Expanding the Space of Cognitive Science

Proceedings of the 33rd Annual Meeting of the Cognitive Science Society

Boston, Massachusetts, July 20-23, 2011

Edited by

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Austin, TX: Cognitive Science Society

Basic Information Processing Effects from Perceptual Learning in Complex, Real-World Domains

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Abstract

Recent research indicates that perceptual learning (PL) interventions in real-world domains (i.e., mathematics, science) can produce strong learning gains, transfer, and fluency. Although results on domain-relevant assessments suggest characteristic PL effects, seldom have real-world PL interventions been explicitly tested for their effects on basic information extraction. We trained participants to classify Chinese characters, based on either (1) overall configurations (structures), (2) featural relations (components), or (3) non-relational information (stroke-count control). Before and after training, we tested for changes in information extraction using a visual search task. Search displays contained all novel exemplars, involved manipulations of target-distractor similarity using structures and components, and included heterogeneous and homogeneous distractors. We found robust improvements in visual search for structure and component PL training relative to the control. High-level PL interventions produce changes in basic information extraction, and sensitivity induced by PL for both relational structure and specific components transfers to novel structural categories.

Keywords: perceptual learning; educational technology; visual search; categorization.

Introduction

Research on expertise has shown that experts effortlessly attend to relevant features and relations (Gibson, 1969), that experts extract larger "chunks" of information, discover higher-order invariance, and do so with low attentional load (Gibson, 1969; Schneider & Shiffrin, 1977). Such changes in information extraction as a result of experience constitute *perceptual learning* (Gibson, 1969; for a recent review, see Kellman & Garrigan, 2009).

Much contemporary research on perceptual learning (PL) has focused on basic sensory discriminations; however, PL effects are not confined to low-level tasks (Garrigan & Kellman, 2008; Kellman & Garrigan, 2009). In fact, the natural function of PL is to improve the extraction of information from complex objects and events (Kellman & Garrigan, 2009). PL also likely involves discovery of abstract relational structures. Such high-level PL is a crucial component of expertise in many domains including reading (Baron, 1978; Yeh et al., 2003), chess (Chase & Simon, 1973), and X-ray interpretation (Chi, Feltovich & Glaser, 1981). In addition, recent research indicates an important role for PL in high-level symbolic domains, such as mathematics and science (e.g., Goldstone, Landy & Son, 2008; Kellman et al., 2008).

In recent research, Kellman and colleagues have shown that PL can be systematically engineered and accelerated using appropriate computer-based technology (e.g., Kellman, Massey & Son, 2010). Their approach to PL methods takes the form of *perceptual learning modules* (PLMs). Rather than focusing on memorization of instances, PLMs employ unique instances and systematic variations in the learning set to promote the learning of invariant or diagnostic structures characterizing a category or concept. Learners engage in short, interactive episodes focused on discrimination or classification. Because specific instances seldom or never repeat in PLMs, learners pick up structural invariance and can generalize it to new instances (Kellman et al., 2010). Recent work suggests that relatively brief PLM interventions can produce dramatic learning gains in challenging mathematical domains, such as fraction learning and algebra problem solving (Kellman et al., 2008; Kellman et al., 2010).

Purpose of Current Work

In applying PL to complex, symbolic, real-world learning domains, a critical question arises - how do we tell that the driver in these effects is *really* PL? Kellman, Massey & Son (2010) set out characteristic design features of perceptual learning interventions and some signature effects that implicate PL. Yet, realistic learning domains are complex and involve synergies between conceptual knowledge and perception of structure. Here we sought evidence of PL effects in a high-level, realistic learning domain, by explicitly testing after PLM use for basic changes in information extraction.

We trained PL for complex patterns in Chinese characters using a paradigm similar to that used to train PL in math and science learning (Kellman et al., 2010). Since Chinese characters are logographic and have both local and global structure, we were able to train participants to recognize characters at 3 different levels of hierarchical organization: stroke, component, and structure. Participants in two PL conditions matched characters by component (featural relations) or overall structure (global configuration). Importantly, in the case of matching by structure, local components were free to vary. Other studies have shown that an expert's ability to use relevant 'chunks' based on components and configural structure has to be nourished by literacy development and cannot be obtained solely through maturation (Yeh et al., 2003), making Chinese characters ideal for our aims. A condition in which learners judged characters' stroke count (high or low) served as a non-structural control task.

Before and after training, we directly tested for basic information processing changes using a visual search task. The visual search task was a transfer task: It tested search efficiencies for stimuli that were never presented in the learning phase. We found consistent and reliable effects on visual search efficiency from structure and component training, relative to the stroke-count control condition, including some effects specifically related to different types of PL training. A key finding was that training to classify based on structure led to markedly improved visual search performance when targets and distractors shared a common structure, even for novel structures.

Method

Participants

108 undergraduates participated in the experiment for course credit. All reported normal or corrected-to-normal vision. No participant reported any prior experience learning Chinese characters.

Materials

1136 images of actual Chinese characters were used (1102 in the training phase, and 34 as novel items in the visual search task). Images were presented in .png format in white SimSun 36-point font on a black background. The visual search task was presented using the Psychophysics Toolbox (Brainard, 1997), and the learning phase was a perceptual learning module (PLM) presented within a web-based Flash environment.

Learning Phase In the learning phase, participants learned to classify Chinese characters in a PLM, which consisted of many short classification trials. On each trial, a given character appeared in the upper middle part of the screen with two separated characters presented below (Figure 1). Participants were instructed to select which of the two lower characters was in the same category as the upper character. The task was a discovery task, in that learners had to discover structural characteristics that led to correct answers and were guided only by accuracy feedback. (No further information about the category was provided.) There were three between-subject conditions: (1) Structure PLM, (2) Component PLM, and (3) Stroke PLM**.** *Strokes* are simple features such as dots, lines, and curves. The characters used in this study ranged from 5 – 17 strokes, and were sorted into three categories of stroke count: Low, Medium, and High. In the Stroke PLM condition, two characters were defined as a 'match' (same category) if they shared either Low or High stroke counts. Incorrect answer choices also contained those with Medium stroke count. A *component* (or radical) refers to the sub-character unit formed by a group of strokes that recurs in different characters. Most

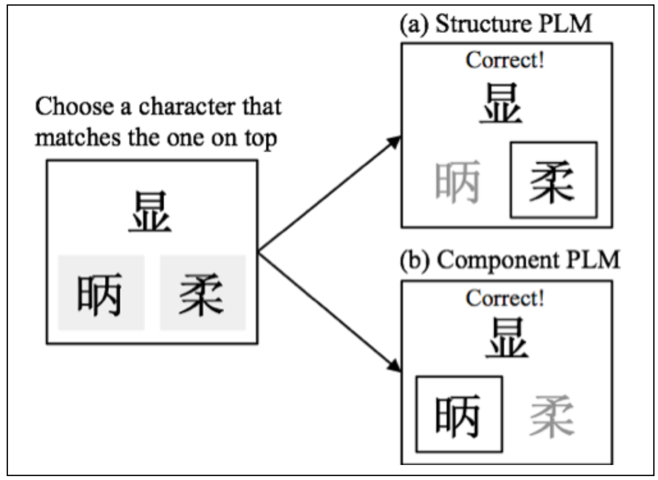

Figure 1: Sample PLM trial. On each trial, participants selected one of two choices to match a given Chinese character (on top). (a) In the Structure PLM training condition, characters 'matched' if they contained the same configural structure (Vertical shown). (b) In the Component PLM training condition, characters 'matched' if they shared the same component (日 shown).

components occur in a certain position within characters, but the components used in this study varied in their positions within a character. For example, the component 口 can occur on the left (e.g., 吃), right (e.g., 和), bottom (e.g., 吉), or top (e .g., 員). The proportions of the component usually change when the character structure changes. Irrespective of its structure and the number of strokes or components, each character occupies a roughly constant square-shaped size. The Component PLM group learned to classify characters based on whether they contained the same radical: 土, as in 圣 and 址, or 日, as in 易 and 旼. Incorrect answer choices also contained characters involving other components.

The arrangement of different components at various positions forms the *structure* of the character. Yeh et al. (2003) showed, using hierarchical cluster analysis, that expert readers tend to categorize characters into 5 categories: Horizontal, Vertical, P-shaped, L-shaped, and Enclosed. Participants in the Structure PLM group learned to categorize characters into Horizontal (e.g., 即, 快) and Vertical (e.g., 思, 季) structure categories. Two characters were characterized as a 'match' if they contained the same structure. P-shaped, L-shaped, and Enclosed structures were used as incorrect answer choices in the PLM.

Crucially, all training conditions used the same pool of Chinese characters. Structure PLM training involved abstract PL, because the relevant categories depended across trials on relations rather than recurring concrete features (Garrigan & Kellman, 2008). The Component PLM involved learning of more concrete features, but it was also considered as a type of abstract PL because the components involved shape characteristics rather than discrete features, and varied in size and proportions across characters within a category; thus, some invariants of shape had to be extracted, apart from fixed positions, sizes, or even aspect ratios. The Stroke PLM served as a baseline condition by allowing participants to interact with the same stimuli, but in a classification task in which the components and structural characteristics were not relevant.

Visual Search Task Visual search has been used widely to study PL effects (e.g., Shiffrin and Lightfoot, 1997; Sigman & Gilbert, 2000). A typical trial requires participants to search for a target within a field of distractors that differ from the target in certain features. The number of the distractors is varied, creating different numbers of total items (i.e., set sizes). The dependence of the reaction time (RT) on the number of items (the "search slope") is an indication of search efficiency: the larger the slope the less efficient is the search (Wolfe, 1998). In this task, participants searched for a character of a learned structure or component, among an array of characters that belonged to a different category of structure and/or component. This task consisted of novel characters, never seen in the learning phase, including those of an untrained structure and component category.

Four different target-distractors pairs were created by varying the structure and component factors in a 2 (structure: same or different) x 2 (component: same or different) design. Thus, target characters were paired with the following four kinds of distractors: (a) characters that shared the same structure and one component with the target (SsCs: same structure, same component); (b) characters that shared the same structure with the target but had different components from those of the target (SsCd); (c) characters that differed from the target in structure but shared one component with the target (SdCs); (d) characters that differed from the target in both structure and components (SdCd).

To control orthographic complexity, only characters with 8-10 strokes were included. Eight characters were chosen as targets, each having 9 strokes: (Horizontal) 垟, 垙, 昤, and 昹, and (Vertical) 垡, 垩, 昱, and 昝. Half of each group contained radical 土, and the other half contained radical 日.

The search displays contained 3, 8, or 13 characters randomly positioned in a 4 x 4 matrix (with jitter). For each target-distractor pair, the three set sizes were repeated 10 times, with an equal number of target-present and target-absent trials. This generated 240 trials, in which targets and distractors were novel exemplars of trained or familiar categories. These are referred to as F-F trials.

To investigate the transfer effects of PLM training, 240 more trials were added. 90 of which involved search for exemplars of a trained category among untrained category items (F-U trials). Here, the Structure PLM group searched for a target of a Horizontal or Vertical (trained) structure among distractors of a L-shaped structure (untrained distractors). Distractors shared or did not share a component with those of the target. The Component PLM group searched for a target that contained a trained component, among distractors without those components, but instead contained an untrained component 口. Likewise, distractor items shared or did not share the same structure with those of the target. The opposite pairings generated 90 more trials that involved search for untrained targets among trained distractors (U-F trials). The remaining 60 trials involved untrained targets and untrained distractors (U-U trials). These involved targets and distractors with component 口 and L-shaped structure.

In this task, similarity among distractors within a given display was controlled as a between-subject factor. Half of the participants searched homogeneous displays, in which all distractors were identical. The other half searched heterogeneous displays, in which distractors are different

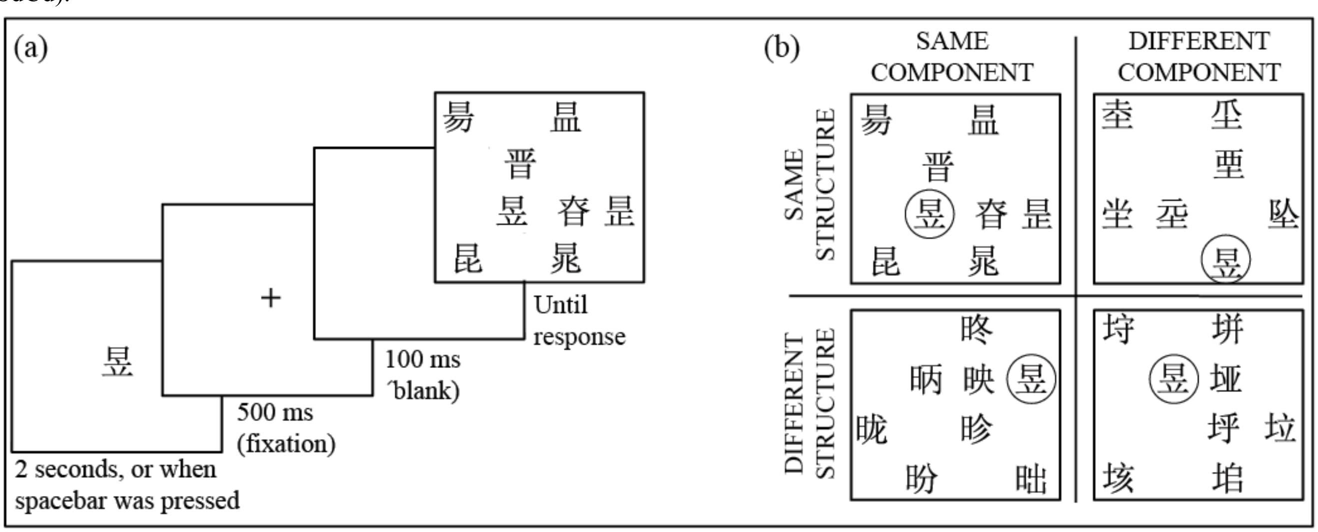

Figure 2: (a) Visual search procedure. This example depicts a set size 8 target-present trial with heterogeneous distractors. The target and distractors shown share the same structure and component (SsCs trial). The inter-trial interval was 1000ms. **(b) Sample search displays with heterogeneous distractors.** In visual search, target and distractors differed based on structures and components. Homogeneous displays contained identical distractors.

exemplars of a particular category. Each participant received 480 trials, given in four blocks corresponding to the search conditions: SsCs, SsCd, SdCs, SdCd. All other variables were randomized within each block. The order of the blocks given was randomized across all participants. The same visual search task was given twice to participants in all training conditions.

Procedure

The experiment began with a visual search task (pretest), followed by a PLM learning phase, and ended with another visual search task (posttest). A search trial progression is shown in Figure 2. Participants were asked to indicate, as accurately and quickly as they could, whether the search field contained the target. No feedback was provided after each trial, but an overall accuracy feedback was presented at the end of the task.

In the learning phase, participants were presented with classification trials in a PLM format. On each trial, they were instructed to select one of two characters that matched a given character presented in the upper middle of the screen. Correct responses were those that appropriately matched the given character, which were dependent upon the learning condition randomly assigned to the participant. Accuracy and RT feedback was given after each trial, after each block of 20 trials, and when participants reached a designated achievement level.

To complete the Structure and Component PLMs, participants were required to reach a predetermined learning criterion of 10 consecutive perfect classifications, with RT $\leq$ 3 seconds, for each type of classification[1]. The Stroke PLM was designed to terminate after 290 trials, if participants did not reach the learning criterion sooner.[2] The learning phase took no more than 45 minutes. After the learning phase, participants were given the posttest visual search task.

Dependent Measures, Data Analysis and Hypotheses Based on Kellman and colleagues' prior work, we expected the PLMs to produce robust classification learning, and as a result, changes in perceptual sensitivity that would be evident in the transfer task of visual search. We expected greater improvement in search slope at posttest for search trials that required participants to distinguish between trained categories. We considered visual search times for correct responses only. To compare performance between pretest and posttest, we calculated the search slope difference, or the decrement of RT per search item, for each participant separately for each search trial type based on structure and component similarity. This was the primary measure in the study.

As no previous work, to our knowledge, has tested transfer effects on visual search from PL classification training, we did not know exactly what effects to expect. We hypothesized that the Structure and Component PLM training would produce greater effects than the Stroke PLM control condition. However, even in the Stroke PLM condition, some PL may have occurred through mere exposure (Gibson, 1967; Logan, 1988). Furthermore, we hypothesized that PL effects should support transfer: Discrimination and fluency improvements relating to structure might improve structure discrimination *in general,* including with novel structures.

Results

PLM Data

The average number of classification trials to complete Structure PLM was 323 trials (range 114 - 727), Component PLM was 398 trials (range 188 - 675), and Stroke PLM was 273 trials (range 197-290). 14 of 36 participants were able to complete Stroke PLM with fewer than 290 trials.

Visual Search Data

Accuracy Error rates were low at pretest (mean 8.5%) and posttest (mean 7.7%). There was no reliable correlation between the error rates and the mean RTs obtained in each of the target-distractor pairs. Thus, there was no speed-accuracy trade-off.

Preliminary Analyses The mean RTs for correct responses for heterogeneous and homogeneous distractor displays at pretest were 2510 ms and 1697 ms, respectively, and at posttest were 2093 ms and 1437 ms, respectively.

Figures 3 & 4 present the main results. PLM training showed robust effect on visual search performance across all transfer trial types, regardless of whether targets and distractors were exemplars of untrained categories (Figure 3). One-way analyses of variance (ANOVAs) on search slope differences by transfer trial types (F-F, F-U, U-F, U-U) showed no differences between transfer trial types, for both heterogeneous displays ($F(3, 212) = 1.84$, *ns*), and for homogeneous displays ($F(3, 212) = 2.47$, *ns*). Thus, we combined all transfer trials in the following analyses.

General Effects of Relational PLM Training As expected, PLM training based on relational configurations produced significantly more improvements in visual search than Stroke PLM training across all trial types. This pattern was confirmed by analyses of PLM conditions in two separate mixed measures ANOVAs on search slope differences: PLM (Structure vs. Stroke and Component vs. Stroke) x display (homogeneous, heterogeneous) x transfer trial types (F-F, F-U, U-F, U-U). Structure PLM and Component PLM training each produced reliably greater increases in search

[1] Types of classification consisted of combinations of category members and distractors that differed by structure, component, and stroke-count. For example, one type of classification for those in the Structure PLM was matching a Low stroke-count Horizontal character with a High stroke-count Horizontal target.

[2] This number was determined by a pilot study as the average number of trials needed for participants in other learning conditions to complete their training.

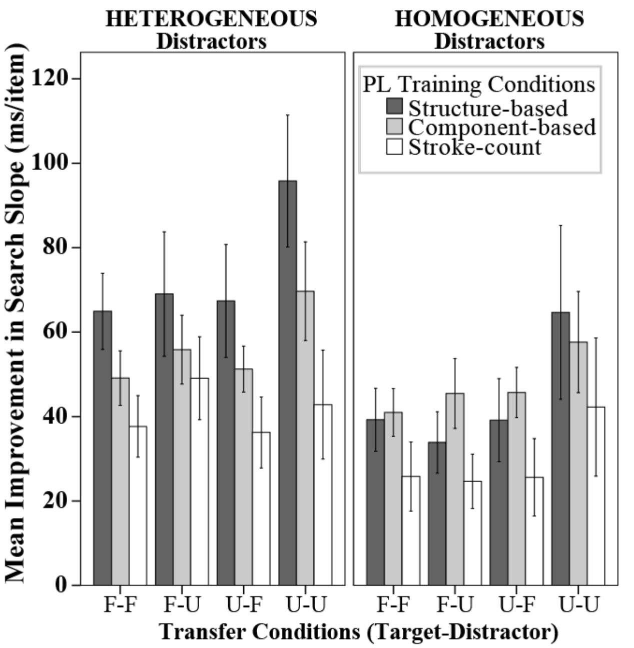

Figure 3: Improvements in search efficiency (ms/item) across different transfer conditions as a function of PLM training. Structure and Component PLM training led to more reductions in search slopes than Stroke PLM across all transfer conditions. (Error bars: ±1 SE)

efficiency than Stroke PLM ($F(1, 68) = 6.39$, $p < .05$ and $F(1, 68) = 5.08$, $p < .05$, respectively), regardless of whether targets and distractors involved structure and components that had been seen in PLM training and whether the search displays contained heterogeneous or homogeneous distractors (See Figure 3).

As expected, Structure and Component PLM training produced significant changes on visual search based on structure and component similarity. The effect of Structure PLM training was most notable in displays with heterogeneous distractors, while Component PLM training produced significant changes in search with homogeneous displays. This pattern was confirmed by a significant interaction of structure-similarity (same structure, different structure) x PLM (Structure, Component, Stroke) x display (homogeneous, heterogeneous) in a mixed measures ANOVA on search slope differences ($F(2, 102) = 3.96$, $p < .05$). Follow-up findings demonstrated that the differential effects on search improvement in each display type were due to the type of classification training.

For heterogeneous displays, the most improved performance was found with Structure PLM training for search when targets and distractors shared the same structure. (See Figure 4, left panel.) Performance in this case was reliably better than when targets and distractors did not share a common structure ($t(17) = -2.48$, $p < .05$; same-structure: 86 ms/item, different-structure: 54 ms/item). As Figure 4 shows, no such pattern was present in the Stroke-count PLM group or in the Component PLM group.

For homogeneous displays, Component PLM training produced reliably more improvement for displays in which targets and distractors shared the same structure than when they did not ($t(17) = -3.31$, $p < .05$; same-structure: 58 ms/item, different-structure: 32 ms/item). (See Figure 4, right panel.)

Discussion and Conclusion

Our results provide a crucial link between basic research in PL and applications of PL to instructional technology, in two ways. First, PLM training in complex, real-world domains produces basic changes in information extraction as shown in a visual search task. Second, these changes involve abstract relations rather than the concrete features used in many PL studies. Consistent with our expectations, PLM training of abstract relations in Chinese characters produced specific changes in visual search, and sensitivity induced by PL for both configural structures and relational components transferred to novel relational categories. No specific characters seen in PLM training were used in visual search; improvements in visual search were therefore based on improved processing of relational structures.

The most general effects were that both PLMs involving classifications of abstract relations produced greater improvements in visual search than a control condition, using the same stimuli, that did not require processing of relations. These effects held across all trial types.

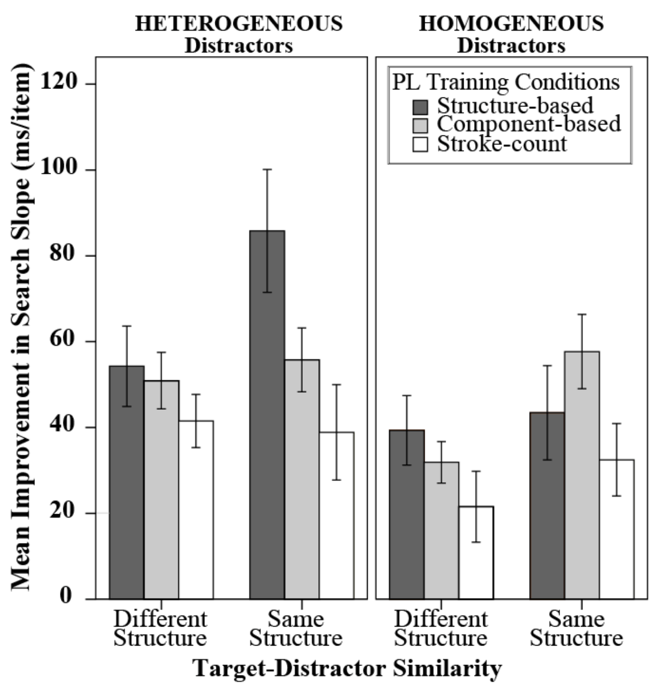

Figure 4: Improvements in search efficiency (ms/item) as a function of PLM training. Structure and Component PLMs led to most improvement in search efficiency when target and distractors shared the same structure, for heterogeneous and homogeneous displays, respectively. (Error bars: ± 1 SE)

As expected, structure-focused classification training produced specific changes in visual search performance when search was based on structural similarity. Interestingly, however, we found most improvement in search when target and distractors shared the same structure than when they differed by structure. This effect was consistent across transfer trial types. One possibility is that expertise of certain categories resulting from structural classification training may have allowed participants to set aside the category-identifying information, when it was not relevant, to facilitate search for a particular target. This advantage was specific to search with heterogeneous distractors. It could be that structure classification enabled learners to process the overall structures of new characters more effectively, allowing them to see relevant parts within complex arrangements. This advantage may have been confined to cases of heterogeneous distractors because this condition posed more varied challenges for finding the relevant information.

An advantage with same-structure search was also found with component-focused training. The Component PLM produced more efficient searches when target and distractors shared the same structure than when they differed by structure, but unlike with the Structure PLM, the effect occurred only for homogeneous distractor displays. One likely possibility was that component-based training may have allowed people to concurrently learn about structure. Although components can appear in various locations within each character, their size and shape varied depending on the character structure. Thus, to learn about the invariant relations defining each component, participants needed to attend to the location of each component and picked up structural relations as a result. While adequate to improve search for homogeneous distractors, this component training may not have provided enough facility with overall structures to benefit variable search among distractors in heterogeneous displays.

In sum, our data provide strong indications that PL training produced changes in sensitivity seen in a transfer task of visual search. Some effects were clearly specific to PL training for structural relations or specific components in that the PLM conditions led to different patterns of improvement. Future studies will be needed to fully understand these results, but the intricacy of the patterns we observed suggests that PL training may have interesting, unanticipated effects on information pickup.

The improved sensitivity in visual search induced by PL for both relational structure and specific components shows that classification experience in complex domains does lead to basic changes in information extraction. Our findings, and future research in studying transfer effects from PL, may help us to understand how PL leverages basic information processing improvements to underwrite expertise in complex, real-world learning domains.

Acknowledgments

We gratefully acknowledge Timothy Burke, Clara Sao, research assistants of the UCLA Human Perception Lab for their expert assistance, and support from US Department of Education, Institute for Educational Sciences (IES Grant #305H06070) to PK. The opinions expressed are those of the authors and do not represent views of the US Department of Education.

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