DEVELOPMENTAL DIFFERENCES IN CUED ATTENTION GIVEN ORDERED INFORMATION

A Thesis
Presented to
the Faculty of the Department
of Psychology
University of Houston

In Partial Fulfillment
of the Requirements for the Degree of
Master of Arts

By
Joseph M. Burling
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Abstract

The two experiments in this paper provide a developmental approach to the decision-making patterns seen in children and adults when trained with overlapping cues. Experiment 1 compares adult performance on different versions of the highlighting task consisting of text based or image based stimuli. Robust order effects were found for both tasks, and the image based version was concluded to be comparable to previous literature (Medin & Edelson, 1988; Kruschke, 2009). Experiment 2 found order effects in preschool-aged children with the image based design, and differences in cued attention based on age. Younger children found it more difficult to learn combined cues separately. Younger children were also more likely to show highlighting effects for the novel cues that equally predict either outcome. Older children were more accurate on singular ambiguous cues. Implications for developmental differences in attending to specific cues over time are discussed.

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Chapter 1

Introduction

Adults have an extraordinary ability to quickly activate stored knowledge—which has been accumulated over time from previous learning experiences—in order to make rapid inferences about their world, and as a result, acquire new information about their environment, all within a brief moment. Consequently, new information will ultimately influence how they perceive and learn from problems presented in the near future. In the long run, the order in which information is presented is crucial in shaping one's experiences, perceptions, and categorical representations. The influence of order effects on categorization builds upon previous work demonstrating how stimulus complexity may influence the classification of categories driven by basic mechanisms such as selective attention (Mackintosh, 1975; Nosofsky, 1986). Cued attention is a key component during learning, especially paying particular attention to repeated information presented across situations. This is often the case given that everyday events are not completely random and contain meaningful repeated and overlapping pieces of information. There are numerous complexities involved when trying to provide explanations and descriptions of learning by factoring in this temporal information; however, the adversity does not prevent researchers from attempting to fully explain this phenomenon. This problem has been confronted from many different approaches, such as in classical conditioning in animal models (Rescorla & Wagner, 1972; Kamin, 1968), trial-by-trial observations in human associative learning tasks and problem solving tasks (Ramscar, Yarlett, Dye, Denny, & Thorpe, 2010; Kruschke, Kappenman, & Hetrick, 2005; Winman, Wennerholm, Juslin, & Shanks, 2005), and computational modeling of decision making (Ramscar et al., 2010; Griffiths, Sobel, Tenenbaum, & Gopnik, 2011; Kruschke, 1996). One intellectually profitable and promising source for answers in regards to the mechanisms behind the transformation and shaping of knowledge (due to temporal factors), and an approach that seems to be overlooked in the literature, can be found by observing developmental trajectories, and how the nature of decision making changes according to a specific developmental period with the possibility of shaping perceptions via domain-general mechanisms such as cued attention. The developmental approach to understanding the formation of this kind of knowledge—combined with behavioral observations—may be just as promising as the previous methods in providing insight into the mechanistic explanations of the phenomenon, which posits that the order of information directly affects and enhances learning. In the following series of experiments, we take this approach in observing the influence of time dependent information on decision making in children and adults by implementing a trial-by-trial task meant to probe for the influence of order effects across development, and discuss the role of cued attention and its involvement during the process.

1.1 Asymmetrical learning paradigms

When administering tasks in which potentially useful information precedes other informative cues with equal salience, behavioral anomalies in decision making are observed when probed with novel combinations of items that seems to contradict statistical expectation. Observing decision making responses in these types of tasks may supply some answers that could explain the processes involved in the type of category formation that takes place during early and late learning (early learning will be referred to as initial exposure to some association of objects or items, while late learning will be subsequent exposure to a different sets of items, with some overlap in information). These asymmetrical response patterns (e.g., responses that deviate from the expectation of equal preference between two or more competing outcome choices) have been observed in a specific phenomenon known as the inverse base-rate effect (Medin & Edelson, 1988), or alternatively referred to as the highlighting effect, in which the latter denotes the prominent role of rapid attentional shifts in late learning (Kruschke, 2003). These response biases seen in tasks involving the inverse base-rate effect are robust across many different iterations of the experimental structure and design. The same type of patterns are seen in each rendition. Alterations in the frequency of object pairs presented during training (thereby manipulating the extent of early and late learning) have shown consistent results in decision making patterns, even with alterations such as changes in disparity of frequency information, dual-task implementations, or time restrictions placed on outcome choice (Lamberts & Kent, 2007; Medin & Bettger, 1991; Shanks, 1992). The validity of the observed response biases is not under scrutiny, given the numerous alternatives of the design and the degree of stability in the type of decisions made; the manifestation of the asymmetry is widely accepted. However, much contention is still derived from the mechanistic explanations provided to account for the observed behavior. The original work of Medin and Edelson (1988) placed considerable weight on base-rate knowledge and causal inference, such as attending to the sensitivity of the frequency of presented cues, and using this information to make judgments about outcomes. Over the course of experimentation on the issue, other influences have been shown to be of particular importance. The bulk of this work will focus not so much on the frequency of information provided, but the order in which it is provided. This process is thought to take place in an associative learning framework, with the focus on competition between given items (cues), and the influence that this type of cue competition has on redirecting attention toward meaningful cues and outcomes.

1.1.1 Different approaches to order effects

The process by which order effects manipulate categorical representations can be accounted for by different models of explanation. These models propose different cognitive influences and may be divided based on their emphasis on either domain-general processes, such as the sensitivity to the covariation of information across time and the role of cue competition (Shanks, 1995; Kruschke, 2001; Lamberts & Kent, 2007), or the use of more probabilistic, top-down processes (Juslin, Wennerholm, & Winman, 2001; Cheng, 1997). The proposed mechanisms based on higher-level inferences can take the form of explicit strategies implemented during a cost-benefit analysis (see Medin & Edelson, 1988), or rule-based processing, in which less familiar categories are actively eliminated as possible candidates during ambiguous forced-choice tasks (Juslin et al., 2001). This last explanation places much more importance on the frequency of information presented, negatively influencing the degree of confidence for infrequent cues, rather than the order in which information is presented. An alternative viewpoint is that the emergent patterns are the result of shifts in attention away from potentially erroneous cues within the training structure, resulting in unequally weighted representations for different cue combinations (Kruschke, 1996). The association between cue and outcome is therefore a byproduct of the interaction between cued attention and prior knowledge of certain items.

Common to both paradigms is the reliance on certain sets of cue combinations (referred to as a conjunctive cue) to be learned before others, which predict their own specific outcomes; however, frequency theorists place little importance on this factor, and instead emphasize causal induction based on total probability. We address the order in which cues are presented as being a critical factor in addition to recognizing the contribution of frequency. Prior experience and perceptual biases accumulates in the form of stored representations. These representations are continuously revisited and revised, especially when faced with the pressure of having to generate quick responses while confronted with ambiguous information. The overlapping nature between past and current knowledge sets the path for the categorization of future knowledge, and the process is then repeated. Therefore, to accurately predict an outcome given the current state of one's knowledge, an individual's entire history of learning must be taken into consideration. Different developmental trajectories will lead to different resolution strategies and a unique set of problem solving skills, which is why the order in which information is presented has a catalytic effect on future decision making, and has a direct impact on the constraints and likelihood of certain outcomes.

1.1.2 Previous research with children

Specific tasks testing for order effects such as the highlighting paradigm can be thought of as a continuous learning trajectory over the course of training, each trial shaping the association between cue and outcome incrementally. A degree of categorical stability is thus maintained well into testing in order to display the types of response biases witnessed during decision making. This notion poses two questions regarding development: (1) are children capable of reaching the same state of cognitive stability, the type of stability seen in past adult literature, which arises from the unequally weighted representations and in turn contributes to the asymmetrical behavioral responses; (2) how does the influence of order differ between young children and adults, and across development in general; i.e., what is the magnitude of temporal influence given the two very different cognitive histories between children and adults, and how do differently aged children respond to such order effects, if at all? The latter concern may address some of the necessary cognitive constraints required for this type of asymmetrical learning by assessing the likelihood of bottom-up and top-down mechanisms, the influence of memory and attention, and the dependence on object saliency for younger individuals.

Concerning the abilities of young children and detecting similar patterns of processing as in adults, both constructs (either rule-based inferences or attentional shifting given specific cues) can potentially lead to the same behavioral outcomes, yet only the rule-based approach posits that children are incapable of showing the same patterns in decision making due to their underdeveloped high-level reasoning skills (Winman et al., 2005). Winman et al. (2005) found that only one third of the tested children ages 8- to 9-years-old showed a clear inverse base-rate effect, suggesting that the children within this age range are at the initial stages of acquiring the necessary cognitive abilities required for deductive reasoning and complex decision making. If the focus is shifted toward frequency explanations and away from effects of temporal order, it is likely that the difficulties inherent in an inference-heavy task structure—such as the one mentioned in the previous study—may be a result of the design itself and may not be a suitable measurement of order effects on conjunctive cue categorization for young children. It is determined that alternative explanations of processing, a shift away from explanations of deductive reasoning and top-down knowledge toward cued attention and object associations, may possibly be required to witness equivalent asymmetrical biases in children, the same type of biases exhibited from adult judgments when given a purely deductive reasoning task, the kind seen in Experiment 1.

In this paper we propose an alternative approach that may be better suited for testing young children, with an emphasis on visual processing and association of predictive items by means of cued attention. This is achieved through the implementation of child-friendly imagery that serves as the basis for creating asymmetrical associations over time. Beforehand, using adults as controls we will make preliminary comparisons between learning paradigms that place an emphasis on visual processing of cues versus typical designs investigating learning asymmetries via text based reasoning. Specifically, we will compare a child oriented version of the highlighting task with equal base-rate information, and instead focus on the progression from early to late learning. But first, we'll introduce the implications of the highlighting effect as a domain-general learning mechanism, as well as its potential application toward different types of tasks involving associative learning.

1.2 The role of highlighting in learning

The attention-shifting model, as opposed to pure base-rate knowledge, is of particular interest from a developmental perspective. In contrast to the exclusive use of explicit top-down processes, this model is based on the deployment of basic cognitive mechanisms such as attention and memory. Its low-level yet generative explanations can encompass many types of learning, including language acquisition, pattern recognition, heuristics, and abstract causal inferences. A cued attentional framework, such that asymmetrical representations are driven by cue competition, provides plenty of groundwork for potential application across development. This theoretical foundation of competition among cues and cued attention is especially useful when investigating temporal learning theories at various cross-sectional time periods, which may be overlooked if only considering the effects as pure top-down processes based on frequency of occurrence, which are frequently considered outside of the realm of child capability.

When trying to understand the nature of early learning on later learning, it is important to consider how a temporal factor may interact with existing cognitive abilities during *any and all* given stages of development. The relevancy of items in any given moment may change based on current abilities such as memory and bottom-up driven attention. Better control and flexibility of these processes as time progresses might lead to differences in how items are learned. This notion can be viewed as a constant feedback loop, in which newly acquired information by means of competition resolution directly impacts attentional flexibility and memory, leading to more effective methods of attending to relevant information. Advantages for establishing the highlighting effect as an attentional byproduct is that across the entire lifespan, this model can provide explanations pertaining to the complex dynamics inherent in temporal learning theories, whereas higher level knowledge constrains these effects to later development. A persistent trajectory of generating attentional biases by reallocating cognitive resources helps to overcome the inherent difficulty between distinguishing relevant and irrelevant information, and thus categorizes this information appropriately for later use. It can be postulated that such low-level, domain-general mechanisms such as cued attention are sufficient in being able to account for the type of outcomes driven by order effects. Previous literature has previously demonstrated that young children are more than adequately capable of exploiting such mechanisms for this type of learning via cued attention (Smith, Colunga, & Yoshida, 2010; Fernald, Thorpe, & Marchman, 2010; Yoshida, Darby, & Burling, 2011). By at least preschool age, children's attentional flexibility becomes apparent in that they are capable of taking control over such lower-level mechanisms during this critical point in developmental transition (Rueda, Posner, & Rothbart, 2005). However, relatively little is known about the interactive processes involved between temporal factors and attention for 3- to 5-year-old children, especially with regard to how the order of perceived information assists in constructing certain types of biases that benefit and enhance learning in the long run.

1.2.1 Order effects as cued attention

The structure of the highlighting paradigm initially allows for a pair of items (comprising a conjunctive cue and its respective outcome) to be learned symmetrically during the first few stages of training. For example, the conjunctive cue $I.PE$, where I is a singular item making up one-half the pair and PE is the another item in the pair, predicts the outcome E, which can be any event, concept, label, object, and so on. Symbolic objects such as the ones used in this study (I and PE) are paired cues that initially have equal associative weight in their predictability of outcome E. For example, at first there is no reason to suspect that either cue has an advantage over the other in predicting the outcome paired with these cues; hence, the cues I and PE are equally weighted and equally competitive. It is reasonable to assume that individuals are able to learn this symmetry in structure from the onset of exposure, and developmental differences may play a role in how the strength of this initial symmetry is perceived, such that it may be difficult for younger children to view these items as distinct. Order effects begin to come into play with the later introduction of a new conjunctive cue $I.PL$ predicting a distinct outcome L. Note that one specific element from this pair—cue I—was already introduced and is now repeated across both instances of learning, leading to the classification of such as an *imperfect predictor* of either outcome since it unreliably predicts both E and L across different time points. Its repetitive nature has little informative value (as a predictor of an outcome) given its equal probability as a predictive cue; therefore, cues PE and PL inherit the roles of certainty in terms of predictability, being referred to as *perfect predictors* of their respective outcomes (cue PE is always present during outcome E and never present with L, the same goes for PL and L). Given the timeline between learning that the early set $I.PE \mapsto E$ and the late set $I.PL \mapsto L$, attention is increasingly redirected away from potentially erroneous cues, and as a result reallocated toward more useful pieces of information. Due solely to its place in time, the association between cue I and outcome L is attenuated, or at the very least this association is not as pronounced as it should be given the unreliability of cue I. This is of course assuming that attentional resources are actively and rapidly being focused toward meaningful input, consequently strengthening or highlighting the link between PL

and L—given it is no longer prudent to treat I and PL equally.

The highlighting effect and response biases discussed previously can be observed during testing and probed with novel combinations of cues that were learned during training. Cued attention is built on an architecture that sets into motion how individuals will ultimately decide upon ambiguous sets of items without ever actually being exposed to them. For instance, if given the imperfect cue I in isolation, individuals will choose outcome E a majority of the time, despite it only being seen conjunctively with both outcomes previously. Also, when given both perfect predictors simultaneously as a conjunctive cue, such as $PE.PL$, participants will likely choose outcome L. past literature on the subject has discussed these tendencies in terms of base-rate information, in which it was often the case where $I.PL \mapsto L$ was learned less frequently; however, in the absence of base-rates, the outcome preferences still remain the same (Kruschke, 2009). Therefore, it is the unique role of cued attention that allows for individual cues to compete over time, placing importance on some items while at the same time inhibiting specific associations in order to reduce error in future decision making.

Order effects such as these are one influence among many that can govern the process of category formation. Factors such as memory capacity may influence the ability to store multiple representations, while other factors might depend on feature characteristics of an individual stimulus, which might alter overall saliency of an object. But it is the interaction between selective attention and temporal components, in addition to these other factors mentioned, that give rise to unique patterns of associations over time. This complexity is beyond the scope of explanation provided by classic recency effects, in which the most current inputs are more accessible due to the nature of memory storage and retrieval. If this were in fact the case, a recency account would posit that independently observed cues I and PL will both equally lead to responses of outcome L given these items, due to their later occurrence. This is simply not the case. However, when probing for a response to classify the imperfect cue, the attenuation of cue I during later learning leaves the individual with having to rely on previous knowledge about the nature of cue I, in which it was formerly categorized as belonging to outcome E, quite the opposite of a recency effect.

It is this type of dynamic interaction between temporal factors and cognitive mechanisms discussed that may give rise to the accumulation of the kind of knowledge responsible for forming higher-level generalizations, by implicitly examining the nature of overlapping features during the process, all while being shaped by cued attention. A general learning mechanism responsible for building complex knowledge can serve as a bootstrap for explaining complexity in behavior and cognition, whether manifesting itself as language, or deductive reasoning, or some other behavior that involves making complex decisions. This level of complexity can be derived from a subset of highly influential underlying mechanisms. Through the experiments conducted in this paper, observing similar learning processes in young children can help bridge the gap between adult cognitive literature and developmental literature on these types of processes. Before doing so, we must first demonstrate that the robust highlighting effects witnessed in complex inductive reasoning tasks can also be seen in simple object association paradigms.

Chapter 2

Experiment 1: Highlighting comparisons with adults

Experiment 1 compares behavioral response patterns seen in adults between different designs of the highlighting task. Each adult participated in two tasks in which he/she was required to learn a specific conjunctive cue and its respective outcomes before moving on to learning other cue combinations and outcomes. In both tasks the participant was later tested on items learned during training in addition to novel combinations of the cues viewed during training. The primary difference between designs is the type of information provided in order to learn cue-outcome associations, with one task consisting of an image-based stimulus design, and the other based on textual information only. Direct comparisons were made for each subject between performance on the image-based design and the text based design. It is expected that learning of the training sets, and therefore behavioral response patterns during testing, will be analogous across the different types of tasks (the highlighting effect will be observed regardless of an image or textual stimulus), especially when the participant is prompted with ambiguous testing cues in which mapping the cue(s) to an outcome is theoretically equally probable.

2.1 Method

2.1.1 Participants

Forty-seven adults from the University of Houston or surrounding areas participated in both the image-based and text based task designs. All participants received some form of compensation for their time by either providing them with partial course credit or a $5 gift card as a form of payment.

2.1.2 Stimulus and materials

Objects in the form of images served as cues and outcomes for the image-based design, while only textual information showing a combination of symptoms (predictive cues) and their respective diseases (outcomes) were presented in the text based design. Both tasks were created in the same experimental design software, and were presented on a 19” capacitive touch screen monitor with a resolution of 1280x1024, which recorded the participant’s touch responses. Despite the nature of the stimuli in each type of design, cue combinations and their associated outcomes can be symbolized alphabetically across both tasks to represent the specific role of cue and its outcome—whether or not a cue perfectly predicts its respective outcome or imperfectly predicts its outcome. Table 2.1 lists the items common to both task designs.

Table 2.1: Cue combinations and their expected outcome associations (common to both testing designs). The first two are training items (introduced again during testing), while the last four are novel occurrences presented only during testing. The "." separator denotes a set of paired items/conjunctive cue.

Cue Combination		Expected Outcome
I.PE	$\mapsto$	E
I.PL	$\mapsto$	L
PE	$\mapsto$	E
PL	$\mapsto$	L
I	$\mapsto$	E
PE.PL	$\mapsto$	L

[I] Imperfect predictor of either outcome [PE] Perfect predictor of the early outcome [PL] Perfect predictor of the late outcome [E] Early outcome [L] Late outcome

Image-based task The image stimulus implementation of the highlighting task consisted of a series of two-dimensional, illustrated images presented on the touch screen monitor. Three distinct custom images served as predictive cues (I, PE, and PL) and were used throughout the task. These were taken from a sample of 9 images. Predictive cues were presented side-by-side at the top of the screen. Two different images from a sample of 6 served as outcomes E and L and were presented side-by-side at the bottom of the screen overlayed on top of an image of a brown box. The total number of available images allowed for the assignment of three unique groups, or different sets of stimuli consisting of training items $I.PE \mapsto E$ and $I.PL \mapsto L$. Predictive cues took the form of familiar objects, while outcomes were represented as known animals. Table 2.2 illustrates the nature and quality of the images used throughout the task. A complete breakdown of the images used for each type of cue and outcome between sets can be viewed in Table A.1 from Appendix A.1. The same stimulus sets were pre-arranged and fixed for all subjects to avoid the likelihood of strong pre-existing associations between certain combinations of images.

Text-based task For the symptom/disease task, cues and outcomes in the form of words were displayed from a touch screen monitor. Participants learned two sets of early ($I_1.PE_1 \mapsto E_1$, and $I_2.PE_2 \mapsto E_2$) and late ($I_1.PL_1 \mapsto L_1$, and $I_2.PL_2 \mapsto L_2$) associations in the text design, as opposed to just one set of each in the image design. The terms for symptoms serving as predictive cues and names of diseases serving as outcomes were taken from Medin and Edelson (1988), the exact list of items used from this study can also be viewed in Table A.2 in Appendix A.1. At the start of each run of the experiment, 6 randomly sampled symptoms taken from the list were assigned as conjunctive cues ($I_1.PE_1$, $I_1.PL_1$, $I_2.PE_2$, $I_2.PL_2$), while 4 randomly

Table 2.2: Examples of conjunctive cues and outcomes for image and text based versions of the task.

	Image-based Design	Text-based Design
Cue	 [I] +  [PE]	*"ear aches"* [I] + *"back pain"* [PE]
Outcome	 [E]	*"Terrigitis"* [E]

Note: Conjunctive cues and all possible outcomes were presented simultaneously. For the image-based task, objects such as the spoon and apple serve as the conjunctive cues, while the elephant is an example of a predicted outcome. For the text based task the paired cues are "ear aches" and "back pain" while the correct outcome is a novel disease "Terrigitis." The superscript labels denote the following types of cues: [I] Imperfect predictor. [PE] Perfect predictor of the early outcome. [E] Outcome associated with the early set.

sampled diseases were assigned as outcomes (E_1, L_1, E_2, and L_2).

2.1.3 Procedure

Instructions and task familiarization phases unique to the type of design were given before initializing training in those tasks. After these instructions, all tasks began with a training phase in which the participants learned early pairs of cue-outcome associations before gradually moving on to learning later pairs. After training, the testing phase consisted of probes of cue combinations that required a response, i.e., choosing the preferred outcome, before completing the trial and moving on to the next probe. Previously learned cues were present during testing as well as novel cue combinations. Novel probes provided critical information about the influence of early versus late training on outcome preference, given those novel configurations at the start of each testing trial. The order of tasks completed (image task first vs. text task first) was counterbalanced between participants.

Image task procedure Six training trials designed to familiarize the participant with using the touch screen monitor—while simultaneously instructing him/her on the procedure for completing a trial—were implemented before the cue-outcome training session. The participant was required to drag a pair of triangles at the top-center of the screen that matched one of the boxes which were presented along the bottom of the screen; afterwards, the participant pressed a button on the top right corner to accept his or her response.

After these initial instructions, all tasks began with a training phase in which the participant proceeded to learn the outcomes associated with early conjunctive cues before moving onto the later learning phase with a majority of the trials being late conjunctive cues predicting late outcomes. The participant was instructed to drag the conjunctive cues placed at the top-center of the screen down to one of the outcomes placed at opposite ends along the bottom of the screen. Dragging either of the predictive cues led to both items moving across the screen synchronously. Auditory feedback was given after the paired cues were placed in the box displaying the image of one of the outcomes, and the participant's outcome choice was recorded. Left and right orientation of cues and outcomes were randomized across all trials. The frequency and onset of exposure of items in the training phase was taken from

Kruschke's (2009) canonical design which equally exposed participants to early and late training trials, but maintained the order effects of learning multiple sets of items (see Table 2.3 for a summary on how this was conducted). The gradual progression from early learning to late learning was achieved by implementing three distinct phases of training (Early, Mixed, & Late) used to keep track of the participant's progress; consequently, the total number of training trials per participant depended upon his or her performance. This structure allowed for the participant to become equally exposed to the different sets ($I.PE \mapsto E$ and $I.PL \mapsto L$) while keeping intact the progression from early to late learning. The participant progressed through each phase without interruption, and was not informed when one type of training phase progressed to the next.

Every participant began with four consecutive early training trials before training accuracy was assessed. If the participant reached at least 75% accuracy after these initial four trials, he or she moved on to the mixed phase, otherwise another block of two trials was added until both of those trials were correctly answered. The total number of blocks was recorded for determining the length of the final training phase. The mixed phase served as a gradual introduction to the late training items. It contained four trials with three of them being early training, and the other trial consisting of a single introduction to the late training set. Accuracy was again assessed with a criterion of 75% for the mixed phase, and additional blocks were added as necessary, and the total number of blocks was recorded. The final phase contained a block of four trials with three of them being late training items, and one being an early training item. The total number of blocks in the final (late) training phase was calculated based on the sum of the total number of early and mixed blocks. If a participant required no additional blocks, the exact number of early training items learned during the entire training session was ten, with the total number of late training items also being ten.

After the training phases, adult subjects entered the testing phase and were told that they were going to see pictures that they saw before, and to do their best in choosing only one box to put them in. Items shown during the testing phase were presented on the screen in the same fashion as in training, except that novel combinations of paired cues and unpaired single cues were introduced, as well as previously seen training items. Five repeated trials of each type of combination presented in Table 2.1 were randomly assigned, resulting in a total of 30 trials for the testing session. No feedback was given after each testing trial, and the completion of a single trial immediately led to the next one. After testing was completed, adult subjects performed the entire task an additional two times in order to make use of all possible sets of images (See Table A.1 for a list of sets), and the order of sets was randomly assigned for each subject.

Text task procedure The equal exposure design referred to in the image-based task training was also used for the symptom diagnosis task. The main distinction is the number of early and late items learned, such that participants simultaneously learned two different sets of early and late cue-outcome associations in addition to having a fixed but substantially larger number of trials during training. For example, during the early learning phase, the set of items $I_1.PE_1 \mapsto E_1$ and $I_2.PE_2 \mapsto E_2$ were both presented throughout this phase, but not in the same trial. The mixed and late learning phases contained the previously mentioned items in addition to $I_1.PL_1 \mapsto L_1$ and $I_2.PL_2 \mapsto L_2$, with a fixed frequency of each in all phases. Table 2.4 provides a summary of the items learned as well as the frequencies of each type. Notice that the

Table 2.3: Example of the items presented during each phase of image training.

Phase	# Trials per Phase*	# Blocks per Phase*	Item Type & # Trials per Block		
Early	4	$N_1 = 2$	I.PE $\mapsto$ E ($\times$2)		
Mixed	4	$N_2 = 1$	I.PE $\mapsto$ E ($\times$3)	+	I.PL $\mapsto$ L ($\times$1)
Late	12	$N_3 = N_1 + N_2$	I.PE $\mapsto$ E ($\times$1)	+	I.PL $\mapsto$ L ($\times$3)

Note: Accuracy was assessed at the end of each phase, and additional blocks were added as necessary. The total number of blocks in each phase was recorded to determine the final number of blocks in the Late training phase.

* The number of blocks—and therefore trials—per phase represents the minimum number that participants were exposed to if they met the accuracy criteria throughout the entire training session.

sum of frequencies for each training items results in equal exposure for all types.

A set of initial instructions were presented to the participant before training began in the form of text containing the following passage:

> "In this experiment you will see some common symptoms on the top of the computer screen and fictional diseases on the bottom of the screen. Your job is to learn which symptoms indicate which disease. You can press any of the diseases. When the symptoms are presented, you make a guess by touching one of the diseases."

Predictive cues were centered at the top of the screen with one symptom displayed directly on top of another. The vertical orientation of the cues was randomized for every trial to avoid an orientation bias. All four disease outcomes were displayed along the bottom of the screen, equally spaced and surrounded by a thin rectangle. The same four outcomes were present throughout the entirety of the task with the order of items displayed being random for each trial in order to prevent the participant from associating outcomes with a particular location along the bottom of the screen. The participant made a response by touching the name of the disease within the boundaries of the rectangle. Corrective feedback was provided if necessary after each response. A total of 112 trials were carried out in the training session alone.

After training, the following instructions were displayed on screen before starting testing:

> "Now you will diagnose diseases based on previous symptoms, some combinations may be new. You will choose the appropriate disease based on the given symptom/s. Please make an informed choice. You will touch the disease on the screen to make your choice."

The testing procedure was identical to the training procedure except for the different types of predictive cues given during each trial, and no feedback was provided. Learning of multiple sets of early and late training items allowed for testing novel combinations between these distinct sets. For example, participants could be presented with a testing probe referred to here as $I.PE.PL_O$, and asked to choose from the four possible outcomes given the probe, where the above example can denote the possibilities $I_1.PE_1.PL_2$ or $I_2.PE_2.PL_1$. The subscript "O" indicates the *other* cue of that type, or the one that was never presented along with the rest of the conjunctive cues during training. Table A.3 in Appendix A.2 lists all possible testing items and the frequencies of each type. Overall, the participant responded to a total of 60 testing trials.

Table 2.4: Frequency of items presented during text training.

Phase	Training Items & Frequency			
Early	$I_1.PE_1 \mapsto E_1$ ($\times 8$)	+	$I_2.PE_2 \mapsto E_2$ ($\times 8$)	
Mixed	$I_1.PE_1 \mapsto E_1$ ($\times 12$)	+	$I_2.PE_2 \mapsto E_2$ ($\times 12$)	$+\ldots$
	$I_1.PL_1 \mapsto L_1$ ($\times 4$)	+	$I_2.PL_2 \mapsto L_2$ ($\times 4$)	
Late	$I_1.PE_1 \mapsto E_1$ ($\times 8$)	+	$I_2.PE_2 \mapsto E_2$ ($\times 8$)	$+\ldots$
	$I_1.PL_1 \mapsto L_1$ ($\times 24$)	+	$I_2.PL_2 \mapsto L_2$ ($\times 24$)	

2.2 Results and discussion

2.2.1 Learning criteria for adults

Performance on novel testing items can only be accurately assessed if participants learned the correct cue-outcome associations during training. For the text-based version, accuracy for training items during the testing phase was calculated for each individual and at least 6 out of 8 correct responses for each type of training item were required (Kruschke, 2009). Unlike the fixed text-based design, the extent of the image task training varied according to participant performance, with a mean of 60.4 trials completed when incorporating all image sets (sets A, B, & C) for each subject. Given individual differences in learning for Early and Mixed training in this task, learning criteria were assessed based on the last phase of training and cut-off values were allowed to vary between subjects. Late training trials were summed across all sets and the minimum number of correct $I.PE$ and $I.PL$ trials significantly above chance ($p < 0.05$) were calculated for each participant. The difficulty of the original text-based task structure when compared to the image-based version was apparent, with 15 adults removed from the analysis due to failure to adequately learn the training items in the text-based version, while only 1 additional participant failed to learn both training items for the image-based version of the experiment. Removals due to these learning criteria resulted in a total of 31 participants used in the subsequent analysis.

2.2.2 Image association results

Decision making proportions between the two possible outcomes E and L for this particular design are based on the frequency of choosing either the early or late outcome given the 6 different testing items (Table 2.5). A chi-squared statistic was obtained via Pearson's test for frequency data, using the total observed counts of outcome preferences; i.e., participant's individual repeated responses for E and L given each testing probe were collapsed across all subjects and these observed frequencies were compared against equal expectation (50:50) under the assumption of a chi-square distribution. Each testing item from the table was based on a total of 465 observations (5 repeated responses per item $\times$ 3 stimulus sets $\times$ 31 participants). All observed responses for each test item were significantly different from expected frequency ($E = 232.5$, & $L = 232.5$) with, $p(\chi^2 \mid [I.PE,\ I.PL,\ PE,\ PL,\ I,\ PE.PL]) < 0.001$). These results for the image-based task testing phase are displayed in detail in Table 2.6.

The high proportions for choosing the correct outcome on the training items $I.PE$ and $I.PL$ indicate that participants were able to learn these conjunctive cues well enough to extend this knowledge into the testing phase with additional intermixed sets of cues. Mean accuracy for $I.PE$ was 98.5%, and for $I.PL$ mean accuracy was

95.5%. The same level of accuracy was observed for the perfect predictors PE and PL, with mean accuracy of 96.3% and 98.5% respectively. Correct identification of these unpaired cues with their predicted outcomes was robust given that participants were viewing these cues separate from their imperfect counterpart for the first time, which indicates they are able to disaggregate conjunctive cues with a high level of accuracy when necessary. Also, a robust highlighting effect was observed for the critical ambiguous cues I and $PE.PL$. There were asymmetrical responses despite both items being equally probable of either outcome. Participants showed a strong preference for the early outcome given the imperfect cue, and a strong preference for the late outcome given both perfect predictors in conjunction. Mean accuracy for I was 65.2%, while mean accuracy for $PE.PL = 68.2\%$. The accuracy for these two ambiguous items is similar to that seen in previous literature (Kruschke et al., 2005; Kruschke, 1996).

2.2.3 Symptom diagnosis results

A subset of the results from the symptom diagnosis task is presented in Table 2.5, which displays testing items that are common to both task designs, only these comparable items will be discussed. For a complete list of the testing items used in the entire task, and the proportions of each outcome for all possible testing items, see Table A.3 in Appendix A.2.

High accuracy was achieved for the trained conjunctive cues and unpaired perfect predictors, with each of the items having an accuracy $> 92\%$. The critical testing trials show similar results from the image task; decision making preferences given cues I and $PE.PL$ were asymmetrical, even when provided with additional answer

Table 2.5: Results of adult decision making proportions given the following testing cues common to both types of designs.[†]

	Image Version Outcomes		Text Version Outcomes			
Testing Cue	E	L	E	E_O	L	L_O
I.PE	**0.98***	0.02	**0.95***	0.01	0.03	0.02
I.PL	0.05	**0.95***	0.07	0.00	**0.92***	0.01
PE	**0.96***	0.04	**0.93***	0.03	0.02	0.02
PL	0.02	**0.98***	0.06	0.00	**0.93***	0.01
I	**0.65***	0.35	**0.63***	0.06	0.21	0.10
PE.PL	0.32	**0.68***	0.35	0.02	**0.63***	0.00

[†] Bold items indicate expected outcome choice for that design

[*] Indicates a significant difference from expected frequency, $p < .001$

choices. When presented with an imperfect cue that can belong to either an early or late outcome of the same set, participants reliably choose the early outcome instead of the later one 63% of the time, and only choose the later outcome 21% of the time. For the conjunctive cue comprised of two perfect predictors, participants choose the later outcome 63% of the time and the early one only 35% of the time.

2.2.4 Task design comparison

The accuracy scores between the two tasks show similar patterns in decision making despite the differences between symptom-disease training and learning to associate a

Table 2.6: Results of adult decision making frequency data given the following testing cues common to both types of designs.

Testing Cue	χ^2	*df*	*N*	*p*
Image Version				
I.PE	437.4	1	465	$< .001$
I.PL	384.8	1	465	$< .001$
PE	399.5	1	465	$< .001$
PL	437.4	1	465	$< .001$
I	42.8	1	465	$< .001$
PE.PL	61.4	1	465	$< .001$
Text Version				
I.PE	643.84	3	248	$< .001$
I.PL	591.79	3	247	$< .001$
PE	300.58	3	123	$< .001$
PL	308.71	3	123	$< .001$
I	100.77	3	124	$< .001$
PE.PL	135.11	3	123	$< .001$

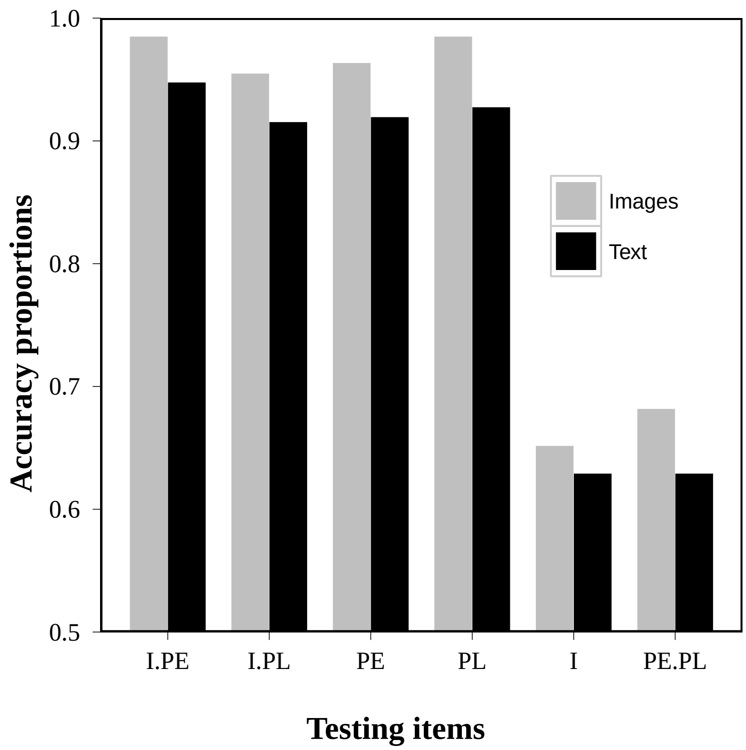
set of images. Statistical tests for differences between proportions were conducted for each of the 6 testing items and for the entire task as a whole (see Table A.4 in Appendix A.2). Overall accuracy, disregarding the performance on individual items, was 87% for the image-based design and 85.4% for the text-based design with a nonsignificant difference in accuracy of 1.6% between tasks. The accuracy difference when considering all the testing items individually ranged from 2.3% (probe I) to 5.8% (probe PL), with reliable ($p < .05$)—although small differences—seen in the training items $I.PE$, $I.PL$ and the highlighted probe, PL. The results summarized in Figure 2.1 indicate that accuracy between tasks is relatively consistent between individual testing items and between the two tasks as a whole. The cues easiest to obtain high accuracy scores—the training items and the highlighted cue—were found to be slightly easier for the image-based task design.

It is of particular interest to determine whether the decision making patterns seen from the highlighting phenomenon are based on individual differences or the average tendency across all participants. In other words, can the asymmetrical biases be attributable to a select few individuals who repeatedly choose in favor of one outcome over the other across different situations (task designs), or are the selection biases for a particular individual inconsistent across situations—even though the average effect still remains constant between subjects? Individual performance on one of tasks was compared to their performance on the other while calculating concordant and discordant decision making choices between the two task designs. The correlation between designs for all items combined was found to be moderate, with Kendall's $\tau = 0.38, p < .001$; however, much of the concordance between tasks could be attributed to the unambiguous items. Given that performance on the training items and single perfect predictors was close to ceiling for both tasks, the correlation of those testing items between designs is of little interest. For this reason, correlations between the image task and text task on critical I and $PE.PL$ probes were analyzed separately. Accuracy on these items within the image task was not found to be dependent upon accuracy in the text task. Rank-based correlation coefficients were nonsignificant, with $p(\tau_I = -0.02) = 0.89$, and $p(\tau_{PE.PL} = 0.083) = 0.56$.

2.2.5 Results discussion

Results for the two different highlighting tasks were found to be consistent despite the nature of learning between tasks and the type of features presented. Individuals routinely selected items in line with their selections on the previous task, considering selection preferences for outcomes E and L given each of the 6 different testing probes. Notwithstanding overall concordance, performance on the ambiguous items was found to be independent of design type. Nonsignificant correlations between designs for the crucial testing items indicates that some participants showed a slightly stronger highlighting effect for those items in the image-based design, while others did not, and instead, tended to show performances in line with expectation for the text-based design. However, such incongruence in selection biases—and differences in accuracy between tasks—was small enough to warrant the conclusion that overall similarity between the image and text-based designs was reliably consistent, and accuracy was well above chance for all testing items regardless of the task design. The small difference in accuracy for some items is likely due to the additional outcomes presented and number of cues expected to be learned for the text-based version, as opposed to the nature of the stimulus in each design. This last point coincides with the significant difference in accuracy for the highlighted cue PL. Cued attention is

Figure 2.1: Mean accuracy of testing items for adult participants given both the text-based and image-based versions of the highlighting task.*



* Adult participants were tested on additional conjunctive cue combinations for the text-based version. Only testing trials common to both tasks are shown. See Table 2.5 for alternative outcome proportions.

proposed to have a relatively stronger contribution when the number of associations expected to be learned is reduced, as in the image-based design (one instance of PL versus two simultaneously). Taking into consideration these results as a whole, the image-based design utilized in the current experiment is determined to be sufficient to elicit the kind of response biases seen in previous literature.

Chapter 3

Experiment 2: Highlighting evidence in children

Experiment 1 compared two versions of the highlighting paradigm with adult participants. The stimulus set that was used for the image-based version was created so that children could also perform the exact same task with the expectation that they would show similar asymmetrical associative learning patterns as seen with adults. A replication of the text-based, symptom diagnosis task with young children would be inappropriate for detecting evidence of highlighting effects given the population observed in Experiment 2. Generating object associations by means of visual images was found to be sufficient in probing for order effects when tested on novel combinations of previously learned items. Therefore, the question is whether children show similar decision making strategies and are capable of the following: (1) adequately learning the sets of early and late items during training, i.e., whether or not they are capable of categorizing sets of visual cues and updating their categorical knowledge over the course of training; (2) if so, extending this knowledge further into testing, and deconstructing conjunctive cues, as observed in Experiment 1 with adults on singular items. This second point implies that children must perceptually disaggregate conjunctive cues when necessary, and implicitly consider the relevancy of individual items in order to target them as possibly being erroneous or unpredictable; (3) showing biases in decision making when confronted with ambiguous sets of cues. This third point will depend on how effectively children overcome the hurdles of points 1 and 2. Children—like adults—are expected to successfully implement such operations through the process of cued attention, but do so differently depending on their age, and thus the cognitive strategies used in order to adjust to inconsistencies in cue predictability are also expected to be dependent upon their current stage of development.

3.1 Method

3.1.1 Participants

Forty-three children ages 33.9- to 71.4-months-old with a mean age of 53.4 months participated in the task in exchange for a small gift at the end of the session. Six children were removed from the subject pool for failure to adequately learn both $I.PE$ and $I.PL$ sets by the end of the training phase (late phase training accuracy for either set was $< 50\%$). This resulted in a sample size of 37 for the subsequent analysis.

3.1.2 Stimulus and materials

The same materials used to conduct the image-based task in Experiment 1 were also used in Experiment 2.

3.1.3 Procedure

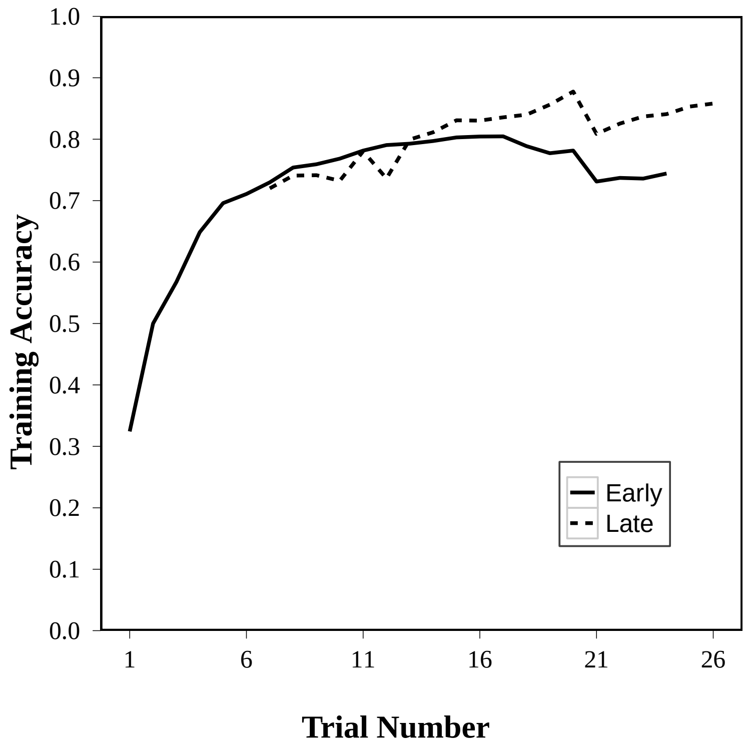
The procedure was the same as in Experiment 1 except that a single child did not complete all stimuli sets as the adults were required to do, given that the completion of a single set took approximately 15 minutes. Children were randomly assigned to one of the three sets seen in the previously referenced Table A.1, and the experimental session ended after the completion of one of these sets. The mean number of training trials completed for all ages was 25.19 (See Fig. 3.1) with each child also completing 30 testing trials.

3.2 Results and discussion

3.2.1 Highlighting results from all children

The results for all children are displayed in Table 3.1, and direct comparisons between children and adults for individual testing items can be seen in Figures 3.2a and 3.2b. The main findings taken from these data are the following: (1) children are able to adequately learn the items in which they were trained on, as proportions for choosing $E|I.PE$ and $L|I.PL$ were significantly above equally expected frequency; (2) similar proportions were also reliably obtained from the singular cues. Notice that

Figure 3.1: Average training progress for all children (mean age = 53.4 months) for both early and late training sets.



Note: The horizontal axis extends to the mean number of trials performed for both age groups.

whereas the adults were close to ceiling for these items, children ranged from 63% to 76% accuracy, indicating a greater difficulty in mapping cues to their respective outcomes when compared to adult performance. This reduction in accuracy for those particular trials, and especially when considering the singular cues, could be contributing to the results seen for the critical ambiguous testing items. Finally, (3) all age groups showed preferences for $E|I$ and $L|PE.PL$, and were both significantly above chance for ambiguous cues I and $PE.PL$ with $\chi^2_I(1, N = 181) = 23.34, p < .001$ and $\chi^2_{PE.PL}(1, N = 184) = 5.57, p = .02$.

The proportions for the ambiguous items are theoretically equal in strength—when not considering the influence of order effects demonstrated in this experiment—with a difference in accuracy between the two outcomes E and L expected to be 0% (for example, $p(E|I) = p(L|I) = 0.5$). Considering how the imperfect cue (I) presented in isolation should equally predict either outcome, children showed an 18.6% deviation from equal expectancy, a nonsignificant 3.4% increase over the adults' bias for the early outcome E (for the bias difference between children and adults, $p = 0.56$). This trend is reversed for the conjunctive cues consisting of both perfect predictors (trial type $L|PE.PL$). Children's accuracy for this probe was 8.9% above chance levels, in which their performance was 9.3% less than the adult bias for this same type of trial; this difference in proportion between samples is significantly different from the null expectation of equal performance across groups with $p(\chi^2_1 = 4.83) = .028$.

In summary, the reduction in accuracy in children was consistent when compared to adults for five of the six different testing cues, with the exception being the imperfect cue I, in which children showed a slight increase in preference for the early outcome over adult participants. Despite the expected differences in accuracy

Table 3.1: *All children.* Results of child decision making frequencies and proportions given the following testing cues. Mean age = 53.4 months, n = 37. Correct and incorrect counts are based on expected outcome preferences (see Table 2.1). Chi-square statistics and their corresponding p-values are presented based on the frequency data with $df = 1$.

Testing Cue	Incorrect	Correct	Proportion Incorrect	Proportion Correct	χ^2	p
I.PE	44	140	0.24	0.76	50.09	$< .001$
I.PL	61	123	0.33	0.67	20.89	$< .001$
PE	67	116	0.37	0.63	13.12	$< .001$
PL	47	138	0.25	0.75	44.76	$< .001$
I	58	123	0.31	0.69	23.34	$< .001$
PE.PL	76	108	0.41	0.59	5.57	0.02

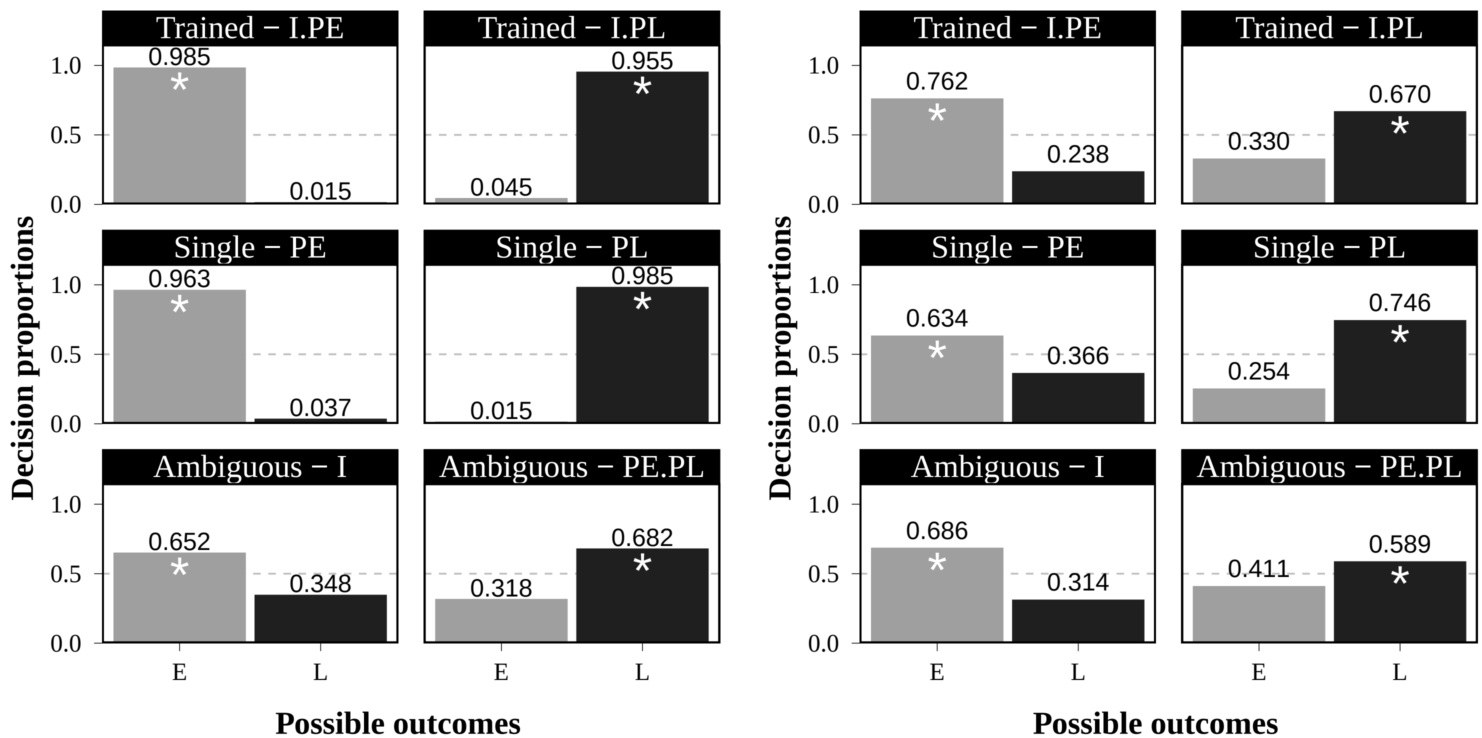
Note: Each testing item was presented five times. Data were used in the analysis if at least 95% of the total testing trials were completed.

between children and adults, children were still able to show robust order effects when given ambiguous information, which is in direct contrast with results seen in previous literature observing children older than that of the current experiment (Winman et al., 2005).

Figure 3.2: Comparison of decision making proportions between children and adults. The ⋆ symbol indicates a significant difference from the expected choice frequency between the two possible outcomes using Pearson's goodness of fit test. See Table 3.1 for a breakdown of the child frequency data.

(a) Adults

(b) Children, 3- to 6-years-old

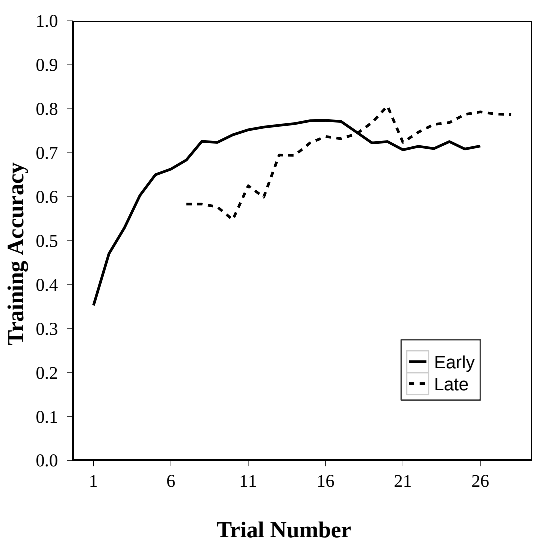


3.2.2 Age-related differences in decision making

The previous results demonstrate that 3- to 6-year-old children make decisions about ambiguous information in a similar manner to that of adults. However, this is not to state the their behaviors are identical, or that the same strategies implemented during decision making during these tasks exist across all stages of development. When observing the data obtained in Experiment 2 using age-related cutoff values, thereby grouping younger and older children, it is clear that certain patterns in outcome preferences are unique to a specific developmental period. The typical results—as seen in previous highlighting literature—may appear in the combined participant pool as an indication that all children are equally capable of the types of decision making ability seen with adults, but this may not explain much of the variability as observing younger and older children separately does. It also leads to different inferences about child capabilities dependent upon age. Therefore, children were split into two separate groups and their accuracy and performance were analyzed for each group individually. The cutoff age for the younger group of children (mean age = 3.7 years old) was less than 54 months, with 17 participants meeting this criterion. Twenty children 54 months and older (mean age = 5.1 years old) were placed into the older group. A comparison of training performance between the two sub-groups is shown in Figure 3.3, and the performance comparison for individual testing trials is shown in Figure 3.4. Notice that the training trajectory plots and the accuracy comparisons show different patterns for the two age groups, whereas the combined results fail to consider these differences in task performance between younger and older children.

Figure 3.3: The left panel (a) illustrates the average training progress for 3-year-olds (mean age = 44.4 months), while the right panel (b) shows average training progress for 5-year-olds (mean age = 61.1 months).

(a) younger children



(b) older children

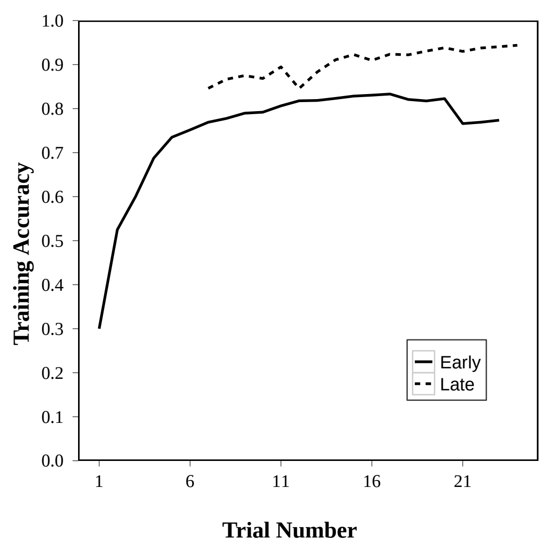
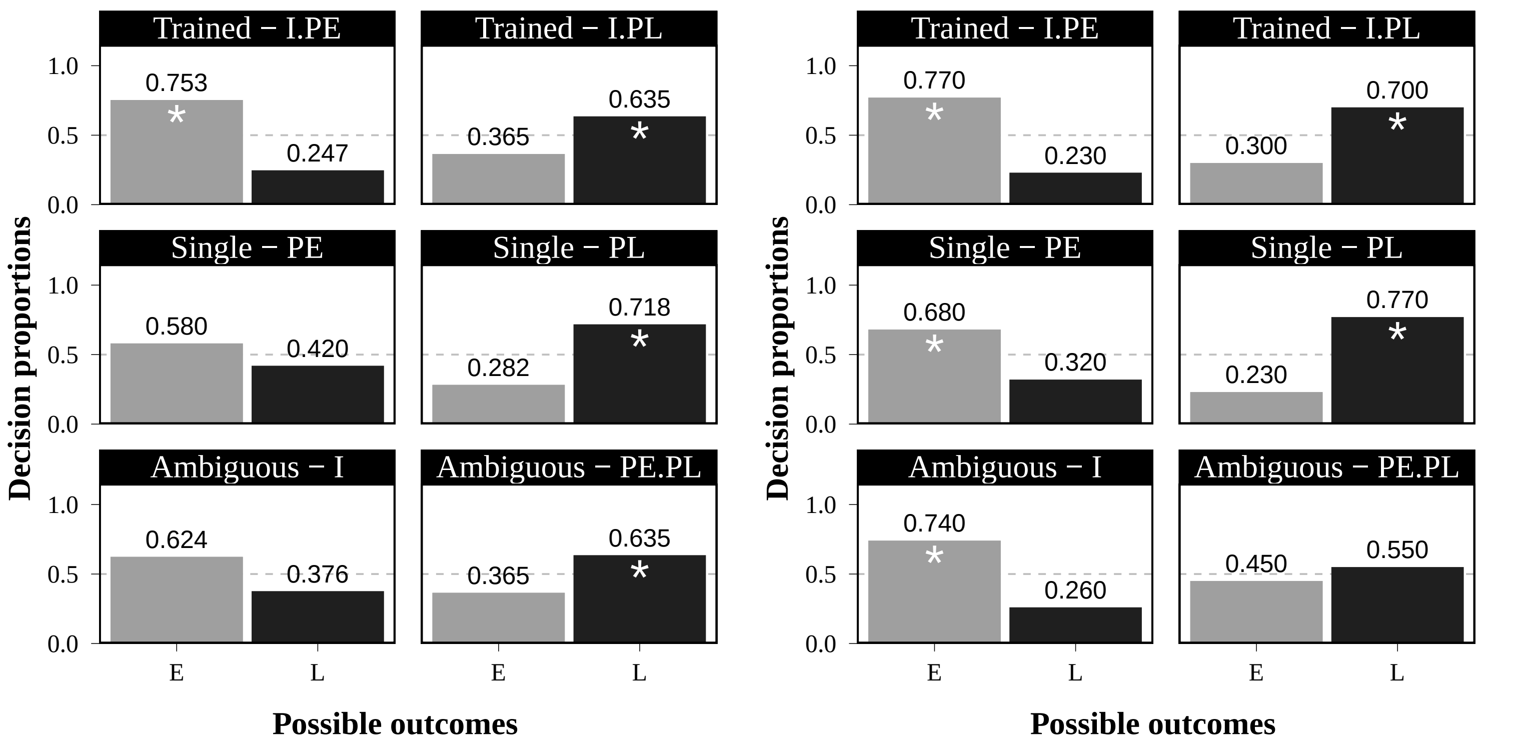


Figure 3.4: Comparison of decision making proportions between younger and older children. The $\star$ symbol indicates a significant difference from the expected choice frequency between the two possible outcomes using Pearson's goodness of fit test. See Tables 3.2 and 3.3 for a breakdown of the frequency data for young and old children, respectively.

(a) Children, 3- to 4.5-years-old

(b) Children, 4.5- to 6-years-old



Younger children The structure of the experiment required that the children achieve a certain level of accuracy before progressing to the last phase of training; this allowed for some participants to increase the number of trials in the Early and Mixed phases as needed based on their performance. Three-year-olds required 27.2 trials on average before allowing them to move on to the testing portion of the task (Fig. 3.3a). During their first introduction to the late training set, $I.PL \mapsto L$, this group of children was equally likely to choose either outcome, despite already being exposed to at least six trials of $I.PE \mapsto E$. Also, their accuracy for choosing $E|I.PE$ during training declined once a majority of the training consisted of late learning items. The training trajectory for three-year-olds indicates that younger children have difficulty with maintaining the learned associations during training, as indicated by the number of trials required to reach the last phase, in addition to the lower overall accuracy at the end of the session.

Frequencies and statistics for the items presented during testing for 3-year-olds are presented in Table 3.2. The testing results revealed that the younger children learned the trained items as well as the older children. The difference, however, lies within the singular cue PE. Younger children were unable to successfully map this item with it's early outcome counterpart above equal frequency, $\chi^2(1,\ N = 83) = 2.04,\ ns$. This was also the case when the imperfect predictor I was presented in isolation. Children showed a preference for the early outcome which approached significance, $\chi^2(1,\ N = 81) = 3.57,\ p = .06$. In fact, the only singular item that was successfully mapped according to expectation was the highlighted cue PL. These results, along with the preference of $L|PE.PL$, indicate that conjunctive cues for this particular age group aren't as easily dissociable unless presented with clear evidence stating otherwise, as observed in the saliency of $PL \mapsto L$.

Table 3.2: *Younger children*. Results of child decision making frequencies given different testing cues. Mean age = 44.4 months, $n = 17$. Correct and incorrect counts are based on expected outcome preferences (see Table 2.1). Chi-square statistics and their corresponding p-values are presented based on the frequency data with $df = 1$.

Testing Cue	Incorrect	Correct	χ^2	p
I.PE	21	63	21.00	$< .001$
I.PL	31	53	5.76	.02
PE	35	48	2.04	.15
PL	24	61	16.11	$< .001$
I	32	49	3.57	.06
PE.PL	31	53	5.76	.02

Note: Each testing item was presented five times. Data were used in the analysis if at least 95% of the total testing trials were completed.

Older children The five-year-olds required fewer training trials (23.5) than the younger children. They also maintained a more consistent level of accuracy over the course of training (Fig. 3.3b). On average, the older children were able to successfully map $I.PL \mapsto L$ on their first exposure to this conjunctive cue, which is in contrast to the equal association seen in younger children. Mean accuracy was $> 80\%$ when first introduced with this type of training trial. This suggests that older children are able to successfully utilize prior knowledge to deduce that the new set of cues observed does not belong to the outcome that already maintains a previous association, despite the objects containing some overlapping information; instead, it is likely that the older children infer that the current set of objects belongs to the novel outcome.

The frequency data along with the χ^2 statistics for each testing probe are presented in Table 3.3 for the older children. The main distinction between the performance of older and younger children is that the older children are able to deconstruct conjunctive items and associate singular cues in accordance with typical decision making patterns. Even for the imperfect cue, a strong preference for $I \mapsto E|I$ was observed for this group of children. However, being able to recall previous items and the ability to deconstruct conjunctive cues does not imply that older children will readily choose outcome L when probed with $PE.PL$. Their equal preference for either outcome given the probes $PE.PL$ is in contrast with the choices observed in younger children. These choices in decision making indicate that older children are extremely efficient at being able to segregate sets of items, and have no trouble associating conjunctive cues with their respective outcomes as long as both items are congruent. It is when novel combinations of items from different sources are presented simultaneously that older children are unable to inhibit their propensity to give equal treatment to the current cues, and therefore unable to generalize and

Table 3.3: *Older children.* Results of child decision making frequencies given the following testing cues. Mean age = 61.1 months, n = 20. Correct and incorrect counts are based on expected outcome preferences (see Table 2.1). Chi-square statistics and their corresponding p-values are presented based on the frequency data with $df = 1$.

Testing Cue	Incorrect	Correct	χ^2	p
I.PE	23	77	29.16	$< .001$
I.PL	30	70	16.00	$< .001$
PE	32	68	12.96	$< .001$
PL	23	77	29.16	$< .001$
I	26	74	23.04	$< .001$
PE.PL	45	55	1.00	.32

Note: Each testing item was presented five times.

evaluate complex combinations outside of their previous exposure.

Chapter 4

General discussion

4.1 Discussion of developmental differences

The results obtained from Experiment 2 indicate that children process and learn overlapping sets of information differently across development. The response choices seen in younger children may on the surface seem similar to that of older children, especially when considering certain testing items, but accuracy on the critical probes indicate different strategies used to make decisions about these items.

4.1.1 Capabilities of younger children

Cue disaggregation With respect to both the training trajectories and selection preferences for younger children, the results obtained are suggested to be influenced by the current abilities and biases present during that particular developmental period. For instance, during early learning of $I.PE \mapsto E$, the simultaneous presentation of cue I with cue PE makes it much more difficult for these children to completely disjoin these items over the course of early training, perhaps because conjunctive cues are constantly linked as they are moved about the screen (seemingly adding to the effect of them being inseparable). Therefore, the realization that each individual object within the pair has its own degree of predictability toward outcome E is not fully reached due to the perception of these items as an inseparable, combined set of cues, as if the conjunctive items makes up an aggregated category on its own. In other words, instead of concluding—as adults and older children do—that $I.PE \mapsto E$, it is more as if they are perceiving early training as a singular item $A \mapsto X$.

Initial exposure to late items As the later set of items are introduced and presented on the screen (with one of the cues having already been seen before) the younger child does not automatically assume that this new conjunctive item $I.PL$ belongs to the outcome that they did not see in previous learning, i.e., $p(E|I.PL) = p(L|I.PL)$. If younger children are less likely to be able to deconstruct conjunctive cues, it also less likely that they will be able to use prior knowledge about a single cue to conclude that the overlapping item indicates a one-to-one relationship with the previous outcome. This can be illustrated in Figure 3.3a, which shows that young children are equally likely to assign $I.PL$ to either outcome during the initial introduction of the late learning trials, whereas older children readily assume that these items belong to the category which has not been previously seen before.

Different selection preferences Given the tendency for younger children to perceive a conjunctive item as a singular category, this bias in perception could potentially explain the selection preferences during testing. Young children performed at chance when given single cues I and PE, both early learned items. They were only able to successfully choose $L|PL$. This successful mapping of the highlighted cue may be driven by the novelty of the item PL when given $I.PL$ in conjunction. It could be argued that if children completely perceive items $I.PE$ as a single entity, such as A, then the presence of $I.PL$ during late learning would make it so that both I and PL are to be perceived as novel in comparison to A, instead of just cue PL. In addition, if it is much more difficult for younger children to be able to revisit past information, such as remembering what cue I was in previous learning, this lends more credence to the supposition that cues $I.PL$ are equally salient and novel during first exposure. However, we assume that children by this age do not create such hard and fast rules, especially with absolute certainty that the conjunctive item $I.PE$ is a singular item with no component parts, and that children have no recollection of previous items, but instead, these representation are essentially graded. Therefore, the initial exposure of object PL is treated as being the most salient cue during that moment.

This novelty effect can also be responsible for why children equally choose between E and L when given $I.PL$ for the first time, as mentioned previously. A novel and highly salient PL can belong to either outcome unless suggested otherwise through feedback (the influence of novelty and saliency overpowering prior knowledge and therefore the assumption that outcomes are mutually exclusive). Over the course of training, driven by the novelty of PL and the feedback provided, these children quickly learn that a strong relationship exists between PL and outcome L, so when presented with ambiguous information such as $PE.PL$, children less than 4.5 years old will likely choose outcome L, despite these conjunctive cues being equally probable of either outcome.

These same constraints are discussed in terms of the selection patterns seen when given the other singular items, such as cue I alone: (1) children must be able to recognize this item as belonging to an outcome without its conjunctive partner; (2) they must be able to repeatedly revisit past information and conclude that this cue was also present during early learning of $I.PE \mapsto E$ (it is less likely they would assume $I \mapsto L|I$, given the highlighting effect occurring with PL and L). The observed responses seem to be a competition between graded representations of these constraints, in terms of recognizing I as a separate entity, remembering that I was part of $I.PE$, and accounting for the associative strength picked up when I was paired with PL, in order to conclude that I belongs to PE. As follows, the amount of exposure of I throughout *all* of training helps the revising process, which is why young children are likely to map I to E more so than they could PE to E, given that: (1) they've never seen cue PE in isolation; (2) they've seen this cue much less often than its conjunctive counterpart.

4.1.2 Capabilities of older children

The outcome preferences seen in children 4.5 years old to 6 years old coincide with what is observed in adults, except for the ambiguous probe $PE.PL$. Let us restate what was observed for this age group. Cue PL was successfully highlighted, there was a significant preference for this item when given this probe during testing, and preference for $L|PL$ was stronger than for $L|I.PL$ (the item they were trained with). With increased attentional control and flexibility, older children are able to assume that during the initial exposure of $I.PL$, it is likely that this conjunctive cue belongs to the new outcome by revisiting and deconstructing the nature of the imperfect cue

I (see Fig. 3.3b). The selection preferences for probes I and PE alone also reflect this increase in attentional flexibility, and less of an influence by pure bottom-up driven preference for saliency, as seen in younger children. However, difficulties arise when having to interpret the nature of two perfectly predicting cues, $PE.PL$.

The testing preferences witnessed in older children imply that successful building of knowledge requires a series of skills which may not be fully developed during this age. These include: (1) the ability to revisit past information quickly when necessary; (2) the ability to deconstruct previous knowledge into its component parts; and lastly, (3) the ability to reconstruct past components into new configurations given novel experiences. It seems older children may have difficulty to some degree with this last step. Older children may be unable to move past their pre-configured representations of the individual cues $PE.PL$. Just as younger children are not likely to deconstruct complex items into sub-components, such as their tendency for perceiving $I.PE$ as a single item A. The same but reverse concept can be argued for older children, where $PE.PL$ is less likely to be constructed into a single category, A. Instead, when given the probe $PE.PL$, for some trials they may focus solely on PE, therefore choosing outcome E, and other trials focus on PL, choosing outcome L. They give equal preference to the individual items despite being presented in pairs. As in adults, generally accepting the relationship between $PE.PL$ as a new category, and relying on cued attention toward informative information such as PL, they are more willing to place this singular category with outcome L, instead of focusing on individual objects separately, trial-by-trial. As the ability of complex category formation develops, the effectiveness of cued attention increases, leading to the formation of even more complex categorization and greater control over attention.

4.2 Summary

Experiment 1 demonstrated that the image-based version of the highlighting task with equal base-rate information elicits similar effects as seen in previous literature. Visual association of objects seems to be just as effective in creating response biases, if not more so. It was also found that performance on one type of task was not dependent upon performance on the other for the ambiguous items, but across all items, the two tasks were found to be moderately correlated. Differences in accuracy between tasks remained consistent, and so an image-based version of the paradigm was found to be sufficient for use in younger populations. Experiment 2 showed that order effects do matter when certain sets of cues are presented before others; early and late learning created certain response biases in children during testing. These biases were not the result of base-rate information, given that the training provided equal exposure to early and late sets of information. Cued attention interacts with the order of presented information to form specific biases between sets of cues and outcomes, even in the absence of frequency information. The combined results of the child data showed highlighting effects consistent with previous literature investigating the phenomenon with adults. These results seem to suggest similar learning strategies, and the influence of order differentially affecting representations based on constraints during a specific developmental period.

The main point that could be obtained from these two experiments is that order effects play a much larger role than previously given credit for, and the complexities inherent in the highlighting effect are even more so across different developmental periods, but the underlying mechanisms of cued attention and the ability to revisit past knowledge remain present throughout the process. These fundamental mechanisms directly influence how information is categorized, which results in decision making behavior inconsistent with statistical probability. Further research must be conducted to understand the nature of the complex interactions taking place between order and cued attention to get a better grasp of the graded representations of knowledge across development, and the influence of certain cognitive processes taking over the focus of cued attention. Order effects do have an impact at multiple levels of processing across different age ranges, in which the building of knowledge over time can be explained by basic properties inherent within all individuals. Therefore, it is important to address all factors that may play a role in shaping this knowledge, and gauging the influence of each across development.

Appendix A

Supplementary materials & results

A.1 Materials

Table A.1: A complete list of images used for the image based task design. Each set remained fixed across all participants.

Type	Set 1	Set 2	Set 3
I	cup	apple	chair
PE	glasses	spoon	shoe
PL	strawberry	hat	cake
E	duck	elephant	cat
L	cow	monkey	dog

Table A.2: A complete list of textual cues used in the text based task design. Symptoms and diseases were assigned at random during task onset.

List of Symptoms	List of Diseases
earaches	Burlosis
yellow eyes	Namitis
rash	Terrigitis
dizziness	Coralgia
sore muscles	Gouphosis
nausea	Midosis
hair loss	Althrax
coughing	
fever	

A.2 Results

Table A.3: The following testing probes were used in the text based design for the testing phase of the task. The responses for each probe are presented as proportions. The "*O*" symbol denotes the *other* cue of the same type.

		Response			
Test Items	# Trials	E	E_O	L	L_O
I.PE	8	0.9476	0.00806	0.0282	0.01613
I.PL	8	0.0648	0.00405	0.9190	0.01215
PE	4	0.9268	0.03252	0.0244	0.01626
PL	4	0.0569	0.00000	0.9350	0.00813
I	4	0.6290	0.06452	0.2097	0.09677
PE.PL	4	0.3496	0.01626	0.6341	0.00000
I.PE.PL	4	0.3672	0.03125	0.5781	0.02344
I.PE_O	4	0.1575	0.70866	0.0945	0.03937
I.PL_O	4	0.0787	0.04724	0.1102	0.76378
I.PE.PL_O	4	0.4567	0.01575	0.0394	0.48819
I.PE_O.PL	4	0.0312	0.21875	0.7266	0.02344
PE.PL_O	4	0.2913	0.03150	0.0157	0.66142
I.PE_O.PL_O	4	0.0551	0.26770	0.0709	0.60630

Table A.4: Mean differences in proportion are displayed as accuracy percentages between common testing items of the image and text based task for adult participants.

Test Item	Accuracy Difference Image−Text	χ^2	p
I.PL	4.0%*	3.87	0.049
I.PE	3.7%*	6.97	0.008
PE	4.4%	3.40	0.065
PL	5.8%*	10.2	0.001
PE.PL	5.3%	1.0	0.317
I	2.3%	0.13	0.718

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