

Children's Cross-Feature Transfer in the Feature Length Array Display

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Abstract: Children's cross-feature transfer in the feature length array display was examined. In Experiment 1, 4- and 6-year-old children were shown a display of 6 items, each with a unique length and color. They were asked to identify the item that was the same length as the one they were shown. In Experiment 2, 4- and 6-year-old children were shown a display of 6 items, each with a unique length and color. They were asked to identify the item that was the same color as the one they were shown. Results showed that children in both experiments performed better than chance, indicating that they were able to transfer information from one feature to another. The results also showed that children's performance was higher when they were asked to identify the item that was the same length as the one they were shown than when they were asked to identify the item that was the same color as the one they were shown. This suggests that children are better at transferring information from length to length than from length to color.

Keywords: children, cross-feature transfer, feature length array display, transfer of learning

Children's ability to transfer information from one feature to another is a key component of their cognitive development. This ability is essential for them to learn about the world around them and to solve problems. One way to study this ability is by using a feature length array display. In this display, children are shown a set of items, each with a unique length and color. They are then asked to identify the item that is the same length as the one they were shown. This task requires them to transfer information from the length of the item they were shown to the length of the items in the display.

Research has shown that children are able to transfer information from one feature to another in a variety of contexts. For example, they are able to transfer information from the length of an object to the length of another object (e.g., Kover & Barron, 2018). They are also able to transfer information from the color of an object to the color of another object (e.g., Kover & Barron, 2018).

One of the most interesting findings in this research is that children are better at transferring information from length to length than from length to color. This suggests that children are better at transferring information from one feature to another when the features are the same type (e.g., length to length) than when the features are different types (e.g., length to color). This finding is important because it shows that children's ability to transfer information is not just a general ability, but it is also specific to the type of features they are transferring information about.

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Children's ability to transfer information from one feature to another is a key component of their cognitive development. This ability is essential for them to learn about the world around them and to solve problems. One way to study this ability is by using a feature length array display. In this display, children are shown a set of items, each with a unique length and color. They are then asked to identify the item that is the same length as the one they were shown. This task requires them to transfer information from the length of the item they were shown to the length of the items in the display.

... I... (2005) ... (A..., M..., Ir..., C..., &..., 1986; I..., K..., J..., & B..., 1977; J..., 1980; ..., 1970). ... (Ir..., 2000; J..., M..., A..., &..., 2013), ... D... (1996) ... D... L (1998) ... A... (..., &..., 2009).

... I... (Ir..., 2000) ... A... (..., B..., &..., 2016).

... (..., 2008; ..., 2016; ..., &..., 2010), ... (..., 2016; ..., &..., 2016).

Experiment 1

In Experiment 1 ... (2005), ... Error = 2.4 ... 1-H ... 6-H.

... (A..., M..., Ir..., C..., &..., 1986; I..., K..., J..., & B..., 1977; J..., 1980; ..., 1970).

Method

Participants. ... (11 ... 19 ... ; $M = 21.2$... , $SD = 2.2$...) ... (... ≤ 20 B HL ... 0.5-6-H) ...

Sample size. ... (A-F... 900 ... F... 2B ... , M..., & F..., 2010). ... 80% ... $p = .05$, ... $d = 1.22$... I... , ... H... 10 ...

Apparatus. A ... 3.0 ... (..., 1997) ... 15- ... M B ... HD-499 ... (G... H & C... KG, ... G...).

Stimuli and procedure. ... 15- ... 100 ... 6-H.E ... 86.B L ... 5- ... I... (F... I), ... 300 ... 785 ... (..., M..., F..., (2010). ... 50%, ... 1.414 ... 79% ... 60

A. G. A. I. G. A. G. H. A. G. A. D.

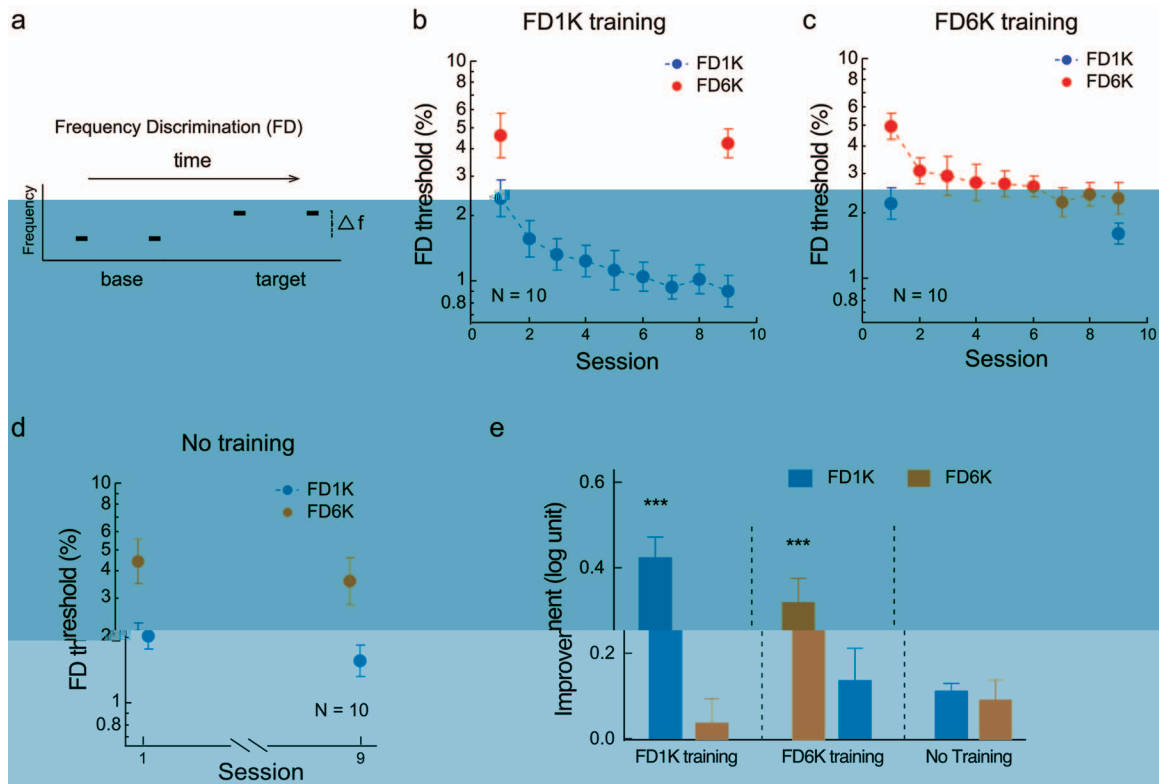


Figure 1. Frequency Discrimination (FD) training results. (a) Schematic of the FD task. (b) FD1K training results. (c) FD6K training results. (d) No training results. (e) Improvement in log unit for FD1K and FD6K groups. Error bars represent ± 1 SE. FD: Frequency Discrimination. *** $p < .001$.

... 10 ...

Experimental design. ... 1 ... 6 Hz ... FD1K ... FD6K ...

Data processing and statistical analysis. ... (C ... 2015). I ... $p < .001$... 1 Hz ... $p < .001$... 6 Hz ...

... ; $p = .67$... 1 Hz ... $p = .10$... 6 Hz ...

A ... (LME) ... Error ... (... & B ... 2000). ... (... 6 Hz), ... (...), ... (... , FD1K ... FD6K ... Error ... 1; FD6K ... ID1 ... Error ... 2, ... FD1K ... 6 Hz ... Error ... 3) ... Error ...

Results

FD1 1-H 0.42 ± 0.05 ($M \pm 1$), 1-H 0.04 ± 0.06 , 6-H ($F(1, 190) = 120.99, p < .001$), 6-H 0.32 ± 0.06 , 6-H 0.14 ± 0.08 , 1-H ($F(1, 190) = 141.90, p < .001$), 1-H 0.11 ± 0.02 , 1-H 0.09 ± 0.05 , 6-H ($F(1, 190) = 3.89, p = .001$).

LME $F(1, 190) = 120.99, p < .001$; $F(1, 190) = 141.90, p < .001$; $F(6, 190) = 6.87, p < .001$; $F(6, 190) = 3.19, p = .005$; $F(6, 190) = 3.89, p = .001$.

1-H ($t = 6.06, p < .001, 95\% CI -0.29, 0.57, C' d = 1.92$), 6-H ($t = 0.54, p = .59, 95\% CI -0.10, 0.18, C' d = 0.17$; $F(1, 190) = 1.32, p = .25$), FD1 ($t = 4.60, p < .001, 95\% CI 0.18, 0.46, C' d = 1.45$), 1-H ($t = 1.95, p = .053, 95\% CI -0.002, 0.27, C' d = 0.62$; $F(1, 190) = 3.89, p = .001$), 1-H ($t = 1.59, p = .11, 95\% CI -0.03, 0.25, C' d = 0.50$); 6-H ($t = 1.32, p = .19, 95\% CI -0.04, 0.23, C' d = 0.42$; $F(1, 190) = 3.89, p = .001$).

Discussion

1-H, 6-H (Cohen & Ferriter, 2005).

Experiment 2

Experiment 2... 6-H... 1-H... 6-H... 1-H... 6-H... 1-H...

Method

Participants.

12... = 22.8... SD = 2.7...

Stimuli and procedure.

6-H... 1-H... 6-H... 1-H...

1-H... 50... 10... 1... 60... 6-H... 1-H... 6-H... 1-H...

Experimental design.

1-H... 12... 6-H... 12... 1-H... 1.5... 12... 1-H... 1... 9... 14... 2...

Results

0.46 ± 0.05... 6-H... 0.31 ± 0.06... 1-H ($F(1, 190) = 120.99, p < .001$), 1-H... 1-H... 0.08 ± 0.05... ($F(1, 190) = 3.89, p = .001$).

LME... 1) $F(1, 190) = 120.99, p < .001$; $F(1, 190) = 141.90, p < .001$; $F(6, 190) = 6.87, p < .001$; $F(6, 190) = 3.19, p = .005$; $F(6, 190) = 3.89, p = .001$.

1-H ($t = 6.06, p < .001, 95\% CI -0.29, 0.57, C' d = 1.92$), 6-H ($t = 0.54, p = .59, 95\% CI -0.10, 0.18, C' d = 0.17$); FD1 ($t = 4.60, p < .001, 95\% CI 0.18, 0.46, C' d = 1.45$), 1-H ($t = 1.95, p = .053, 95\% CI -0.002, 0.27, C' d = 0.62$); 1-H ($t = 1.59, p = .11, 95\% CI -0.03, 0.25, C' d = 0.50$); 6-H ($t = 1.32, p = .19, 95\% CI -0.04, 0.23, C' d = 0.42$).

Discussion

6-H... 1-H... 6-H... 1-H...

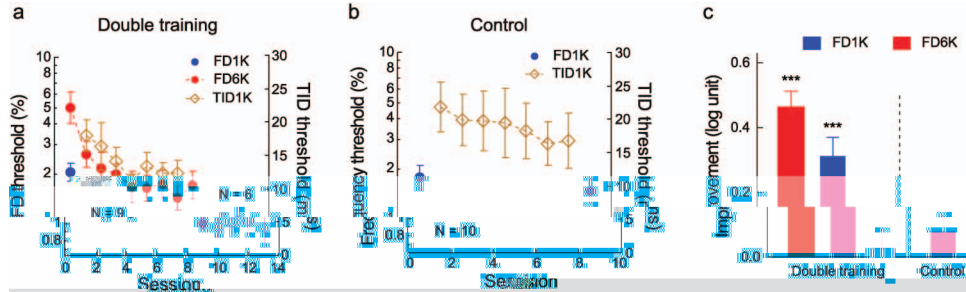


Figure 2. Error rates for Experiment 1. (a) Double training (N = 6). (b) Control (N = 10). (c) Impairment (log unit) for Double training (N = 6) and Control (N = 10) groups. Error bars represent ± 1 SE. FD = frequency threshold; ID = impairment. *** $p < .001$.

Experiment 3

Experiment 3 was similar to Experiment 2, but with a different stimulus set. The stimuli were 1-H and 6-H words. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively.

Method

Participants.

Thirteen participants (7 males; age = 24.1 years, $SD = 3.1$ years) participated in Experiment 3.

Stimuli and procedure.

The stimuli were 1-H and 6-H words. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively.

Experimental design.

Experiment 1. I. Error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively.

Experiment 2. Error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively.

Results

Double training. Error rates for 1-H and 6-H words were 0.42 \pm 0.05 and 0.31 \pm 0.05, respectively. The error rates for 1-H and 6-H words were 0.42 \pm 0.05 and 0.31 \pm 0.05, respectively. The error rates for 1-H and 6-H words were 0.42 \pm 0.05 and 0.31 \pm 0.05, respectively.

Discussion

Control. Error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively. The error rates for 1-H and 6-H words were 1.1% and 1.6%, respectively.

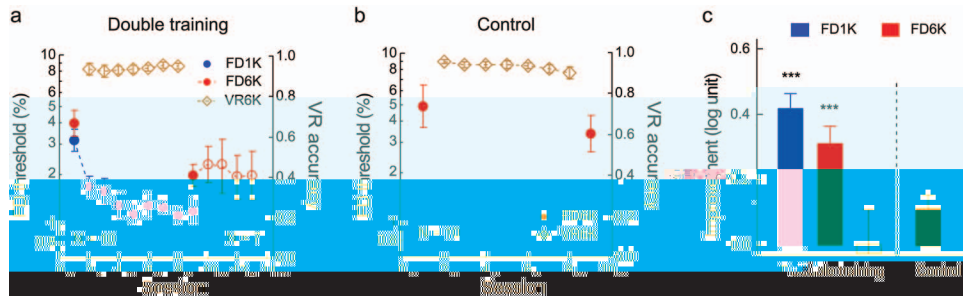


Figure 3. Performance metrics for Double training (a), Control (b), and Comparison (c) conditions. VR accuracy (left y-axis, %) and VR threshold (right y-axis, %) are shown for each condition. Error bars represent ± 1 SE. FD = frequency doubling; VR = vertical resolution. *** $p < .001$.

Experiment 4

Horizontal resolution (H) is a key metric for VR systems. In this experiment, we compared the performance of different VR systems under various conditions. The results show that the performance of the VR systems is significantly affected by the resolution and the frequency doubling (FD) factor. The VR accuracy and threshold are shown for each condition. Error bars represent ± 1 SE. Significance markers (***) indicate $p < .001$.

Method

Participants. A total of 14 participants (7 males and 7 females) were recruited for this experiment. Their mean age was 23.6 years, $SD = 3.0$ years.

Tasks. Participants performed a series of tasks. Error bars represent ± 1 SE. Significance markers (***) indicate $p < .001$.

Experimental design.

Experimental design. The experiment was designed to compare the performance of different VR systems under various conditions. The results show that the performance of the VR systems is significantly affected by the resolution and the frequency doubling (FD) factor. The VR accuracy and threshold are shown for each condition. Error bars represent ± 1 SE. Significance markers (***) indicate $p < .001$.

Data analysis. A LME model was used to analyze the data. The results show that the performance of the VR systems is significantly affected by the resolution and the frequency doubling (FD) factor. Error bars represent ± 1 SE. Significance markers (***) indicate $p < .001$.

Results

Results. The performance of the VR systems is significantly affected by the resolution and the frequency doubling (FD) factor. Error bars represent ± 1 SE. Significance markers (***) indicate $p < .001$.

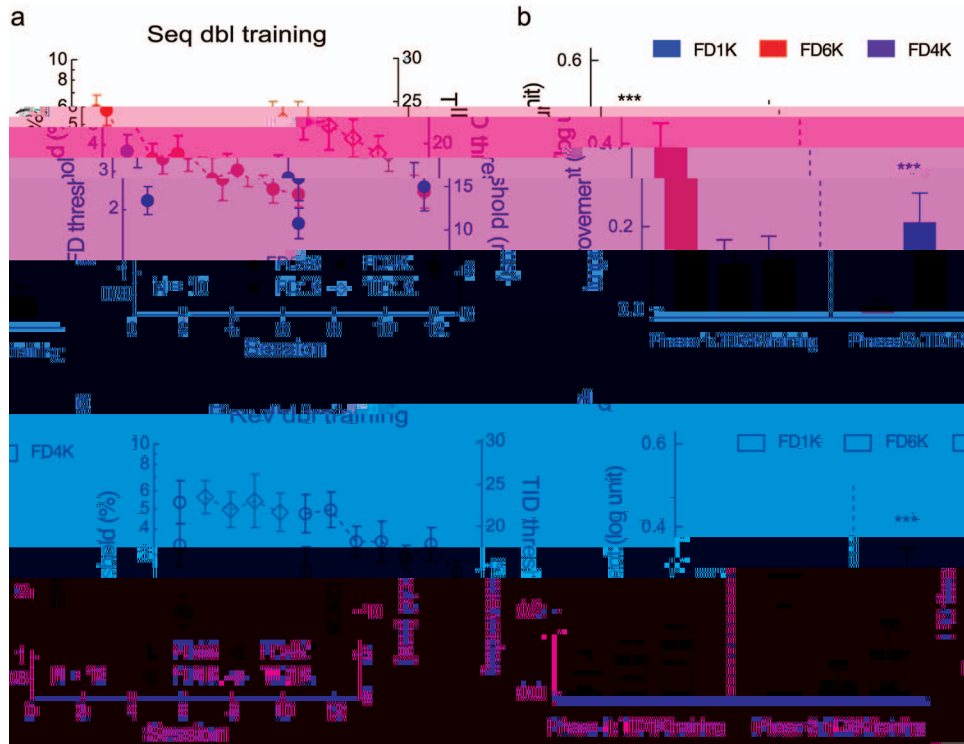


Figure 4. Genomic tracks for Seq dbt training (a) and Key dbt training (b). The top panel (a) shows Seq dbt training with tracks for FD threshold (log unit), TID threshold (log unit), and gene models. The bottom panel (b) shows Key dbt training with tracks for FD threshold (log unit), TID threshold (log unit), and gene models. Legend: FD1K (blue), FD6K (red), FD4K (purple). Error bars represent ± 1 SE. FD = false discovery rate; ID = identification. *** $p < .001$.

For Seq dbt training, the mean FD threshold (log unit) was 0.08 ± 0.05 for 1_H, 0.12 ± 0.05 for 4_H, 0.05 ± 0.04 for 6_H. For Key dbt training, the mean FD threshold (log unit) was 0.02 ± 0.04 for 1_H, 0.09 ± 0.07 for 4_H, 0.28 ± 0.07 for 6_H (Figs 4 and 4).

LME analysis showed significant differences between training methods, $F(2, 144) = 43.06, p < .001$; between H levels, $F(2, 144) = 32.44, p < .001$; and between training methods and H levels, $F(1, 18) = 0.68, p = .42$. Significant differences were also observed between H levels, $F(2, 144) = 3.60, p = .008$; between training methods and H levels, $F(4, 144) = 6.96, p < .001$.

For Seq dbt training, the mean TID threshold (log unit) was 6.94 for 6_H ($t = 6.94, p < .001, 95\% \text{ CI } 0.26, 0.52, C_{95\%} d = 2.19$), 1.94 for 1_H ($t = 1.94, p = .16, 95\% \text{ CI } -0.02, 0.24, C_{95\%} d = 0.61$), 2.15 for 4_H ($t = 2.15, p = .10, 95\% \text{ CI } -0.01, 0.25, C_{95\%} d = 0.68$). For Key dbt training, the mean TID threshold (log unit) was 6.94 for 6_H ($t = 6.94, p < .001, 95\% \text{ CI } 0.26, 0.52, C_{95\%} d = 2.19$), 1.94 for 1_H ($t = 1.94, p = .16, 95\% \text{ CI } -0.02, 0.24, C_{95\%} d = 0.61$), 2.15 for 4_H ($t = 2.15, p = .10, 95\% \text{ CI } -0.01, 0.25, C_{95\%} d = 0.68$).

($t = 3.61, p = .001, 95\% \text{ CI } 0.07, 0.34, C_{95\%} d = 1.14$), 4.91 for 4_H ($t = 0.82, p = 1.00, 95\% \text{ CI } -0.09, 0.18, C_{95\%} d = 0.23$), 0.21 for 6_H ($t = 0.21, p = 1.00, 95\% \text{ CI } -0.12, 0.15, C_{95\%} d = 0.07$; Figs 4 and 4).

For Seq dbt training, the mean FD threshold (log unit) was 0.08 for 1_H ($t = 1.46, p = .44, 95\% \text{ CI } -0.05, 0.22, C_{95\%} d = 0.46$), 0.12 for 4_H ($t = 2.14, p = .10, 95\% \text{ CI } -0.01, 0.25, C_{95\%} d = 0.68$), 0.05 for 6_H ($t = 0.94, p = 1.00, 95\% \text{ CI } -0.08, 0.19, C_{95\%} d = 0.30$). For Key dbt training, the mean FD threshold (log unit) was 0.02 for 6_H ($t = 4.91, p < .001, 95\% \text{ CI } 0.14, 0.41, C_{95\%} d = 1.55$), 0.09 for 1_H ($t = 0.36, p = 1.00, 95\% \text{ CI } -0.11, 0.15, C_{95\%} d = 0.11$), 0.28 for 4_H ($t = 1.57, p = .36, 95\% \text{ CI } -0.04, 0.22, C_{95\%} d = 0.50$; Figs 4 and 4).

Discussion

The results of this study demonstrate that the Seq dbt training method is more effective than the Key dbt training method in identifying differentially expressed genes. This is evident from the higher FD and TID thresholds observed for Seq dbt training across all H levels. The LME analysis further supports these findings, showing significant differences between training methods and H levels. The results suggest that Seq dbt training is a more robust method for identifying differentially expressed genes in this context.

... M ...

General Discussion

I ... (Fr ... 1), ... (Fr ... 2 ... 3). I ... (Fr ... 4).

... (C ... & D ... , 2008; G ... , 2011; K ... , Gr ... & H ... , 2011; L ... & G ... , 2008), ... (D ... , ... , & C ... , 2015; H ... , G ... , & ... , 2012; ... , 2008; ... & ... , 2019; ... , 2016; ... , ... , 2010; ... , ... , K ... , L ... , & ... , 2010).

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I ... A ... (... , ... , ...), ... (... , ... , ... , ... , ...), ...

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M ... (D ... & L ... , 1998; J ... , 2013). I ... (J ... , 1980; ... , 1970). A ... (A ... , 1986; I ... , 1977). B ...

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