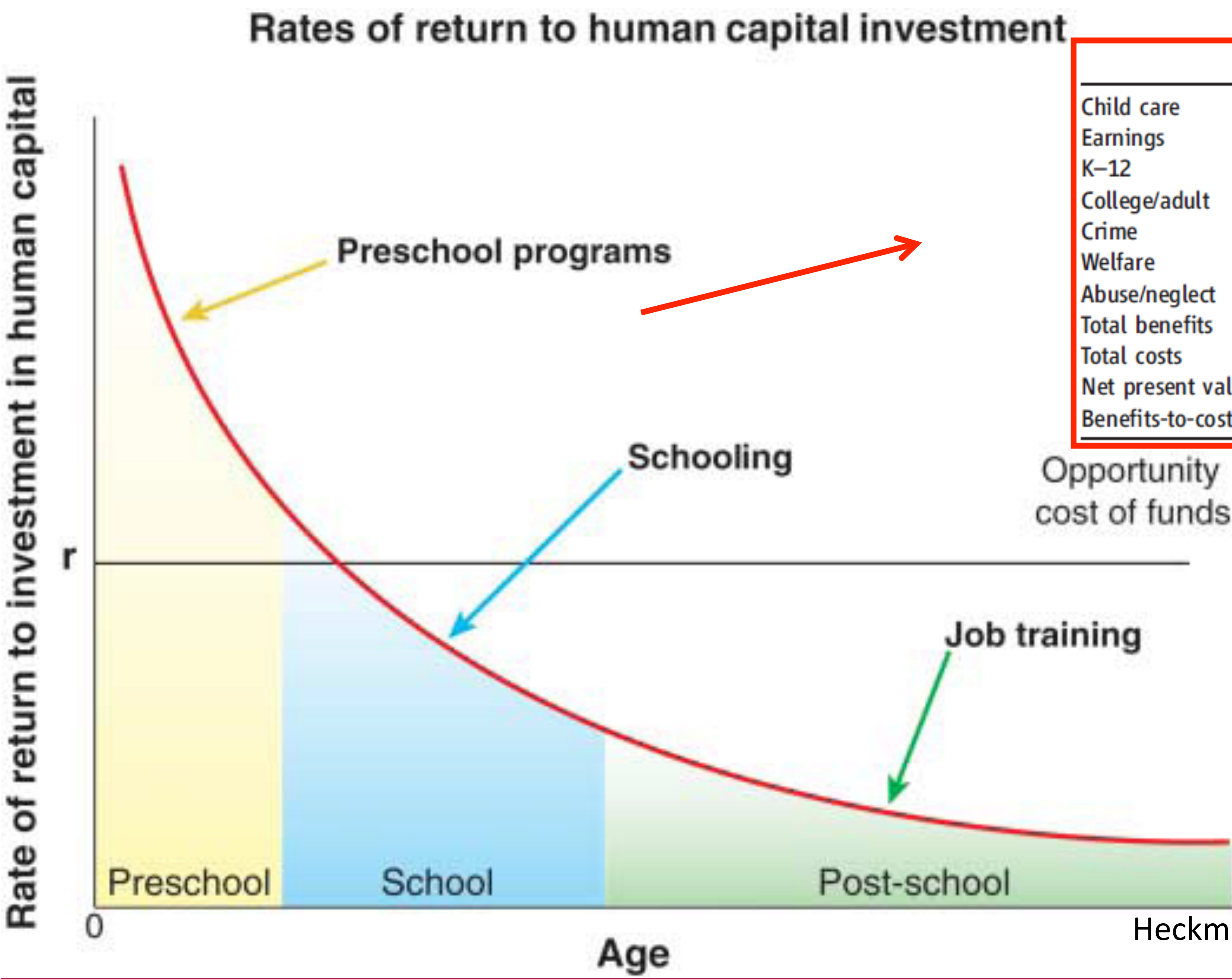
Periods of Relative Plasticity

- Suggests windows of opportunity (malleability) for top-down skills (although clearly plasticity across lifespan)

- *Also*:
- Easier to build good habits when don't first need to break bad habits

- Boost in EF prior to a sharp increase in demands placed on children's EF (e.g., kindergarten)

- Initiate a cascade of positive events: > motivation to learn, good relationships w/ teachers, < in problem behaviors



	Perry Preschool
Child care	$986
Earnings	$40,537
K–12	$9184
College/adult	$–782
Crime	$94,065
Welfare	$355
Abuse/neglect	$0
Total benefits	$144,345
Total costs	$16,514
Net present value	$127,831
Benefits-to-costs ratio	8.74

Heckman, 2006; Barnett, 2004

Effective EF Interventions

- Provide opportunities for children to practice reflection and specific EF skills, learn by doing
  - Practice reflection (pausing, considering options and goals)
    - Aware of EF skills
    - Recognize when to deploy them
  - Practice paying attention, thinking flexibly, keeping information in mind
  - Increasing challenges

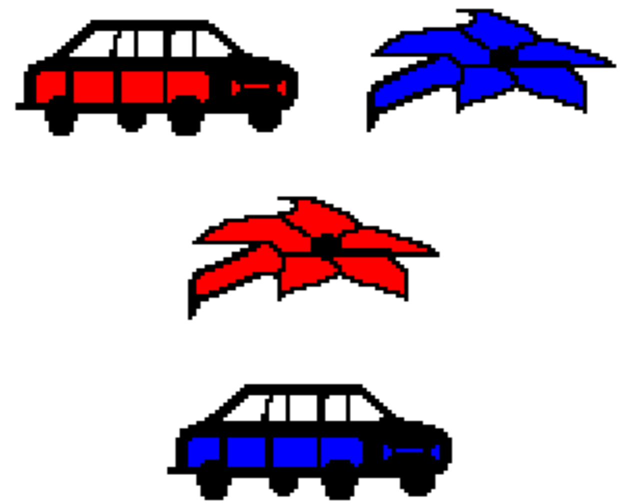
Espinet, Anderson, Zelazo (2013, *DCN*)

- 3 studies preschoolers (Mean age = 42 m, range: 34-50)
- Children who failed DCCS assigned to:
  - Reflection training (from 20-40 minutes) on DCCS
  - Various control conditions
    - Mere Practice with DCCS
    - Corrective feedback with DCCS but no reflection training
- Tested on DCCS (different shapes and colors) and other tasks, including false belief
  - Blind examiner

Reflection Training

– Practice pausing, stepping back, reflecting, formulating a higher-order rule

– "Oops. When you saw the red one, you pressed the button with red on it, that means you looked at the color… Now, we are playing the *shape* game - the game with boat and rabbit."

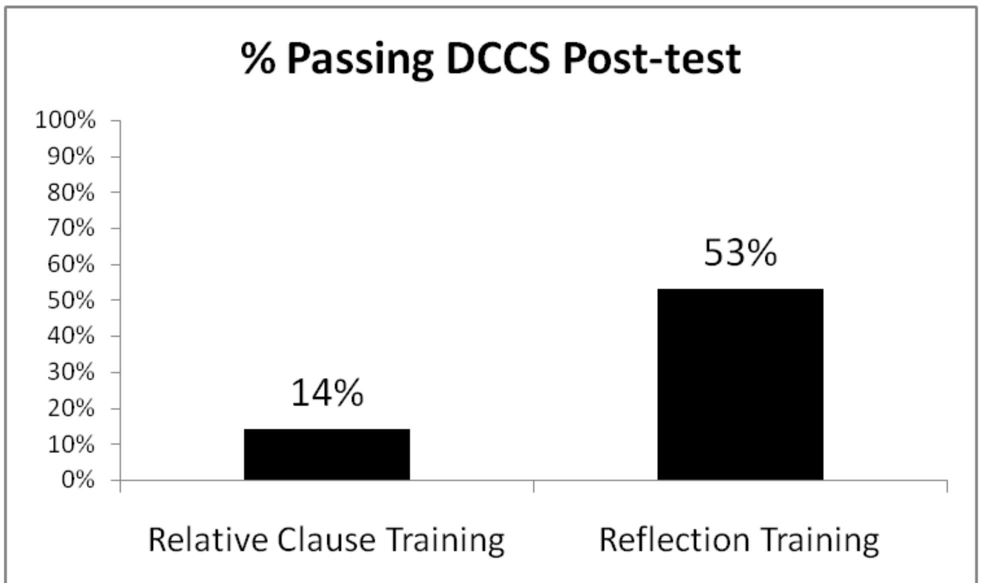


DCCS: 3-year-olds tend to perseverate

Espinet, Anderson, Zelazo, 2013, *DCN*

Effects on EF and Brain

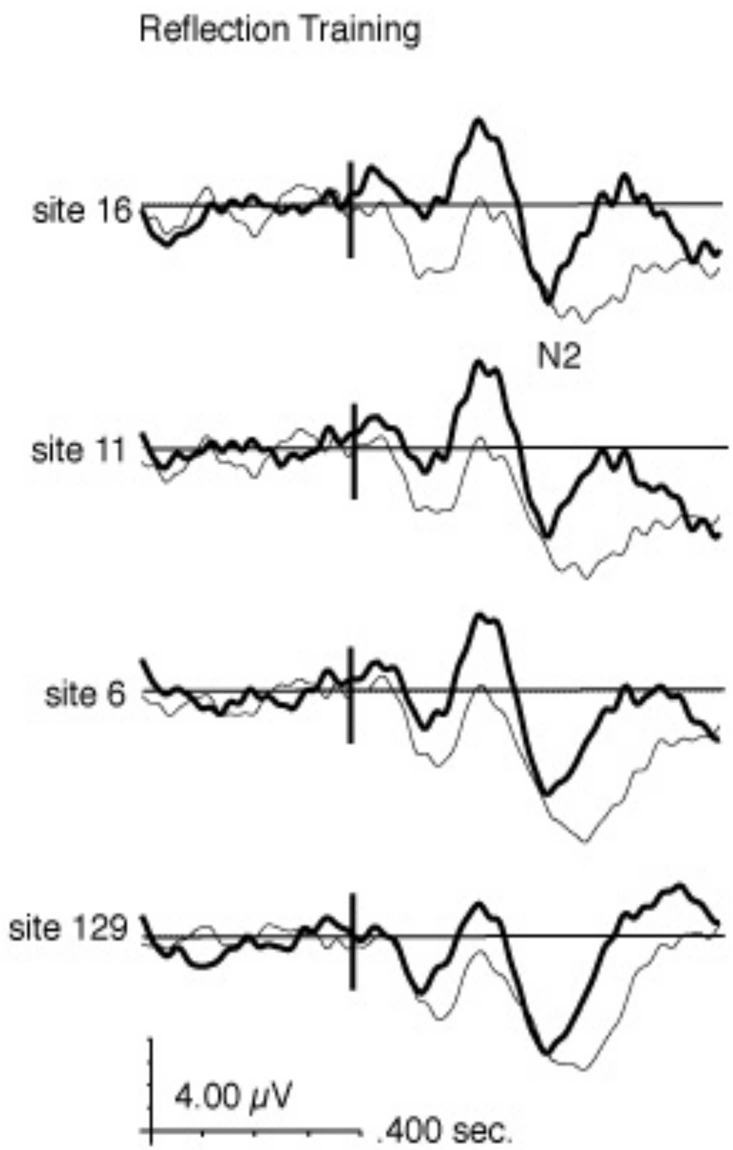
- In all 3 experiments training improved EF
- Also improvement on other tasks



Different versions of the DCCS

Theory of mind: Flexibly taking someone else's perspective

Espinet, Anderson, Zelazo, 2013, *DCN*



- Reflection training → Changes in the brain (< in the amplitude of the N2 ERP)
- Trained children not only did better, but their neural responses now looked like those of older children

Espinet et al. (2013, *Dev Cog Neuro*)

Mindfulness

- “Mindfulness means paying attention in a particular way; on purpose, in the present moment, and nonjudgmentally.”

  Kabat-Zinn (1994)

- Mindfulness trains sustained reflection while *also* creating conditions conducive to reflection
  - Reducing stress (↓ cortisol)
  - Increasing openness and curiosity (↑ dopamine)

Ready 4 Routines

- Collaborative goal-oriented problem solving
- Context in which to promote relationship, reflection, autonomy, mindfulness
- Provide structure, predictability, opportunities for reflection

Take Home Messages

- EF skills needed for learning and adaptation
- Different from IQ , develop rapidly in childhood
- Predict academic and other outcomes
- Effective interventions promote reflection and provide opportunities to practice EF skills

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Latent Class Analysis of Children with Math Difficulties and/or Disabilities: Do Measures of Cognition Play an Important Role?

H. Lee Swanson
University of California and University of New Mexico

Presented: STEM Education, Learning Disabilities, and the Science of Dyslexia Conference, Sept. 26, 2017

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Primary Research Questions

- Does a good model fit emerge supporting a discrete latent class of children with Math Difficulties (MD) or Math Learning Disabilities (MLD) independent of reading problems when using common cut-off points.
- Which domain specific and/or domain general cognitive processes uniquely predict latent classes?
- Do the cognitive processes that correlate with discrete latent classes vary as a function of cut-off points?

Assumptions

1. Several studies have highlighted subgroup heterogeneity even when using strict cut-off score criteria to define children at risk for MD or MLD. A rationale for using latent class or mixture modeling is that although math skills can be represented as a continuous outcome variable, the sample may be composed of different groups (latent classes) of individuals.

2. There is a high probability that children labelled as MD or MLD do not reflect a diagnostic category that is completely independent of reading difficulties

3. The advantage of LCA when compared to other procedures, such as cluster analysis, is that it offers a probalistic model of the distribution latent classes in the data. Further, the selection process allows for goodness of fit indices of latent measures, contrary to most clustering techniques that focus on algorithms related to distance measures.

Manifest Measures for Latent Class Analysis Grade 3 Total Sample (N=447/51%male,Caucasions 49%, Hispanic 33%, other 18%)

	Mean	SD	Min	Max	Kurtosis	Skewness	Reliability
Classification Measure							
Calculation							
WIAT	98.69	12.67	67	141	0.17	-0.24	0.84
WRAT-A	98.77	10.36	66	134	0.03	0.53	0.80
Math Prob. Solving							
TOMA	78.50	21.02	40	140	0.65	-0.17	0.94
WISC-A	97.61	31.46	10	180	-0.38	0.18	0.96
CMAT	66.73	30.02	0	150	0.05	-0.99	0.97
Key-Math	94.77	34.7	10	170	0.4	0.05	0.97
Reading							
WRAT-R	103.81	12.36	66	153	0.27	1.32	0.82
TORC	92.84	23.19	30	160	-0.16	0.09	0.94
Fluid Intelligence							
Raven	100.07	15.15	42	128	-0.69	0.64	0.93

Cognitive Predictors

Phonological

– STM (digits, words, pseudowords)
– Naming speed (letters, numbers)

Domain Specific

-Ident. Word Prob. Solving components (5 propositions)
-Line Estimation (consistent line, line variation)
-Magnitude judgement (largest number, smallest number)

Executive Processing

_WM (updating, listening span, conceptual span)
_Random generation-inhibition (letters, numbers)
_Visual-Spatial WM (matrix, mapping)

Fix Indices for Six Latent Class Models

Note. LC=Latent Class*,* AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; LMR = Lo-Mendell-Rubin Test; BLRT = Bootstrap Likelihood Ratio Test.

Cut off at or < 25						
	LC=1	LC=2	LC=3	LC=4	LC=5	LC=6
Log-likelihood:	-2232.86	-1994.98	-1950.58	-1946.89	-1933.29	-1921.38
G-squared:	835.95	360.2	271.4	264.01	236.82	212.99
AIC:	853.95	398.2	329.4	342.01	334.82	330.99
BIC:	890.87	476.15	**448.37**	**502.01**	535.84	573.04
CAIC:	899.87	495.15	477.37	541.01	584.84	632.04
Adjusted BIC	862.31	415.85	356.34	378.24	380.34	385.8
Entropy	1	0.75	0.75	0.80	0.82	0.85
Degrees	502	492	482	472	462	452
LMR (p-value)	-	0	0	0.34	0.27	0.17
BLRT (p-value)	-	0	0	0.66	0.36	0.42

Fix Indices for Six Latent Class Models at Two Cut-off Points

Cut off at or < 25						
	LC=1	LC=2	LC=3	LC=4	LC=5	LC=6
Log-likelihood:	-2232.86	-1994.98	-1950.58	-1946.89	-1933.29	-1921.38
G-squared:	835.95	360.2	271.4	264.01	236.82	212.99
AIC:	853.95	398.2	329.4	342.01	334.82	330.99
BIC:	890.87	476.15	**448.37**	**502.01**	535.84	573.04
CAIC:	899.87	495.15	477.37	541.01	584.84	632.04
Adjusted BIC	862.31	415.85	356.34	378.24	380.34	385.8
Entropy	1.0	0.75	0.75	0.80	0.82	0.85
Degrees	502	492	482	472	462	452
LMR (p-value)	-	0	0	.34	.27	.17
BLRT (p-value)	-	0	0	.66	.36	.42
Cut off < 11	LC1	LC=2	LC=3	LC=4	LC=5	LC=6
Log-likelihood:	-1882.47	-1687.33	-1643.29	-1633.22	-1624.42	-1618.48
G-squared:	633.81	243.53	155.45	135.3	117.71	105.83
AIC:	651.81	281.53	213.45	213.30	215.71	223.83
BIC:	688.73	359.48	**332.42**	**373.30**	416.73	465.88
CAIC:	697.73	378.48	361.42	412.30	465.73	524.88
Adjusted BIC	660.17	299.18	240.39	249.53	261.23	278.64
Entropy	1.0	0.72	0.75	0.74	0.71	0.72
Degrees	502	492	482	472	462	452
LMR (p-value)	-	0	.0180	.034	.19	.31
BLRT (p-value)	-	0	0	.065	.15	1.0

Item Probabilities of Assignment to Latent Classes

[a] Note. = rho estimates >.70 were considered high probability of Risk for MD (< 25th percentile) or MLD (< 11th percentile)

		At or < 25th percentile				< 11th percentile		
GAMMA		Probabilities						
Latent Class		1	2	3		1	2	3
		0.32	0.15	0.53		0.35	0.10	0.55
Rho Estimates[a]		Math Difficulties (MD)				Math Learning Disabilities (MLD)		
Latent Class		1	2	3		1	2	3
Calculation								
WIAT		0.003	0.82	0.24		0.00	0.59	0.08
WRAT-A		0.006	0.46	0.13		0.01	0.40	0.01
Math Problem Solving								
TOMA		0.28	0.92	0.81		0.31	0.96	0.83
WISC-A		0.07	0.80	0.36		0.08	0.76	0.42
CMAT		0.23	1.00	0.88		0.26	1.00	0.90
KEYMATH		0.03	1.00	0.50		0.03	1.00	0.56
Reading								
TORC		0.07	0.87	0.33		0.09	1.00	0.36
WRAT-R		0.01	0.42	0.06		0.00	0.30	0.05
Fluid Intelligence								
Raven		0.11	0.42	0.19		0.06	0.23	0.10

Normative (Standard Scores for Manifest Variables at the 25th Percentile Cut-off

	LC=1		LC=2		LC=3	
At or < 25th percentile						
Variable	Mean	SD	Mean	SD	Mean	SD
Calculation						
WIAT	108.01	9.27	83.68	8.12	97.29	10.8
WRAT-A	105.06	9.32	87.29	8.86	98.18	8.28
Math Problem Solving						
TOMA	96.45	19.57	64.15	14.13	71.87	15.98
WISC	119.15	23.25	65.69	23.78	93.61	28.44
CMAT	96.38	20.43	56.62	17.88	77.51	22.33
KEYMath	124.11	28.81	57.08	18.85	87.76	26.82
Reading						
TORC	107.16	18.72	64.77	15.92	92.03	19.82
WRAT-R	111.35	11.72	91.20	11.1	102.8	9.67
Fluid Intelligence						
Raven	105.69	15.49	92.26	14.22	98.88	14.01

Norms for Manifest Measures at the 11th Percentile cut-off

< 11th percentile	LC=1		LC=2		LC=3	
Variable	Mean	SD	Mean	SD	Mean	SD
Calculation						
WIAT	106.82	10.32	81.26	7.57	96.64	10.94
WRAT-A	104.42	10.11	84.92	9.59	97.6	8.04
Math Problem Solving						
TOMA	95.84	19.52	60.51	10.50	71.24	15.92
WISC-A	119.33	23.56	64.87	28.27	90.04	27.99
CMAT	95.91	20.24	54.62	19.17	74.79	21.88
KEYMath	123.76	28.82	54.36	18.75	84.17	26.63
Reading						
TORC	106.51	19.24	59.49	14.86	90.00	20.02
WRAT-R	111.22	12	87.49	10.56	102.01	9.48
Fluid Intelligence						
Raven	105.37	15.75	93.2	14.18	98.04	14.05

Effect Size Differences Between Latent Classes when switching Cut-off points (MD vs. MLD)

	Transition		Stable		ES
	M	SD	M	SD	ES
Classification					
Calculation					
WIAT	87.21	7.63	81.00	7.51	0.82
WRAT	90.61	6.44	84.78	9.67	0.72
Problem Solving					
TOMA	68.93	16.63	60.54	10.79	0.61
WISC-A	70.00	18.66	62.43	26.81	0.33
CMAT	58.93	15.48	54.86	19.53	0.23
KEYMath	60.71	18.04	54.32	19.23	0.34
Reading					
TORC	72.50	14.04	58.92	14.87	0.94
WRAT-R	96.82	9.40	86.95	10.46	0.99
Fluid Intelligence					
Raven	91.75	14.47	92.64	14.23	-0.06

Note. Transition= Children defined as math difficulties at 25th percentile cut-off but not 11th percentile cut-off Stable=children who retained math risk status at both cut-off points (children with MLD). ES=Cohen's effect size

Logistic Regression Predicting Latent Class with Cognitive Measures at two Cut-off points

		At or <25th Percentile					< 11th percentile		
Parameter	Odds	Estimate	SE	Wald χ2		Odds	Estimate	SE	Wald χ2
Full Model									
Phonological Storage									
STM	1.13	0.12	0.08	2.23		1.28	**0.24**	0.09	7.86**
Speed	0.87	-0.14	0.08	3.11		0.82	-0.19	0.09	5.04*
Domain Specific Knowledge									
Component	1.16	0.14	0.05	7.88**		1.25	**0.22**	0.06	15.58***
Estimation	0.77	**-0.27**	0.08	10.35***		0.83	-0.19	0.09	4.63*
Numeracy	1.12	0.11	0.06	3.47		1.10	0.10	0.06	2.48
Executive Processing									
WM-E	1.25	**0.23**	0.08	7.50**		1.29	**0.25**	0.09	8.26***
Inhibition	0.81	-0.21	0.13	2.74		0.87	-0.14	0.13	1.12
Vis-WM	1.14	0.13	0.09	2.30		1.19	0.18	0.09	3.73*

Means (z-scores), Standard Deviations and Effect Size Comparisons among Stable Latent Classes (LC1-average achievers, LC2 MLD, LC3-poor problem solvers)

	LC=1, N=141)		LC=2, N=37)		LC=3, N=231)		Effect Sizes		
	M	SD	M	SD	M	SD	LC1 vs. LC2	LC1 vs. LC3	LC2 vs.LC 3
Storage									
STM	0.63	1.09	-0.97	1.08	-0.09	1.33	1.47	0.60	-0.73
Speed	-0.41	1.39	0.60	2.08	-0.07	1.44	-0.58	-0.24	0.38
Domain Specific									
Component	1.38	1.67	-2.16	2.35	-0.27	2.26	1.76	0.84	-0.82
Estimation	-0.64	1.28	1.22	1.40	0.01	1.31	-1.39	-0.49	0.90
Numeracy	0.79	1.83	-1.51	1.69	-0.18	1.71	1.31	0.55	-0.78
Executive									
WM-E	0.63	1.62	-0.59	1.06	-0.22	1.22	0.91	0.60	-0.32
Inhibition	0.18	0.88	-0.55	0.69	0.01	0.84	0.93	0.21	-0.72
Vis-WM	0.38	1.3	-0.27	0.84	-0.14	1.21	0.61	0.41	-0.13

General Findings;

1. Heterogeneity-

The results show that a latent class emerges related to math difficulties (MD) and math learning disabilities (MLD) within a heterogeneous sample of learners.

However, a key issue was whether a separable latent class of children with math problems would emerge without reading problems.

2. Cognitive Models- Domain Specific processing, Phonological storage, and Executive component of WM each uniquely predicted latent class---none in isolation provides a complete picture

The largest beta-weight loadings from the logistic regression full model were measures of domain specific knowledge (word problem solving components and estimation) and the executive component of WM.

Implications

1. Contributes to the emerging literature that children with MD as well as MLD represent an identifiable group.

2. Probability of finding a latent class of children with MD or MLD completely independent of reading problems may be quite low (at least in this sample).

Limitations

1. Although we used cut-off points identified in the literature as important in identifying children at risk for MD or MLD, we have not shown that the identification of latent classes validates a specific cut-off point.

2. The stability of math performance across multiple grades was not established.

3. Outliers (those who could do none of the problems) were not removed from the data analysis.

4. There is an absence of intervention information.

Does Embedding Language Comprehension Instruction in Word-Problem Intervention Improve Word-Problem Outcomes?

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Why Focus on WPs at First Grade?

- First-grade number knowledge intervention with speeded arithmetic practice dramatically narrows the arithmetic achievement gap.

- At the same time, the WP achievement gap widens dramatically. This is problematic because
  - WPs represent a major emphasis in almost every strand of the math curriculum.
  - WP performance is a strong predictor of wages in adulthood.

- Yet, early math research has focused dominantly on number knowledge and arithmetic, with only minor focus on WPs, in the service of supporting number knowledge.

Why Focus on Language Comprehension to Improve WP Performance?

- Based on Kintsch et al. (1985), WP solving is an interaction between math problem-solving strategies, which rely on reasoning and WM, and language comprehension processes.
- When faulty problem solving is computationally modeled with math problem-solving errors v. LC errors (Cummins et al.,1988)
  - Correct problem representation depends more on LC
  - Changing wording in minor ways dramatically affects accuracy.
- Common assumption: Students have the LC for understanding problem statements and building an appropriate problem model.
- But for at-risk children, this assumption is shaky. Instructional focus on LC processes as well as the mathematical aspects of WP solving may be required.

Why *Embed* Language Instruction in WP Intervention?

(instead of providing conventional language therapy)

- Language therapy improves oral language comprehension, but transfer to academic performance is limited (Catts & Kamhi, 2017), despite a strong association between LC and academic performance.
- Transfer from language therapy to academic performance may be especially difficult for at-risk students who
  - Have an inadequate foundation of academic skill
  - Experience substantial challenges with transfer.
- This argues for conducting language instruction in the context of direct skills intervention. We adopted this approach in the present study.

Our Intervention Approach to Math Problem-Solving Strategies

- We rely on a form of schema-based instruction, explicitly teaching step-by-step strategies to reduce demands on reasoning and WM.
- This includes strategies for understanding WPs as belonging to WP types and strategies for building WP models.
- At grade 1, we address 3 problem types:
  - Combine (2 or more parts are combined to form a total)
  - Change (2 quantities are compared)
  - Change (an even occurs to increase or decrease a starting amount)

Our Intervention Approach to Math Problem-Solving Strategies

We teach the mathematical structure of each problem type.

- Role playing the problem type's central mathematical event using intact numbers stories (no missing quantities to solve for), concrete objects, & the child's/tutor's names
- Connecting the mathematical central event to a schematic, into which story numbers can be entered, and a hand gesture to remind students of that schematic
- Connecting a problem model number sentence
  - Combine: P1 + P2 = T
  - Compare: B – s = D
  - Change: St +/- C = E
- Introducing problems (with missing quantities) using role playing, the schematic & hand gesture, and number sentence.

Our Intervention Approach to Math Problem-Solving Strategies

- We then teach step-by-step strategies for building WP models and solving the problems.

- RUN through the problem.
  - Read the problem (for most children, tutor reads as child reads along).
  - Underline the question.
  - Name the problem type.
- Write that problem model's number sentence.
- Enter relevant quantities from the WP statement into the problem model, while crossing out "extra" numbers.
- Solve for the missing quantity.

Combine or "Total" Problem Type

Kathy has 5 pencils and 3 erasers. Pamela has 7 pencils. How many pencils do the girls have in all?

T

Combine or "Total" Problem

Kathy has 5 pencils and 3 erasers. Pamela has 7 pencils. How many pencils do the girls have in all?

T

P1 + P2 = T

Combine or “Total” Problem

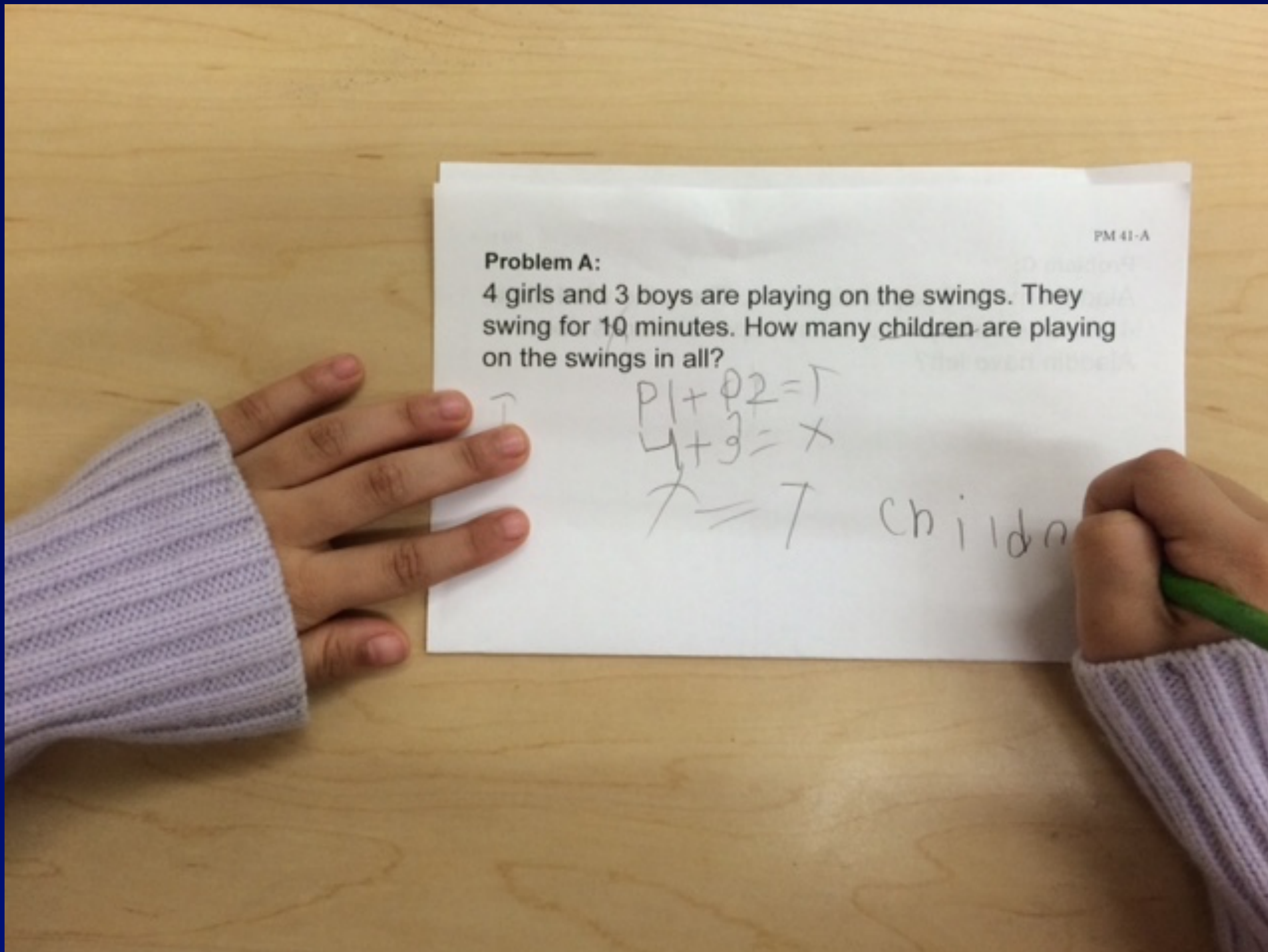
Kathy has 5 pencils and ~~3 erasers~~. Pamela has 7 pencils. How many pencils do the girls have in all?

T

$$P1 + P2 = T$$

$$5 + 7 = x$$

$$x = 12 \text{ pencils}$$


PM 41-A
Problem A:
4 girls and 3 boys are playing on the swings. They swing for 10 minutes. How many children are playing on the swings in all?

Our Embedded LC Focus:
WP Vocabulary and Language Constructions

- Combine WPs
  - Joining words (e.g., *altogether, in all*)
  - Superordinate categories (e.g., *animals* = *dogs* + *cats*)
- Compare WPs
  - Compare words (e.g., *more, fewer, than*, -*er* words)
  - Adjective -*er* v. verb -*er* words (e.g., *bigger* vs. *teacher*)
- Change WPs
  - Cause - effect conjunctions (e.g., *then, because, so*)
  - Implicit quantity change verbs (e.g., *cost, ate, found*)
  - Time passage phrases (e.g., *3 hours later*, *the next day*)
- Confusing cross-problem type constructions (e.g., *more than* vs. *then … more*)
- "Tricky" labels (e.g., questions with superordinate category words, without a label, with a noun that's the wrong label)

Study Purposes

- Increase understanding about the role of language comprehension in WPs and arithmetic
- Assess the potential of embedding cognitive training (such as LC) within direct skills intervention
- Address WP difficulty early, in 1st grade when individual differences in WP competence are growing rapidly

Study Overview

- Risk = low arithmetic & math concepts/applications at start of 1st grade

- Students randomly assigned to 4 conditions
  - WP intervention
  - WP intervention + embedded LC instruction
  - Number knowledge intervention
  - Control (school program, most with math intervention)

- Each active intervention condition
  - Lasts 15 weeks, 3 sessions per week, 30 min per session
  - Includes 5 min of speeded, strategic arithmetic practice

- 400 students to enter; we report on the first 159 students completed

Number Knowledge Intervention Condition

Is transfer from arithmetic to WPs sufficient to support WP development?

- Explicit instruction on numbers, relations, principles
- Strong focus on number families and decomposition of number sets
- Strong reliance on the number line, manipulatives, and games to reinforce mathematical ideas

Findings to Date: Arithmetic Outcomes

WP+L = WP = NK > C

<u>Effect Sizes</u>

NK v. C = 0.81

WP v. C = 1.27

WP+L v. C = 1.68

WP Outcomes

WP+L = WP > NK = C

<u>Effect Sizes</u>

NK v. C = 0.10

WP v. C = 0.79

WP+L v. C = 1.16

WP+L v. WP = 0.37 (p = .06)

- Both WP conditions are producing significantly better outcomes than NK & control, but differences between WP and WP+L are not significant. If ES of 0.37 holds, will be significant with full sample.

Word-Problem Language Outcomes

WP+L > WP = NK = C

Effect Sizes

NK v. C = 0.01

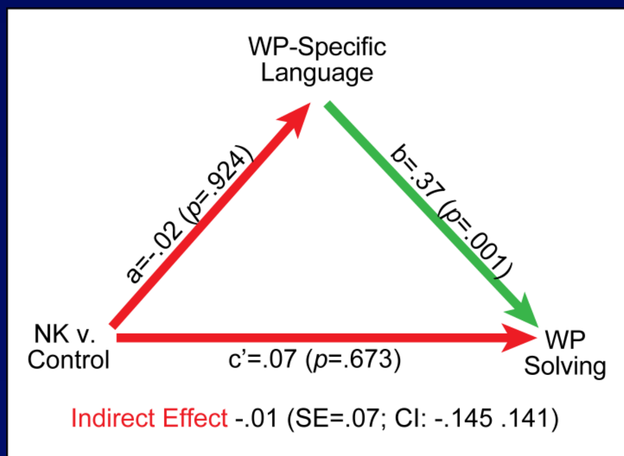
WP v. C = 0.08

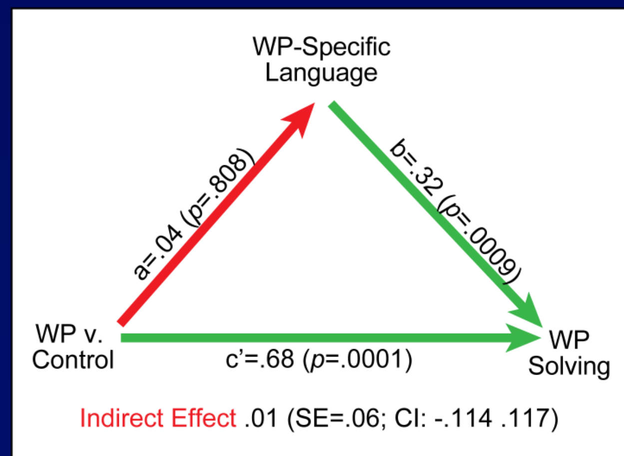
WP+L v. C = 0.50

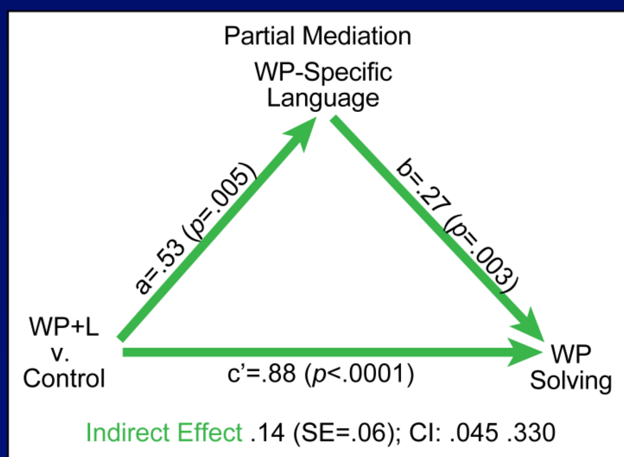
WP+L v. WP = 0.42

Does End-of-Treatment Word-Problem Language Mediate Condition Effects on WP Solving?

Each model controls for pretest WP and arithmetic.







Preliminary Conclusions

- On WP solving, NK intervention does not provide added value over control (ES=0.10), despite that NK intervention improves arithmetic performance (ES=0.81). Raises questions about whether transfer from arithmetic to WPs is sufficient to support WP development.
- On WP solving, embedding LC instruction in direct skills WP intervention appears to offer added value over WP intervention alone (ES=0.37).
- The mediation effect indicates this added value occurs via embedded LC instruction.
- Results strengthen evidence for the role of LC in WPs and suggest promise for an expanded intervention framework that embeds training on language (and perhaps other cognitive processes) within direct skills intervention. Results also suggest a connection between math-problem solving and reading comprehension, via language comprehension.

Does a link between WP and RC, via LC, provide direction for understanding comorbid difficulty across WP & RC?

- An experimental manipulation testing the effects of instructional scaffolding that connects WP, RC, & LC in a sample of students with comorbid difficulty (2 P20 HD075443)

- Study conditions
  - Direct skills WP intervention with embedded WP-L instruction
  - Direct skills RC intervention with embedded RC-L instruction
  - Control

- Conduct 2 tests of the "comorbidity hypothesis"
  - Whether reciprocal effects occur for
    - WP intervention on RC outcomes
    - RC intervention on WP outcomes
  - Whether LC improvement serves as a mediator of reciprocal effects, which would indicate LC is a common process linking WP & RC