Opening Up the Cuebox:
A Developmental Perspective

D i s s e r t a t i o n

zur Erlangung des akademischen Grades

doctor rerum naturalium (Dr. rer. nat.)

im Fach Psychologie

eingereicht an der

Mathematisch-Naturwissenschaftlichen Fakultät II

der Humboldt Universität zu Berlin

von

Dottore Magistrale in Filosofia, Azzurra Ruggeri

Präsident der Humboldt-Universität zu Berlin

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Tag der Einreichung: 20 Juni 2012

Tag der Verteidigung: 3 Dezember 2012

Acknowledgements

This dissertation is the result of three intense years of research at the Center of Adaptive Behavior and Cognition (ABC), at the Max Planck Institute for Human Development, in Berlin, as a fellow of the International Max Planck Research School on Adapting Behavior in a Fundamentally Uncertain World (IMPRS Uncertainty).

When I was writing my Master Thesis in Philosophy at the University of Pisa on the work of Gerd Gigerenzer and the ABC Group, being part of this group was only a dream. First of all, then, I thank Laura Martignon, whom I met for the first time at the Summer Institute on Bounded Rationality 2008, for helping me to make this dream come true. And for putting me in Konstantinos' care. I would have never been able to get anywhere without his guidance, his suggestions and comments. Thanks Konstantinos, for the support, the presence, the encouragement, for being a perfect, lovely advisor and a very good friend.

Thanks to Gerd Gigerenzer for giving me the opportunity to work at ABC, an incredibly rich, polychrome and inspiring research environment. Thanks to my colleagues and collaborators, especially Henrik Olsson, for sharing their knowledge and expertise with enthusiasm and passion, for leaving the doors of their offices always open.

Thanks to Markus, for singing with me Mina, the ABBA and Mama Cass, for the countless dinners, discussions, films, concerts, baking and cooking sessions we enjoyed in these years.

Thanks to Jan, Nadine, Kibby, Juliane, Florian, Bjoern, Ozgur, Mirta and Christian. You made me feel home here, all in different ways.

Thanks to Fei Xu for the great opportunity to visit her infant lab in Berkeley. It was my first experience in a developmental psychology department, two exciting and insightful months that definitely strengthened my desire to work with children.

Thanks to Sylvaine and Ilona, for the hours spent sorting out my travel plans and filling my German forms, for being so patient with me, and so helpful.

Thanks to my friends and family in Livorno. In particular, thanks to my mum, for the effort spent in learning how to use Skype and emails to stay close, for attempting (with obvious success) to learn English to communicate with my international friends. For respecting and supporting my decisions. Thanks, because every time I come home it's a party, but at the same time you let me feel like I never left. Thanks for still believing that very soon I'll be back home ("just a matter of months, no? ..ok, maybe years?").

Finally, thanks to Nicolai, the best present the ABC group could give me – even in unsuspected times. What a gift….*and I feel like an ocean, being warmed by the sun*.

English Summary

My dissertation addresses the questions 1) what cues children and adults have in their cuebox (i.e., the set of cues available for making inferences or categorizing), 2) how people's intuition about the importance of the cues drives their information search, and 3) how the framing of a problem and the experimental design influence these intuitions. A *first project* investigated developmental differences in how children and adults solve a sequential binary categorization task. Results show that, apart from age-related differences, children's but not adults' inquiry strategies improve if objects are represented at the basic level (e.g., dog) but not if represented at the subordinate level (e.g., Dalmatian) or when the basic level is specified by additional features (e.g., dog, kennel, to wag, collar). Explanations are that, unlike other representations, basic level objects trigger features that are useful for categorization, and therefore help children ask more effective questions. A *second project* tested children and young adults on two inference problems, by manipulating whether cues were generated or given. Results show that, only when generating their own cues, younger children matched or even outperformed the accuracy of older children and young adults, by generating cues that were as informative as the those generated by older children and young adults. A *third project* examined the type, amount and informativeness of the cues in people's cuebox. Further, it investigated the influence of the type of cues on the ability of children and young adults to *generate* or *select* the most informative cue available. Results show that children's cuebox contains more perceptual cues than young adults'. We found no difference between the two age groups in terms of informativeness of the cues generated. Young adults showed the tendency to systematically consider non-perceptual cues more informative than perceptual cues. Children showed such tendency only in a cue-selection task.

Keywords: development, cues, inferences, information search.

Deutsche Zusammenfassung

Die Dissertation untersucht 1) welche Cues Kinder und Erwachsene in ihrer Cuebox haben, d.h. welche Cues für Inferenzen herangezogen wird, 2) wie Intuition über die Wichtigkeit von Cues die Informationssuche beeinflusst, und 3) wie das Framing eines Problems und das experimentelle Design die Intuition beeinflussen. Das erste Projekt untersucht den Effekt verschiedener Domänen und Objektrepräsentationen auf Erfragungsstrategien von Kindern und Erwachsenen in einer Kategorisierungsaufgabe. Ergebnisse zeigen, dass eine Basis-Level-Repräsentation (z.B. Hund) das Generieren von höher geordneten Merkmalen, welche die Objekte innerhalb einer übergeordneten Kategorie unterscheiden, für Kinder erleichtern und dadurch benutzt werden können, um effektive Fragen zu stellen. Dieser Effekt wurde nicht gefunden, wenn Kinder nicht selbst solche Merkmale generierten, sondern aus einem vordefinierten Set auswählen mussten. Das zweite Projekt untersuchte Kinder und junge Erwachsene bezüglich zweier Inferenzprobleme. In einer Bedingung mussten Cues selbst generiert werden, in einer anderen wurde ein Set von Cues vorgegeben. Ergebnisse zeigen, dass nur, wenn Cue selbst generiert wurden, junge Kinder gleich gut oder besser als ältere Kinder oder Erwachsene abschnitten, da sie Cues generierten, die ebenso informativ waren wie die der anderen beiden Altersgruppen. In dem dritten Projekt wurde getestet, wie die Art, Anzahl und Qualität der Cues die Fähigkeit von Kindern und jungen Erwachsenen beeinflusst, die informativsten Cues zu generieren bzw. auszuwählen. Ergebnisse zeigen, dass die Cuebox von Kindern mehr perzeptuelle Cues beinhaltet als jene junger Erwachsener. Dennoch war der Informationsgehalt der generierten Cues in beiden Gruppen gleich. Junge Erwachsene zeigten die Tendenz, nicht-perzeptuelle Cues systematisch als informativer zu erachten als perzeptuelle Cues. Kinder zeigten die gleiche Tendenz nur dann, wenn sie aus einem vordefinierten Set auswählen mussten.

Keywords: Entwicklung, Cues, Inferenzen, Informationssuche.

To Nic

And, of course, Alla mia mamma

The most interesting information comes from children,

for they tell all they know and then stop.

Mark Twain

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Chapter 1

Introduction

Chapter 1

Introduction

My research is deeply rooted into the approach of the Adaptive Behavior and Cognition (ABC) group of the Max Planck Institute for Human Development, where I have been working for the last three years. In particular, my investigation is embedded in the bounded and ecological rationality frameworks. From these programs my investigation inherits a distinctive definition of concepts such as cues, domain, heuristics and adaptive toolbox of strategies and the focus on the process more than on the outcome. Above all, my work shares the understanding of rationality as a match between the mental abilities of a subject and the structure of the environment in which the subject acts (Gigerenzer, Todd and the ABC Research Group, 1999; Todd & Gigerenzer, 2007; Todd, Gigerenzer and the ABC Research Group, 2012). These are the two blades of a pair of scissors, as described metaphorically by Herbert Simon (1991). This view of rationality implies that human minds, with limited cognitive and computational resources, can be successful by exploiting pre-existing structure and regularity in the environment. It also suggests that strategies, and the pieces of information (i.e., cues) they are often based on, are not good or bad a priori. As tools in a toolbox, no strategy or cue is suitable for all problems, because different tasks require different tools.

Little is known about how the individual adaptive toolbox (Gigerenzer & Selten, 2001; Gigerenzer et al., 1999) changes over the lifespan (Gigerenzer, 2003; Mata, Schooler, & Rieskamp, 2007; Mata, von Helversen, & Rieskamp, 2011; Todd et al., 2012), and even less–if anything–is known about how the *cuebox* develops across the life span. By cuebox I mean the set of the cues, information, features and concepts available for making inferences, for categorizing, for interpreting every real world experience, for coming up with explanations, and for building hypotheses.

My dissertation aims at filling this gap by investigating the development of intuitions about the importance of real cues in the real world. Do children and adults search and focus on the most effective piece of information when making inferences or categorizing? Specifically, my thesis addresses the following questions: 1) what type of cues children and adults have in their cuebox, 2) how people's intuition about the importance of the cues drives their information search and inquiring strategies, therefore constraining their inferences and decisions, and 3) how the framing of a problem and the experimental design influence these intuitions, sometimes boosting or limiting our information search strategies.

These questions spring from my experience with children at school, when leading workshops of creative theatre, and as a scout leader. Children ask thousands of questions about everything. They ask questions to obtain answers, and this is not trivial: There is a concrete intention underlying their inquiring behavior, intended to search and collect the information needed to fill a gap in their knowledge, to disambiguate an unclear or surprising situation or to resolve some detected inconsistency (Gopnik & Meltzoff, 1997; Gopnik, Meltzoff, & Kuhl, 1999; Gopnik & Wellman, 1994; Piaget, 1954; for models explaining and predicting question asking in the adults literature, see Graesser and McMahen, 1993; Graesser and Olde, 2003). Children need questions to move their knowledge structures closer to adults-like states (Chouinard, 2007). For this reason, they sometimes ask questions we adults would have never asked, and seem to pay attention to different layers of things, often not overlapping with the information we consider relevant. Though, I realized that their questions are sometimes very insightful and, above all, effective. I was curious to test this intuition, to investigate the conditions under which children can ask effective questions and to compare their performances with the adult's ones. I always thought this is how research should work: Back to the basics. Observe the world, investigate what you find intriguing, and try to solve the puzzle (Bodemer & Ruggeri, 2012).

I believe that the problems we find interesting and relevant should be shaping our methodologies. I learned that the choice of the methodological tool has to be driven by the research question, and not the other way around. In particular, how can we possibly study the contents and the development of our cuebox (in terms of number, type and quality of the cues people have available for different inferences) by implementing the traditionally used cue-selection design, where participants are provided a set of cues they can select among (see Chapter 4)? Moreover, this design might not be suitable to investigate children's decision-making, although successfully used for studying adults' cue-based inferences (see Chapter 3). First, it requires the children to assess and compare the usefulness of exogenously given cues they might not be familiar with, or the meaning of which they might not know (such as horsepower, see Mata et al., 2011). Second, a set of cues to choose from is a necessarily constrained selection that might not include all the information one consider useful.

In Chapter 2, 3 and 4, I applied a method of “open questioning”: I did not provide participants with a limited set of cues, but instead prompted them to *generate* their own cues, by letting them ask anything they wanted about the objects they had to make inferences or decisions about. This methodology, to my knowledge, has never been used for studying cue-based decision-making. It is inspired by the early developmental studies that analyze the questions children spontaneously ask in their everyday life (Callanan and Oakes, 1992; Piaget, 1926; Sully, 1896), and by the experimental research focusing on the linguistic development of children’s ability to form questions (Solè Planas, 1995), and on how acquiring information with questions supports the building and expansion of the child’s conceptual structures and knowledge (Chouinard, 2007; Harris, 2000; Vosniadou, 1994).

In Chapter 2, my coauthor and I investigated developmental differences in how children and adults solve a sequential binary categorization task. We used a computerized version of the Twenty Question game, which entails guessing a target object by ruling out the alternatives with yes/no questions. We ran three experiments to replicate and extend prior work showing that, apart from age-related differences, children’s but not adults’ inquiry strategies improve if objects are represented at the basic level (e.g., dog) but not if represented at the subordinate level (e.g., Dalmatian) or when the basic level is specified by additional features (e.g., dog, kennel, to wag, collar). Possible explanations are that, unlike other representations, basic level objects (a) trigger features that are useful for categorization, and (b) help children ask more effective questions. To test (a), we ran Study 2 and found that in both children and adults basic-level objects tend to trigger features that help to distinguish among groups of objects (e.g., does it have four legs) rather than object-specific features (e.g., does it bark), which are less suited for efficient categorization. To disentangle (a) and (b), we ran Study 3 and found that, if children do not generate but select questions from a given set, object representations have no effect on categorization performance. This suggests that object representations trigger features more or less suited for categorization but do not "teach" participants to identify more effective questions, an ability that remains tied to cognitive development.

In Chapter 3 we addressed the following question: Are children capable of focusing on the most informative cues? Previous research on cue-based inference suggests contradicting answers that we think are derived from the experimental design. We hypothesized that providing participants with a fixed set of cues to choose from handicaps children because it requires assessing and comparing the informativeness of exogenously given cues that they might not be familiar with or would not have generated themselves. We tested second-, third-, and fifth-grade children, and young adults on inference problems (which of two real cars is more expensive and which of two real cities has more inhabitants), manipulating whether cues were generated or given. Results show that younger children matched older children and young adults in accuracy, or even outperformed them, only when participants generated their own cues. Younger children did so by generating cues that were as informative as those generated by older children and young adults.

In Chapter 4 I followed up this line of research. We attempted to open and compare children's and young adults' cuebox by examining the type, amount and informativeness of the cues they have available to make different kinds of inferences. We explore the importance of cues beyond content free representations, by examining the cues participants generate for a range of everyday inference tasks. Further, we investigate how objective informativeness of a cue and type of cue determine children's and young adult's ability to generate the most informative cue in their cuebox and to select the most informative between two given cues. Results show that children's cuebox contains more perceptual cues than young adults'. However, we found no difference between the two age groups in terms of informativeness of the cues generated. Young adults showed the tendency to systematically consider non-perceptual cues more informative than visible cues, whereas children showed the same tendency only in a cue-selection task.

In Chapter 5, finally, I summarized the previous chapters, drawing the general conclusions about what we have learned and outlining some directions for future research.

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Chapter 2

Is Children's and Adults' Categorization Performance Dependent On Object Representation?

Chapter 2

Is Children's and Adults' Categorization Performance Dependent On Object Representation?

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Abstract

This paper investigates developmental differences in how children and adults solve a sequential binary categorization task - the Twenty Questions game - which entails guessing a target from a fixed set of objects by ruling out alternatives with yes/no questions. We ran three experiments to replicate and extend prior work showing that, apart from age-related differences, children's but not adults' inquiry strategies improve if objects are represented at the basic level (e.g., dog) but not if represented at the subordinate level (e.g., Dalmatian) or when the basic level is specified by additional features (e.g., dog, kennel, to wag, collar).

Possible xplanations are that, unlike other representations, basic level objects (a) trigger features that are useful for categorization, and (b) help children identifying more effective questions. To test (a), we ran Study 2 and found that in both children and adults basic-level objects trigger features that help to distinguish among groups of objects (e.g., does it have four legs) rather than object-specific features (e.g., does it bark), which are less suited for efficient categorization. To disentangle (a) and (b), we ran Study 3 and found that, if children do not generate but select questions from a given set, object representations have no effect on categorization performance. This suggests that object representations trigger features more or less suited for categorization but do not help participants to identify more effective questions, an ability that remains tied to cognitive development.

Introduction

In 1911, to be awarded the First Class Boy Scout badge, boys needed to be able to identify "from observation six species of wild birds by their plumage, notes, tracks, or habits" (Boy Scouts of America, 1911, p. 55). For preparation, the *Boy Scouts Handbook* instructed boys to "notice the 'range' of birds in your reference book, and eliminate all those not stated as occurring in your present territory. Notice too, dates of the birds' coming and going, and do not expect to find species at any other time of year than within the dates mentioned. By thus narrowing down the possibilities the task is much simplified" (p. 87). Moreover, the handbook suggested looking for "a match in your reference book by first examining the size of the bird (for example smaller than wren or larger than crow), then the location where the bird is observed (near ground or high up), then the color" (p. 88). This is an example of a fast and frugal tree, a proposed method for modeling object categorization (Berretty, Todd, &

Blythe, 1997; Berretty, Todd, & Martignon, 1999; Martignon, Katsikopoulos, & Woike, 2012).

Formally, this and many other tasks we solve every day are identical. They are sequential binary categorization tasks that can be solved by asking binary yes/no questions (e.g., Is the bird high up?) aimed at categorizing objects as target or nontarget. However, this shared formal structure is often concealed by the domain specificity of objects (objects can be, for example, birds, diseases, or phones) and different levels of abstraction (e.g., distinguishing a bird from other animals or a wren from other birds). We investigated developmental differences in how children and adults solve a sequential binary categorization task, depending on object domain and representation.

The Twenty Questions Game

The development of inquiry strategies in sequential binary categorization tasks has been studied using versions of the Twenty Questions game. This game involves two players, one who asks questions and one who knows and gives the answers to the questions. Specifically, the player asking questions has to guess which object the other player is thinking of. Only yes/no questions are allowed. In its experimental version, participants are presented with a fixed number of objects and their task is to identify the object the experimenter has selected from the set by asking as few questions as possible (see Denney & Denney, 1973; Herwig, 1982; Mosher & Hornsby, 1966; Siegler, 1977; Van Horn & Bartz, 1968). Overall, experimental results show that (a) younger children, as well as elderly people, need more questions to identify the target object, and (b) the inquiry strategies' effectiveness in ruling out nontarget objects improves with age and declines in old age. That is, younger children and elderly people ask almost exclusively questions concerning particular objects (i.e., so-called hypothesis-scanning questions, such as “Is it the dog?”), whereas older children and adults ask more questions about features of the objects that help rule out more than one object at a time (i.e., so-called constraint-seeking questions, such as “Does the animal fly?”). The observed transitions are explained as a shift from a perceptual focus on individual stimuli to a tendency to recognize higher order features that can be used to group and cluster similar objects into categories (e.g., flying animals versus nonflying animals) and, by this, to guide inquiry strategies (Mosher & Hornsby, 1966).

A Matter of Representation

The representation of a problem influences performance. For example, it can potentially distract people (Gerofsky, 1996) and lead them to deviate from norms of formal logic (e.g., Tversky & Kahneman, 1974). But the representation of a problem may also facilitate logical reasoning. For instance, certain representations of statistical concepts, such as natural frequencies (Zhu & Gigerenzer, 2006), tinker cubes[1] (Martignon & Krauss, 2009), and icon arrays (Multmeier, Gigerenzer, & Wegwarth, 2012) have been shown to facilitate probabilistic reasoning and inferences in children.

With respect to categorization of objects, Rosch and colleagues found that preschoolers matched adults’ in classifying objects into basic-level categories such as shoes, chairs, and cars but not yet into superordinate categories such as clothes, furniture, or vehicles (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). Indeed, research has shown that objects represented at the basic level are first named and understood by children because

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[1] Tinker cubes are small plastic cubes of different colors that can be assembled to form towers that encode information about one individual in a population.

they mirror natural kinds and the organization of our knowledge (Rosch, 1978) and emphasize information about the structures, functions, and perceptual characteristics of individual objects (Wisniewski & Murphy, 1989).

Taking Rosch et al.'s (1976) results into account, Herwig (1982) tested preschoolers, first, second, and fifth graders on the Twenty Questions game. Herwig hypothesized that categorization performance would be best when children are given objects represented at the subordinate level (e.g., sportscar, van, raincoat, jacket) because they are familiar with features that differentiate the basic-level categories to which those objects belong (e.g., cars and coats). These higher order features are necessary to ask effective questions in the Twenty Questions game. When given objects represented at the basic level (e.g., car and coat), they should perform worse because children are less familiar with features that differentiate between superordinate categories to which those objects belong (e.g., vehicles and clothes). Indeed, children's performance in the Twenty Questions game improved when given subordinate-level objects, but only if they had the chance to group the objects into categories before starting the game. Without training, in contrast, children's performance was best when objects were represented at the basic level. This suggests that basic-level objects help children come up with higher order features that lead them to ask more effective questions in the Twenty Questions game, without requiring prior training. We sought to replicate and explain the facilitating effect of basic-level objects on categorization performance.

Study 1

To test the robustness of Herwig's (1982) findings, we investigated developmental trends in inquiry strategies by manipulating a) the level of abstraction used to represent objects in a computerized version of the Twenty Questions game. We extended earlier findings by (b) providing objects from only one rather than several superordinate categories (i.e., object domains) and (c) comparing the performance of second and fifth graders with adults.

With respect to the level of abstraction used to represent the objects, we created three different conditions, where objects were represented at (a) the basic level (e.g., dog or doctor), (b) the subordinate level (e.g., Dalmatian or dentist), and (c) the basic level enriched by three features (e.g., for a dog the three features were kennel, wags, collar). We will refer to this condition as the feature-enriched condition. Given Herwig's (1982) results, we expected objects represented at the basic level to facilitate categorization performance and we hypothesized the other two conditions would hinder participants' performance. Objects represented at the subordinate level are taxonomically less general than basic-level objects and imply additional features. Similarly, in the feature-enriched condition there are also three additional features, only here they are given and not implicit. We hypothesized that these features would hinder categorization performance because they are object specific and distract from identifying higher order features that help to differentiate between the objects.

With respect to the domain or superordinate category from which objects were drawn, we presented, unlike in Herwig's study, objects from one of two superordinate categories only: animals or professions. There are two reasons for this decision. First, we decided against including objects from multiple superordinate categories (e.g., vehicles and clothes) to reduce the number of differentiating features. We contend that this is a stronger test of the facilitating effect of basic-level objects. Second, we chose these particular domains because children and adults likely differ in how familiar they are with animals, professions, and their differentiating features. Children, in contrast to adults, naturally focus on perceptual features of objects (Flavell, 1985; John & Sujan, 1990; Springer, 2001; Wartella, 1979), and animals' morphological features, learned in school, are often sufficient to differentiate between them. Differences among professions, on the other hand, are less perceptual in nature and are mainly learned later in life. Thus, with respect to object domains, we expected a decline in performance for children asked to categorize professions, but not for adults.

With respect to developmental differences in general, we expected, based on previous research (e.g., Mosher & Hornsby, 1966), that adults would perform better than older children, and older children better than younger children, both in terms of the number and effectiveness of their questions. We also hypothesized the facilitating effect of the basic-level and hindering effects of the subordinate and feature-enriched conditions to be stronger for children than for adults. Adults are more familiar with differentiating features and should be less impacted by the facilitating effects of basic-level objects as well as the distraction effect due to object-specific features.

Method

Participants. We tested 30 second-grade children (17 females, M_{age} = 7.3 years; SD = 0.7), 24 fifth-grade children (12 females, M_{age} = 9.4 years; SD = 0.5), and 20 adults (9 females, M_{age} = 28.2 years; SD = 2). All children were recruited from the Istituto Sacro Cuore primary school in Livorno, Italy. Adult participants were recruited from the University of Pisa, Italy.

Design and procedure. We asked participants to play three rounds of the Twenty Questions game. In each round, they were presented with 20 cards displayed on a computer screen, each consisting of one or more words that represented an object. Participants were randomly assigned to one of the three experimental conditions: The basic-level, subordinate-level or feature-enriched condition. The objects were taken from either the animals or the professions domain and remained the same for the three rounds. All objects presented to participants are listed in the Appendix, sorted by condition and domain.

The computer randomly selected one from the set of 20 objects. Participants had to ask the experimenter yes/no questions to identify this object. Open questions such as "What kind of food does the animal eat?" were not answered or considered in the analyses. After answering a yes/no question, the experimenter crossed out those objects the answer ruled out. The eliminated objects turned darker on the screen to help participants focus on the remaining objects. A round was over when only one object was left or the target object was identified.

Participants were given 60 points at the outset and had to pay 1 point for each question they asked. Participants were given 5 points for identifying the target object. The score was continually updated and appeared in the upper right corner of the screen. Participants were told that the three players with the highest score would be awarded a box of colored pencils (children) or a 20-euro Amazon gift card (adults).

Dependent measures. Results were analyzed with respect to developmental differences on three outcomes: (1) the number of questions needed to reach the solution; (2) their effectiveness, measured in terms of the information gain of the questions asked; and (3) the type of questions asked. We will explain Outcomes 2 and 3 in turn.

Following previous research on the Twenty Questions game (Nelson, Divjak, Martignon, Gudmundsdottir, & Meder, 2012), we used information gain to measure the effectiveness of the questions asked (see also Nelson, 2005; Oaksford, & Chater, 1994; Oaksford, & Chater, 1996). As defined within the framework of information theory, information gain (Lindley, 1956) refers to the expected reduction of entropy (Shannon, 1948). Imagine 15 animals and the question "Can this animal fly?" that splits the 15 objects into 5 flying and 10 nonflying animals. To measure its information gain I, we subtract the posterior from the prior entropy. The prior entropy for 15 objects $H_{\text{prior}} = \log_2(15) = 3.91$. If the target animal is a bird, then the posterior entropy $H_{\text{fly}} = \log_2(5) = 2.32$; if not, $H_{\text{not fly}} = \log_2(10) = 3.32$. Thus, on average the posterior entropy $H_{\text{posterior}} = (5/15 * 2.32) + (10/15 * 3.32) = 2.98$, and the question's information gain $I = H_{\text{prior}} - H_{\text{posterior}} = 3.91 - 2.98 = 0.93$. According to this measure, the maximum information gain of a question is 1.0, obtained by a question that splits the remaining objects in half.

Regarding Outcome 3, we followed the previous literature (Denney & Denney, 1973; Herwig, 1982; Mosher & Hornsby, 1966) and coded the questions as hypothesis scanning (i.e., questions concerning particular objects, as in "Is it the dog?"), constraint seeking (i.e., questions concerning features useful for splitting the remaining objects, as in "Does it have four legs?"), or pseudoconstraint seeking (i.e., questions concerning features related to only one object, as in "Does it bark?"). Of course, the three types of outcomes are correlated. In particular, both hypothesis-scanning and pseudoconstraint-seeking questions yield lower information gain than constraint-seeking questions so that, on average, inquiry strategies based on the former would require more questions to reach the solution.

Results

For each dependent measure, we ran a repeated-measures analysis of variance (ANOVA), with the results of three Twenty Question games as the within-subject factor and age group, representation, and object domain as between-subjects variables. In general, we found no significant within-subject effects, that is, no learning during the three rounds.

Number of questions. As expected, we found a main effect for age group, $F(2,56) = 10.15$, $p < .001$, $\eta^2 = .27$, with post hoc analyses showing that adults needed fewer questions to reach the solution ($M_{\text{adults}} = 4.4$; $SD = 1$) than children ($M_{\text{younger\_children}} = 7.3$; $SD = 4.4$; $M_{\text{older\_children}} = 6$; $SD = 3.1$). Although we found no main effect or interactions for object domain or representation, children seemed to be more sensitive to representation than adults, who needed a similar number of questions independent of condition (see Figure 1).

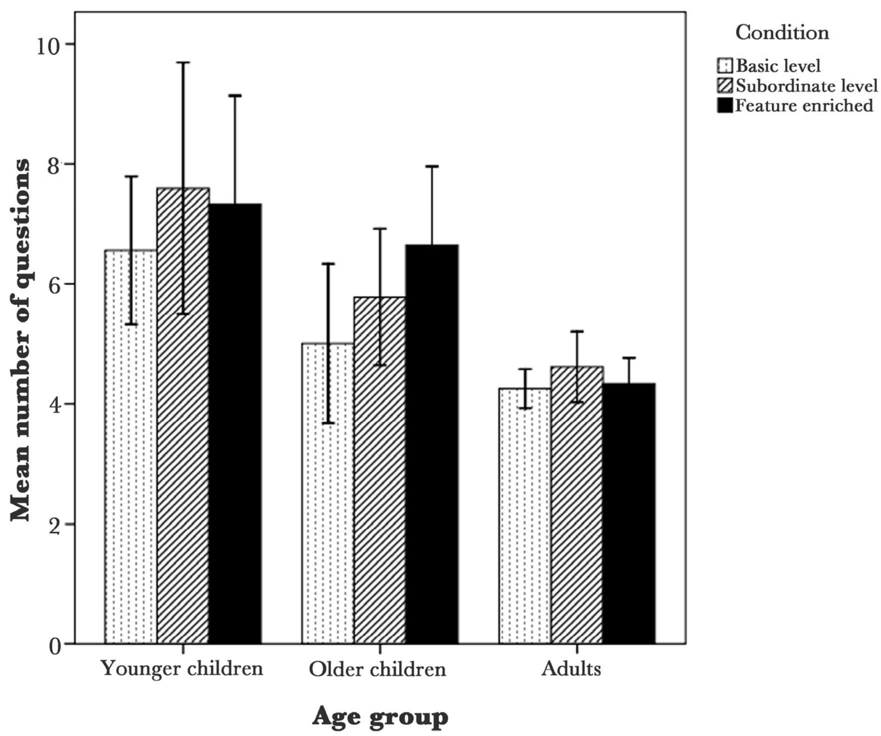


Figure 1. Number of questions needed to reach the solution, by domain (animals, professions) and condition (basic level, subordinate level, and feature enriched). Error bars indicate standard errors.

For both animals and professions, younger and older children tended to need fewer questions in the basic-level condition ($M_{\text{younger\_children}} = 6.8$; $SD = 3.7$; $M_{\text{older\_children}} = 5$; $SD =$

2.7) compared to the feature-enriched ($M_{younger\_children}$ = 7.6; *SD* = 4.5; $M_{older\_children}$ = 6.6; *SD* = 3.5) and subordinate-level ($M_{younger\_children}$ = 8.2; *SD* = 5.2; $M_{older\_children}$ = 6; *SD* = 2.8) conditions

Information gain. As for the number of questions, we found a main effect for age group, $F(2,56) = 45.6$, $p < .001$, $\eta^2 = .62$. Post hoc analyses confirmed developmental differences in terms of information gain. Adults asked questions with higher information gain (M_{adults} = 0.9; *SD* = 0.09) than older children ($M_{older\_children}$ = 0.68; *SD* = 0.17) and older children asked questions with higher information gain than younger children ($M_{younger\_children}$ = 0.52; *SD* = 0.22).

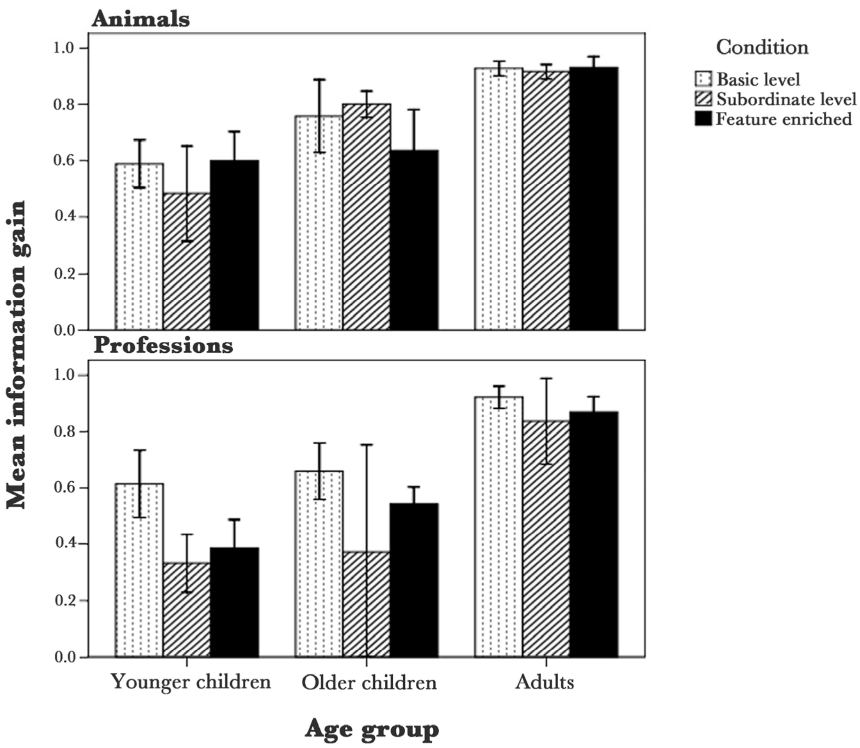
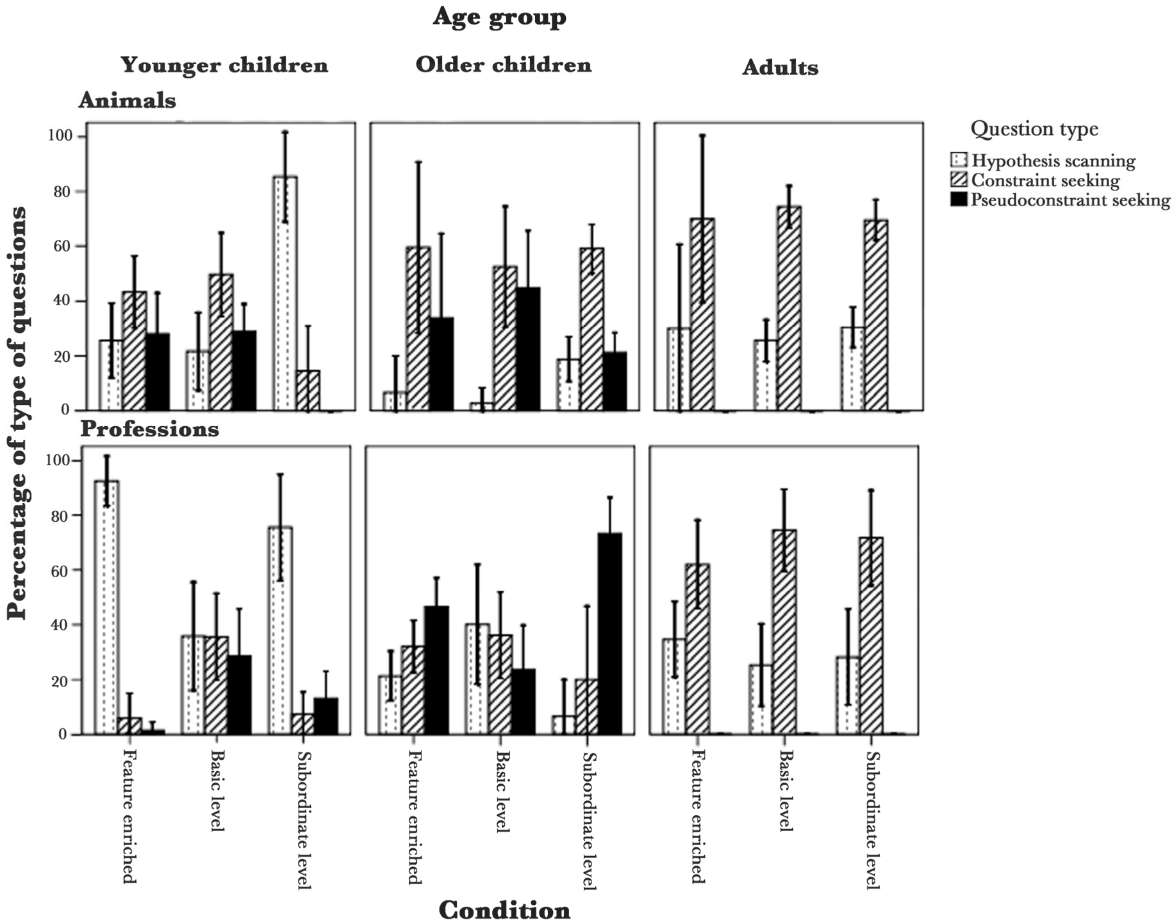


Figure 2. Average quality of participants' questions (in terms of information gain), by domain (animals, professions) and condition (basic level, subordinate level, and feature enriched). Error bars indicate standard errors.

We also found a main effect of object domain, $F(1,56) = 10.7$, $p = .002$, $\eta^2 = .16$, with participants asking questions with higher information gain in the animals than in the professions domain ($M_{\text{animals}} = 0.74$; $SD = 0.21$; $M_{\text{professions}} = 0.61$; $SD = 0.25$). For this reason, in Figure 2 we display information gain separately for the two domains.

Moreover, the analysis revealed a main effect of representation, $F(2,56) = 5.1$, $p = .009$, $\eta^2 = .15$. Post hoc analyses confirmed the facilitating effect of basic-level objects in that participants asked questions with higher information gain when objects were represented at the basic level ($M_{\text{basic-level}} = 0.73$; $SD = 0.22$) compared to the feature-enriched ($M_{\text{feature-enriched}} = 0.63$; $SD = 0.21$) or subordinate-level ($M_{\text{subordinate-level}} = 0.67$; $SD = 0.27$) conditions. We did not find any interaction effects. Similar to results obtained in terms of the number of questions asked, results indicate that children tended to be more sensitive to representation than adults (Figure 2).

Question type. Figure 3 shows the percentage of the type of questions asked by domain and condition. A repeated-measures ANOVA with the proportion of constraint-seeking questions of all the questions asked as dependent variable found main effects for all between-subjects variables, that is, age group, $F(2,56) = 28$, $p < .001$, $\eta^2 = .5$, representation, $F(2,56) = 3.4$, $p = .041$, $\eta^2 = .11$, and domain, $F(1,56) = 10.6$, $p = .002$, $\eta^2 = .16$. Post hoc analyses of the main effect of age group confirmed earlier research in that adults asked a higher proportion of constraint-seeking questions (70%; $SD = 22\%$) than older children (46%; $SD = 28\%$), who asked a higher proportion of constraint-seeking questions than younger children (29%; $SD = 29\%$). The main effect of object domain showed that participants would more readily generate constraint-seeking questions in the animals domain (56%; $SD = 29\%$) than in the professions domain (36%; $SD = 33\%$). Finally, post hoc analyses of the main effect for representation confirmed our hypothesis that participants would generate a higher proportion of constraint-seeking questions in the basic-level condition (54%; *SD* = 31%) than in the feature-enriched (41%; *SD* = 31%) and subordinate-



level (43%; *SD* = 33%) conditions.

Figure 3. Percentage of participants' questions by question type (hypothesis scanning, constraint seeking, and pseudoconstraint seeking), by domain (animals, professions) and condition (basic level, subordinate level, and feature enriched).

The same repeated-measures ANOVA with the proportion of hypothesis-scanning questions of all the questions asked as dependent variable revealed a main effect of age group, $F(2,56) = 15.2$, $p < .001$, $\eta^2 = .35$. The analysis revealed no other main effects but we did find an interaction effect of age group and representation, $F(4,56) = 3.4$, $p = .014$, $\eta^2 = .2$. Post hoc analyses showed that younger children asked the lowest proportion of hypothesis-seeking questions in the basic-level condition (28%; *SD* = 27%) compared to the feature-enriched (54%; *SD* = 40%) and subordinate-level (78%; *SD* = 38%) conditions.

We also ran a repeated-measures ANOVA with the proportion of pseudoconstraint-seeking questions of all the questions asked as dependent variable and found a main effect of age group, $F(2,56) = 17$, $p < .001$, $\eta^2 = .38$, with post hoc analyses showing that older children (35%; *SD* = 27%) asked a higher proportion of pseudoconstraint-seeking questions than younger children (20%; *SD* = 20%), who asked a higher proportion of pseudoconstraint-seeking questions than adults (0%; *SD* = 0%).

Discussion

As hypothesized, objects represented at the basic level facilitated children's but not adults' categorization performance. When given basic-level objects, children needed fewer questions to reach the solution, asked more informative questions, and came up with a higher proportion of constraint-seeking questions. Results suggest that basic-level objects trigger children's knowledge about higher order features that help them differentiate between the objects. In contrast, in the subordinate-level and feature-enriched conditions children may have been distracted by the implied/given features that were specific to the objects. Indeed, these features were not useful for differentiating between the objects within the same superordinate category.

In terms of the effect of object domain, the results suggest that the professions domain was more difficult to categorize than the animals domain for both children and adults.

From a developmental point of view, the performance pattern we identified confirmed previous findings for the Twenty Questions game (e.g., Denney & Denney, 1973; Herwig, 1982; Mosher & Hornsby, 1966; Siegler, 1977; Van Horn & Bartz, 1968). First, the number of questions decreased and information gain increased with participant age. Second, the number of constraint-seeking questions increased linearly from younger to older children to adults. Third, younger children generated the most hypothesis-scanning questions, whereas older children asked the most pseudoconstraint-seeking questions. This developmental difference was particularly strong in the more difficult professions domain and in the subordinate-level and feature-enriched conditions. Interesting from a developmental perspective, adults never asked pseudoconstraint-seeking questions. This finding suggests that older children stopped relying on the hypothesis-seeking strategy but did not yet have the necessary knowledge or skills to ask constraint-seeking questions (see also Mosher & Hornsby, 1963). Thus, they resorted to pseudoconstraint-seeking questions, which might look more like what adults would ask but are in fact only as effective as hypothesis-scanning questions.

In summary, results of Study 1 show that the skills necessary for applying the more efficient constraint-seeking strategy are bound to age-related cognitive differences. However, they also suggest that the facilitating effect of basic-level objects is due to the type of features this level of representation triggers. In the second study, we sought to test the hypothesis that basic-level objects trigger more higher order features than subordinate and feature-enriched objects.

Study 2

To test the hypothesis that basic-level objects trigger more higher-order features than subordinate or feature-enriched objects, we asked second graders, fifth graders, and adults to generate as many features as they could think of to differentiate a given object (e.g., dog or doctor) from any other object in the same superordinate category (i.e., animals or professions). Assuming developmental differences in general knowledge about the given objects, we expected adults to be able to generate more features than older children, and older children to list more features than younger children.

With respect to the effect of representation, we expected the types of features triggered by the representations to differ qualitatively. We hypothesized that participants in the basic-level condition would tend to generate more *higher order* features (e.g., "Dogs have four legs" and "Doctors have a degree"). When given objects represented at the subordinate level, participants would generate more features that were *specific* to the particular animal (e.g., "Dalmatians have black and white spots") or profession (e.g., "A dentist fixes teeth"), rather than higher order features (e.g., "Dalmatians have four legs" or "Dentists have a degree"). In the feature-enriched condition participants would generate features that were similar to the three provided, so again specific to the particular animal or profession. Moreover, the findings of Study 1 led us to expect participants to generate more higher order features when given objects from the animals than the professions domain.

Unlike object specific features, higher order features are not unique to the particular object given but apply to multiple objects in the superordinate category (i.e., to other animals or professions). These features can therefore be used for asking constraint-seeking questions that rule out multiple objects at a time to quickly converge on the target object.

Method

Participants. We tested 43 second-grade children (21 females, M_{age} = 7.5 years; *SD* = 0.5), 60 fifth-grade children (23 females, M_{age} = 9.8 years; *SD* = 0.6), and 33 adults (15 females, M_{age} = 25.5 years; *SD* = 5.4). All children were recruited from the Fondazione San Carlo Borromeo primary school in Livorno, Italy. Adult participants were recruited from the University of Pisa, Italy.

Design and procedure. Participants were randomly assigned to one of the three experimental conditions: The basic-level, subordinate-level or feature-enriched condition. Participants were given one object for each domain in random order and instructed to "please name as many features as you can think of that make the [object] different from other animals (or professions)." For each object given, participants had 5 minutes to verbally list all the features they could think of.

Children who completed the study received a box of colored pencils. Adult participants were entered in a lottery for a chance to win a 30-euro Amazon gift card.

Dependent measures. We analyzed the features generated with respect to (a) the number of features generated and (b) the type of features generated. Apart from higher order features (e.g., "dogs/Dalmatians have four legs and bark" or "doctors/dentists have a degree") and specific features (e.g., "dogs bark" or "Dalmatians have black and white spots"; "doctors operate" or "dentists fix teeth"), we identified a third type of feature. These features were exclusively used by younger and a few older children who lacked knowledge of differentiating features pertaining to the objects they were given. Instead, to differentiate the objects, they stated what a given object was not, by picking other objects from the same superordinate category (e.g., “It is not a snake” for the dog, or “It is not an architect” for the doctor). We refer to this type of feature as a *contrast* feature.

Results

We had given the two feature-enriched objects to 16 of the second-grade and 17 of the fifth-grade children when we decided to discontinue running the feature-enriched condition. Children were thoroughly confused by the three features. Instead of identifying additional differentiating features, they simply rephrased the three features provided with the basic-level object. Given that no additional features were generated, the results from this condition are relevant to answering our research question but were excluded from further analyses.

Number of features. We ran a repeated-measures ANOVA with domain as the within-subject factor and age group and representation as between-subjects variables. As expected given the results of Study 1, we found a main effect of domain, $F(1,97) = 37.4$, $p < .001$, $\eta^2 = .28$, with participants generating more features when asked to differentiate dogs from other animals ($M_{\text{animals}} = 4.1$; $SD = 1.7$) than doctors from other professions ($M_{\text{professions}} = 3.1$; $SD = 1.6$). We also found the hypothesized main effect of age group, $F(2,97) = 4.7$, $p = .011$, $\eta^2 = .09$, with post hoc analyses showing that adults and older children ($M_{\text{adults}} = 3.9$; $SD = 1.4$; $M_{\text{older\_children}} = 3.8$; $SD = 1.6$) generated more features than younger children ($M_{\text{younger\_children}} = 2.9$; $SD = 0.7$).

The analysis also revealed the expected main effect of representation, $F(1,97) = 5.4$, $p = .022$, $\eta^2 = .05$, with participants generating more features when given basic-level objects ($M_{\text{basic-level}} = 3.9$; $SD = 1.4$) than subordinate-level objects ($M_{\text{subordinate-level}} = 3.2$; $SD = 1.3$). Finally, we found an interaction between domain and representation, $F(1,97) = 9.9$, $p = .002$,

$\eta^2 = .1$. The difference between the number of features generated in the basic-level and the subordinate-level condition was larger in the animals ($M_{\text{basic-level}} = 4.7$; $SD = 1.7$; $M_{\text{subordinate-level}} = 3.5$; $SD = 1.4$) than in the professions ($M_{\text{basic-level}} = 3.2$; $SD = 1.6$; $M_{\text{subordinate-level}} = 3$; $SD = 1.6$) domain.

Type of feature. Figure 4 displays the proportions of the three types of features generated—higher order, specific, and contrast—based on object domain and representation. As hypothesized, in the basic-level condition of both domains, participants generated a higher proportion of higher order features, of all the features generated, than in the subordinate-level condition. In the subordinate-level condition, adults and older children mainly generated specific features.

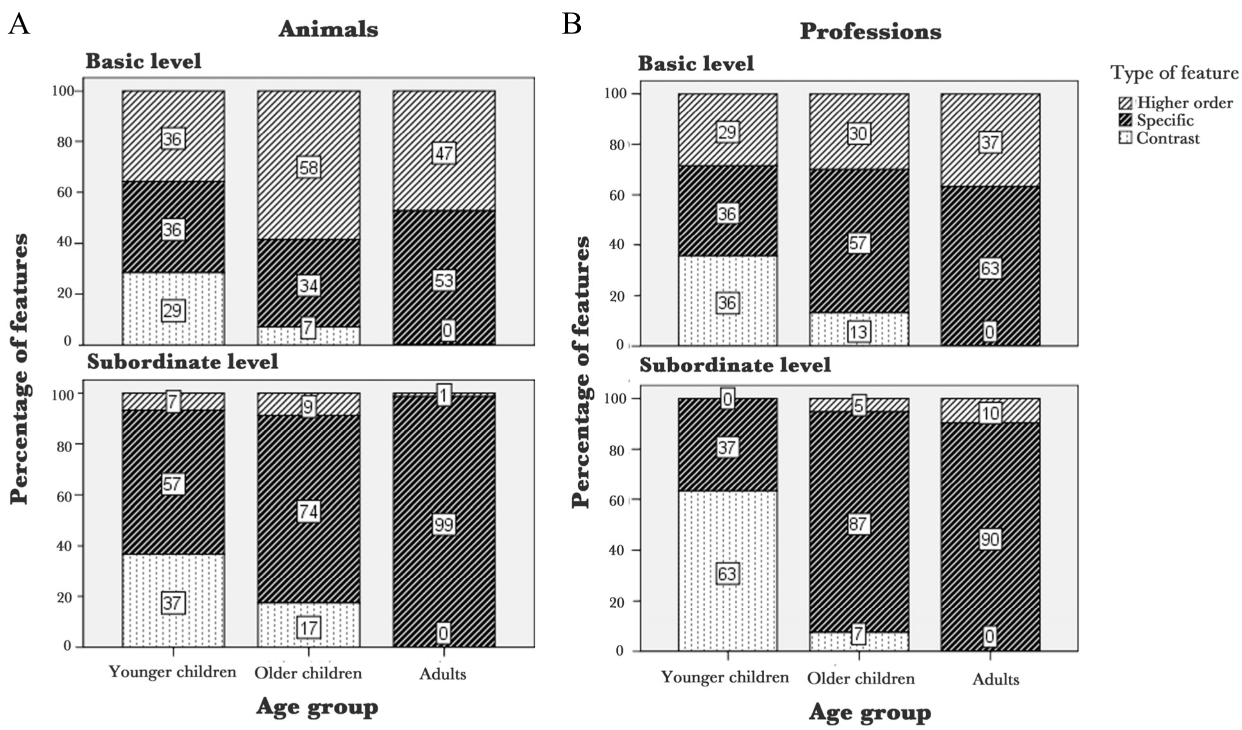


Figure 4. Percentage of features generated by age group, feature type (higher order, specific, and contrast), and condition (basic level and subordinate level) in (A) the animals domain and (B) the professions domain.

The main difference between adults and children is that few of the features generated by older children and many of the features younger children generated were contrast features. The proportion of contrast features was higher in the subordinate-level condition of both domains.

Discussion

Study 2 was designed to test the hypothesis that basic-level objects trigger more higher order features than subordinate-level or feature-enriched objects. Apart from the expected domain and age group effects, we found that the features generated differed quantitatively and qualitatively by the objects' representation. We had to discontinue the feature-enriched condition because children were unable to come up with differentiating features other than those already provided. When the given objects were represented at the subordinate level (e.g., Dalmatian), participants rarely generated higher order features pertaining to the objects' basic-level category (e.g., "Dalmatians have four legs"). Moreover, for younger children, and also older children in a few cases, finding differentiating features in the subordinate-level condition was particularly difficult. Instead, they described what the object was *not* by contrasting it with any other object from the same superordinate category (e.g., "It's not the snake").

Results of Study 2 support the hypothesis that children's performance on the Twenty Questions game is in part facilitated/hindered by the objects' representation because it triggers certain types of features. Whereas basic-level objects trigger more higher order features that can be used to ask more general constraint-seeking questions, subordinate-level and feature-enriched objects trigger specific features that may lead to hypothesis-scanning or pseudoconstraint-seeking questions.

The type of questions asked depends not only on knowledge of differentiating features but also on the ability to identify the most effective among them (Brown, 1978; Gelman, 1978). With Study 3 we sought to test the extent to which the object representation facilitates the generation of higher order features versus the ability to select these features for asking constraint-seeking questions.

Study 3

In Study 2, we found that domain and representation had an impact on children's and, to some extent, adults' ability to come up with higher order features, which are needed to ask constraint-seeking questions. But do domain and representation also help in identifying those features that should be used for effective inquiry strategies? If not, eliminating differences in knowledge of higher order features should make the effects of domain and representation disappear, even though we should still find developmental differences between age groups (Mosher & Hornsby, 1966).

To make the knowledge difference disappear, we used the same setup as in Study 1, but instead of letting participants generate questions we provided a choice set made up of constraint-seeking, hypothesis-scanning, and pseudoconstraint-seeking questions. Thus, participants did not need to come up with features but only had to select the questions with the features they considered most effective.

Method

Participants. We tested 36 second-grade children (18 females, M_{age} = 7.7 years; *SD* = 0.5), 37 fifth-grade children (22 females, M_{age} = 9.7 years; *SD* = 0.6), and 41 adults (17 females, M_{age} = 27.5 years; *SD* = 2.1). All children were recruited from the Fondazione Sacro Cuore primary school in Livorno, Italy. Adult participants were recruited from the University of Pisa, Italy.

Design and procedure. Participants were presented with a computerized version of the Twenty Question game similar to the one used in Study 1. Participants were randomly assigned to one of the three experimental conditions: The basic-level, subordinate-level or feature-enriched condition. They played the same experimental condition in two games: In one game the objects were taken from the animals domain, and in the other from the professions domain (see the Appendix). The order in which the domains were presented was random. Participants could only ask three questions for each game. For each question, they could select from among a set of six options. The six options included always two constraint-seeking questions (i.e., a perfect question, splitting the remaining objects into two equal groups, and a question with lower information gain, splitting the remaining objects into two groups of unequal size), two pseudoconstraint-seeking questions, and two hypothesis-scanning questions.

After participants had asked the third question, they had to guess the object the computer had randomly chosen by selecting one of the remaining objects. Children who guessed the right object in both games received a box of colored pencils. Adults who guessed both the objects were entered in a lottery in which the winner would be awarded a 30-euro Amazon gift card.

Results

As for Study 1, we ran a repeated-measures ANOVA with question number and domain as within-subject factors, and representation and age group as between-subjects variables for all dependent measures.

Information gain. We found no effect of domain or representation but a main effect of age group, $F(2,106) = 19.2$, $p < .001$, $\eta^2 = .27$. Adults selected questions with higher information gain ($M_{\text{adults}} = 0.9$; $SD = 0.03$) than older children ($M_{\text{older\_children}} = 0.75$; $SD = 0.04$), who selected questions with higher information gain than younger children ($M_{\text{younger\_children}} = 0.63$; $SD = 0.03$).

The analysis also showed a main effect of question number, $F(2,106) = 4.88$, $p = .022$, $\eta^2 = .04$. For consecutive questions there was a general improvement in information gain, because the information gain of the hypothesis-scanning and pseudoconstraint-seeking questions increased as the remaining set of objects got smaller.

Question type. The analysis showed a main effect of age group on the proportion of constraint-seeking questions of all the questions selected, $F(2,106) = 21.1$, $p < .001$, $\eta^2 = .5$. Post hoc analyses showed that adults selected a higher proportion of constraint-seeking questions (92%; $SD = 4\%$) than older children (68%; $SD = 5\%$), who in turn selected a higher proportion of constraint-seeking questions than younger children (47%; $SD = 5\%$).

Similarly, with the proportion of hypothesis-scanning questions of all the questions selected as a dependent variable, we also found a main effect of age group, $F(2,106) = 19.5$, $p < .001$, $\eta^2 = .27$. Post hoc analyses showed that younger children selected higher proportion of hypothesis-scanning questions (36%; $SD = 4\%$) than older children (23%; $SD = 4\%$), who in turn selected higher proportion of hypothesis-scanning questions than adults (6%; *SD* = 3%).

With respect to the proportion of pseudoconstraint-seeking questions of all the questions selected, we again found a main effect of age group, $F(2,106) = 10.4$, $p < .001$, $\eta^2 = .16$. Post hoc analyses revealed that younger children selected higher proportion of pseudoconstraint-seeking questions (18%; *SD* = 3%) than older children (10%; *SD* = 3%), who in turn selected higher proportion of pseudoconstraint-seeking questions than adults (2%; *SD* = 2%). We found no other main or interaction effect of domain or representation.

General Discussion

In Study 3, we found that when children did not have to generate features and questions to categorize objects, the effects of domain and object representation did not emerge. This suggests that the facilitating effect of basic-level objects and the hindering effect of subordinate and feature-enriched objects (Study 1) emerge only because of the types of features they trigger (Study 2). The representation does not help participants to identify and select more effective questions from a given set.

These abilities seem to develop across the lifespan, as indicated by the persistent effect of age group across all Studies. Younger children showed the worst performance across all Studies. Compared to Study 1, where they had to generate features and questions, the main differences to Study 3 was that they asked less hypothesis-scanning questions (51% in Study 1 versus 26% in Study 3) and more constraint-seeking questions (29% in Study 1 versus 47% in Study 3). The proportion of pseudoconstraint-seeking questions remained almost identical (20% in Study 1 versus 18% in Study 3). This suggests that although younger children tend to prefer constraint over hypothesis-scanning questions, they are unaware that pseudocontraint-seeking questions are ineffective for categorizing.

For older children the proportion of hypothesis-scanning questions remained identical (19% in Study 1 versus 23% in Study 3). In Study 1, they resorted to pseudoconstraint-seeking questions in 35% of the cases, because, we hypothesized, they realized that hypothesis-scanning questions are not effective but were not yet able to generate features for asking constraint-seeking questions. Study 3 seems to confirm this hypothesis. When asked to choose from a set of question, only 10% of the questions older children selected were pseudoconstraint-seeking, whereas the majority of the questions they selected were constraint-seeking (68% in Study 3 versus 46% in Study 1). This indicates that older children are able to recognize and select the better constraint-seeking features once they see them.

Some Practical Implications and Future Directions

The results of our experiments suggest that the setup of a categorization task (generation versus selection of inquiry questions) and the representation of objects impact children's categorization performance. That is, the facilitating effect of objects represented at the basic level and the hindering effect of subordinate-level and feature-enriched objects only emerged in Study 1, where participants had to generate inquiry questions. Given that in everyday life we are rarely–if ever–presented with a set of questions to choose from, basic-level objects are one effective way to facilitate categorization performance in children. Future research should investigate whether and how basic-level objects can be used to explain and teach children more effectively how to identify good categorization questions, independent of the domain or representation of the objects.

To increase the ecological validity of the categorization task, our findings may also be extended to situations where the set of potential target objects is not given or constrained to a set of 20 alternative objects. Given that in real world situations we are rarely presented with a list of well-defined alternatives to select among, this setup will allow us to explore how people dynamically construct and update a set of possible alternatives while progressing in a categorization task. Further, this investigation would allow us to examine at which level of abstraction and representation children and adults naturally think when building a set of alternatives from scratch.

Author Note

We would like to thank all the students from Fondazione Sacro Cuore, Fondazione San Carlo Borromeo and Istituto Sacro Cuore of Livorno, and University of Pisa, Italy, who participated in our study, as well as Simona Preti, who helped in the organization. We would also like to thank Claudia Mazzeranghi for helping us run the experiments, as well as Anita Todd for her support and helpful comments.

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Appendix

Objects Used in the Experiment, Listed by Domain (Animals, Professions) and Condition (Basic level, Subordinate, Feature-Enriched Basic Level)

Basic level	Subordinate level	Feature-enriched basic-level			
		Animals domain			
Sheep	Lamb	Sheep	Pasture	To bleat	Wool
Dog	Dalmatian	Dog	Kennel	To wag	Collar
Cat	Persian	Cat	Pillow	To purr	Claws
Cow	Calf	Cow	Stable	To moo	Bells
Horse	Pony	Horse	Stable	To neigh	Saddle
Fly	Gnat	Fly	Poo	To hum	Antennae
Bird	Canary	Bird	Nest	Beak	Feathers
Dinosaur	Tyrannosaurus	Dinosaur	Prehistoric	Intimidating	Sharp teeth
Snake	Viper	Snake	Bush	To slither	Forked tongue
Bear	Panda	Bear	Den	To hibernate	Fur
Monkey	Gorilla	Monkey	Tree	To climb	Vine
Bee	Queen bee	Bee	Hive	To make honey	Pollen
Spider	Black widow	Spider	Web	To weave	Eight-legged
Butterfly	Moth	Butterfly	Flowers	To flutter	Colorful wings
Chicken	Chick	Chicken	Coop	To lay eggs	Crest
Pig	Boar	Pig	Sty	To smell	Snout
Frog	Tadpole	Frog	Pond	To croak	Green
Crab	Warty crab	Crab	Rock	To pinch	Claws
Fish	Sole	Fish	Sea	Bait	Fins
Rabbit	Hare	Rabbit	Wood	To burrow	Long ears
		Professions domain			
Doctor	Dentist	Doctor	The E. R.	To evaluate	Stethoscope
Teacher	Kindergarten teacher	Teacher	Classroom	To explain	Roster
Cook	Confectioner	Cook	Restaurant	To taste	Ladle
Police Officer	Detective	Policeman	Station	Investigation	Distinctive
Singer	Soprano	Singer	Stage	Tone deaf	Microphone
Breeder	Shepherd	Breeder	Farm	To milk	Work gloves

Basic level	Subordinate level	Feature-enriched basic-level			
Athlete	Cyclist	Athlete	Stadium	To train	Sports bag
Photographer	Photojournalist	Photographer	Exhibition	To focus	Camera
Musician	Flautist	Musician	Orchestra	To tune	Instrument
Actor	Theater actor	Actor	Dressing room	To act	Script
Soldier	Parachutist	Soldier	Barracks	To defend	Machine gun
Farmer	Winegrower	Farmer	Field	To hoe	Tractor
Craftsman	Carpenter	Craftsman	Laboratory	To draft	Tools
Driver	Bus driver	Driver	Garage	To park	License
Circus performer	Juggler	Circus performer	Tent	To surprise	Costume
Politician	Mayor	Politician	Parliament	To discuss	Tie
Drawer	Cartoonist	Drawer	Desk	To erase	Pencil
Journalist	Sports reporter	Journalist	Editorial office	To interview	Note pad
Coach	Soccer coach	Coach	Bench	To encourage	Stopwatch
Salesman	Florist	Salesman	Shop	To earn	Receipt

Chapter 3

Make Your Own Kind of Cues

Chapter 3

Make Your Own Kind Of Cues

When Children Make More Accurate Inferences Than Adults

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Abstract

In everyday decision making we do not always have the luxury of using certain knowledge but often have to rely on cues, that is, pieces of information that can aid reasoning. Are children capable of focusing on the most informative cues? Previous research on cue-based inference suggests contradicting answers that we argue to be rooted into the design used. We hypothesize that providing participants with a fixed set of cues from which to choose handicaps children because it requires assessing and comparing the informativeness of exogenously given cues they might not be familiar with or would not have chosen if allowed to generate their own cues. We tested second-, third-, and fifth-grade

children, and young adults on inference problems (which of two real cars is more expensive and which of two real cities has more inhabitants), manipulating whether cues were generated or given. Results show that, only when generating their own cues, younger children matched older children and young adults in accuracy, or even outperformed them. Younger children did so by generating cues that were as informative as those generated by older children and young adults.

Introduction

In everyday decision making we do not always have the luxury—the time, the knowledge, the cognitive and computational resources—of using certain knowledge but instead have to rely on cues. For our purposes a cue is a piece of information, such as a question, feature, or concept that is useful for making decisions. We focus here on a special kind of decision, an inference (e.g., which of two real cars is more expensive or which of two real cities has more inhabitants) for which there is an objective answer (one city *is* larger, or one car *is* more expensive). Decision makers have to reach the answer by inferring the relationship between the information collected and a criterion (in this case, the size of a city or the price of a car).

In this paper we address the following question: Are children capable of focusing on the most informative cues? Most research on children's decision making and cue-based inferences has focused on the number of cues children consult, concluding that children rely often on one or a few cues when making their choices or inferences (Bahn, 1986; Wartella, 1979). Because strategies that look at only one piece of information are often easier and quicker, and sometimes more accurate (Gigerenzer, Todd, & the ABC Research Group, 1999), than strategies that rely on more cues, this behavior could be an adaptive response to the cognitive load experienced by children when making decisions (Gregan-Paxton & Roedder John, 1995; Klayman, 1985) or to the general problem of maximizing total utility (Bereby-Meyer, Assor, & Katz, 2004; Mata, von Helversen, & Rieskamp, 2011).

Only a few studies, however, have attempted to investigate the quality of the cues children base their decisions or inferences on. Bereby-Meyer et al. (2004) asked children aged 8–9 and 12–13 years to choose among consumer products, such as bicycles or watches, after being given descriptions of the products' cue values. The authors found that the few cues children based their decisions on were not randomly chosen but were the most important ones. Because in this study each child was asked to personally rate the importance of the cues, children selected the cue that, according *to them,* was the most informative, choosing the alternative that had the highest value on that cue and ignoring all other cues and their values (this strategy is a fast and frugal heuristic because it requires little information and computation; see Gigerenzer et al., 1999).

In a more recent study, Mata et al. (2011) asked 9- to 12-year-olds to infer which of two cars would win a race, after providing descriptions of the cars' cue values (e.g., horsepower or number of cylinders). Here, the children did not personally rate the cues, which were probably unfamiliar to at least some of them. Mata et al. concluded that less than 30 of the children spontaneously used strategies that employed one or just a few cues. The authors suggested that children do not use such strategies because they cannot easily focus on the most informative cues. We propose that the contradictory results and conclusions obtained by Bereby-Mayer et al. (2004) and Mata et al. (2011) might be the result of different experimental designs being adopted. A thought experiment might help illustrate the problem.

Imagine that you are faced with the following inference: Which of two cities is more populous, City 1 or City 2? What would you like to know about these cities before answering? Now suppose you are faced with the same problem but this time you are given a set of available cues whose values you can look up: number of buildings, density of population, tourism, altitude, and area. Is the information you asked for in the first instance included in the set now presented to you? Would you still choose the same information you *generated* in the first place, or would you now select something else you did not think of, realizing it might be more predictive of the population of a city?

We argue that the difference between these two testing methodologies might be crucial, and that choosing from among a set of cues might be problematic for children, even though this is the method traditionally used for testing cue-based inferences. First, it requires the children to assess and compare the informativeness of exogenously given cues they might not be familiar with, or the meaning of which they might not know (such as density of population, in our example). Second, a set of cues to choose among is a necessarily constrained selection that might not include all the possible useful information one could come up with. We argue that, to test children's ability to base their choices on informative cues, a more suitable methodology is required. Thus, in the present study we did not provide participants with cues but instead prompted them to *generate* their own cues by letting them ask anything they wanted to about the objects (e.g., cities) they had to make inferences about. Participants would be familiar with the cues they themselves had generated. The process of searching for information by asking questions from scratch has been thoroughly studied (Graesser & McMahen, 1993; Graesser & Olde, 2003), also as a mechanism for cognitive development and knowledge acquisition (Chouinard, 2007; Vosniadou, 1994). However, to the best of our knowledge, it has never been used in researching cue-based decision making.

In this study, we tested children and young adults by manipulating whether cues were generated (Study 1) or given (Study 2), to investigate if and how these two designs would change the results. We hypothesized that when free to generate their own cues, (a) participants would consult less information, both because generating cues might be more effortful than selecting them, and because they would be more confident in what they had determined were the most informative cues; (b) each age group would generate different cues, because being at different developmental phases, participants would know a different number of cues of different quality; and (c) because of (b), children could generate cues that are objectively as informative as the cues generated by young adults and thus would be able to match the accuracy of young adults.

Study 1: Free-Generation of Cues

Method

Participants. The experiment involved 66 participants: 17 children in the second and third grade (9 females, M_{age} = 7.8 years, SD = 0.39) and 27 children in the fifth grade (14 females, M_{age} = 9.9 years, SD = 0.61) of a primary school[2] in Livorno, Italy, and 22 young adults (12 females, M_{age} = 17.9 years, SD = 0.75) recruited from a high school[3] in Livorno. The participants were all born in Italy and belonged to various social classes. The results of another 11 participants were excluded because of experimental errors or equipment malfunction.

Design and procedure. The experiment was run on a computer and each session

[2] Fondazione Sacro Cuore, Ardenza, Livorno.

[3] Liceo Scientifico "F. Cecioni", Livorno.

consisted of eight trials. On each trial, participants were presented with two objects and asked to infer which object had the higher value on a criterion specified in the instructions for that trial. There were two possible criteria: The population of a city and the price of a car. For example, in one trial the participants had to infer whether Milan or Venice was more populous, and in another trial the participants had to infer whether a Doblò or a Panda was more expensive.

Participants received in each trial a different pair of objects, randomly drawn from two environments: The 60 currently most populous Italian cities and 52 cars currently produced by two Italian car manufacturers (Fiat and Alfa Romeo). Our database included for each object its value on the criterion (city population or car price); there were 28 cue values for cities and 20 for cars. The cues were generated before the experiment in a survey with 15 children aged 8–9 years old and 10 adults who did not take part in the experiment. The objects are listed in Table 1, and the cues are listed in Table 2.

In Table 2 we also list cue *success* (Newell, Rakow, Weston, & Shanks, 2004), which we used in analyzing our results. In both experiments the cues generated (Study 1) or selected (Study 2) might be conflicting, meaning that some cues might point to the correct choice, whereas other cues might suggest an incorrect choice. The success of a cue in a task is the probability, in this particular task, that the cue will lead to a correct inference. To compute the success of a cue, it is assumed that if the cue has a higher value on one of the two objects, then this object will be picked, and if the cue has the same value on the two objects, then an object will be picked randomly.

Besides the inference criterion (car-price or city-population), our second independent variable was whether objects were presented with names (i.e., the name of a city or the model of a car) or with generic labels instead of names (i.e., City 1 and City 2 or Car 1 and Car 2).

Finally, there were two trials for each of the four combinations of the two independent variables. These two trials constituted a block, and the order of the four blocks was counterbalanced across participants.

Table 1

The Objects and Their Criterion Values (City Population and Car Price in Euros)

Object	Criterion value	Object	Criterion value	Object	Criterion value	Object	Criterion value
			City-population task				
Roma	2,724,347	Taranto	194,021	Sassari	130,306	Andria	99,249
Milano	1,295,705	Brescia	190,844	Siracusa	124,083	Udine	99,071
Napoli	963,661	Reggio Calabria	185,621	Pescara	123,022	Arezzo	98,788
Torino	908,825	Prato	185,091	Monza	121,280	Cesena	95,525
Palermo	659,433	Parma	182,389	Latina	117,149	La Spezia	95,372
Genova	611,171	Modena	181,807	Bergamo	116,677	Lecce	94,775
Bologna	374,944	Reggio Emilia	165,503	Forlì	116,208	Pesaro	94,197
Firenze	365,659	Perugia	165,207	Vicenza	115,012	Barletta	93,869
Bari	320,677	Livorno	161,095	Trento	114,236	Alessandria	93,676
Catania	296,469	Cagliari	157,297	Giuliano di Campania	113,811	Catanzaro	93,519
Venezia	270,098	Ravenna	155,997	Terni	112,021	Pistoia	89,982
Verona	265,368	Foggia	153,239	Novara	103,602	Brindisi	89,691
Messina	243,381	Salerno	140,489	Ancona	102,047	Torre del Greco	87,735
Padova	211,936	Rimini	140,137	Bolzano	101,919	Pisa	87,398
Trieste	205,341	Ferrara	134,464	Piacenza	101,778	Lucca	84,186
			Car-price task				
Spider	40,851	159 SW Prog.	25,711	500 Lounge	19,401	Idea BlackStar	14,801
Ulysse Emotion	37,251	Multipla Emotion	25,151	Panda 4×4 Cross	18,701	Punto Evo Fun	14,751
GT Q. Verde	34,601	159 Prog.	24,511	500 MJT Lounge	18,601	Grande Punto Actual	13,501
159 Distinctive Q-T	34,151	Croma Act.	24,101	Sedici 4×2 Dynamic	18,501	Panda 4×4	13,351
Croma Emotion	32,601	Multipla Act.	23,151	Bravo Dynamic	18,101	QUBO Act.	13,051
Spider TBi	31,951	Bravo Dualogic Dyn.	22,251	Doblò Act.	18,101	Panda Emotion Eco	12,351
159 Eco Distinctive	31,651	Idea BlackMotion	22,051	Punto Evo Sport	17,901	Punto Evo Act.	11,951
Ulysse Act.	30,701	500 Rock	21,601	147 Moving	17,481	500 Pop	11,701
Brera TBi	29,951	Sedici Dynamic	21,501	500 by DIESEL	17,351	Grande Punto Act.	11,601
Croma Emotion	28,101	Multipla Dynamic	20,951	Idea BlackLabel GPL	17,151	Punto Classic Act.	11,001
GT Prog.	26,551	Bravo Dualogic Dyn.	20,501	Grande Punto Actual Nat. P.	16,201	Punto Classic	10,301

Object	Criterion value	Object	Criterion value	Object	Criterion value	Object	Criterion value
Sedici Experience	26,501	Giulietta Turbo Prog.	20,451	QUBO Dynamic	16,051	Panda Actual Eco	9,001
Giulietta Prog.	25,851	Doblò Dynamic	20,051	Doblò 1.4 Actual	15,101	600	7,951

Table 2

Study 1: The Cues and Their Success in the Two Tasks

Cue	Success	Cue	Success	Cue	Success	Cue	Success
City-population task							
Families	0.93	University	0.76	Airports (overall)	0.64	Seismic danger	0.53
Buildings	0.92	Museums	0.70	Airports (international)	0.64	Regional capital	0.52
Primary Schools	0.87	Universities	0.69	Hotels	0.62	Area	0.52
Preschools	0.83	Density of population	0.67	Average income	0.61	Being a capital city	0.52
Secondary Schools	0.83	Soccer teams	0.66	Age index	0.58	Climate zone	0.52
High schools	0.80	Airports (civilian)	0.65	Stadiums	0.57	Degree days	0.51
Hits on Google	0.77	Tourism (ranking)	0.64	Altitude	0.56	Airports (military)	0.51
Car-price task							
Horsepower	0.88	Width	0.77	Acceleration	0.63	Fuel consumption (mixed)	0.60
Mass	0.85	Fuel tank capacity	0.71	Brand	0.63	Number of seats	0.58
Capacity	0.84	Coachwork	0.70	Trunk capacity	0.62	Fuel consumption (highway)	0.58
Speed	0.83	Gears	0.68	Fuel consumption (city)	0.62	Height	0.54
Length	0.78	Type of fuel	0.67	Revolutions p.m.	0.60	Doors	0.51

The two objects (cities or cars) were displayed on a computer screen. The participants were prompted to generate cues freely by asking questions about the objects. For example, they might ask if the cities had a university or what the cars' maximum speed was. The only restriction was that cues with subjective values were not allowed: Questions such as "Are these cars cool?" or "Do you think I would like to live in one of these cities?" were not answered or considered in the analysis. When an objective cue (e.g., presence of a university in a city) was generated, the experimenter provided the values of the two objects on that cue by using a database stored in the computer. The values of the cues that participants generated were displayed on the screen until the end of the trial. The participants were allowed to ask for as many cues as they wanted, even none. If participants generated cues not available in the database, they were told that these cue values were not available. Some cues that we did not expect—and hence did not have in our database—were very original and smart, such as number of McDonald's in a city (generated by a 10-year-old child) and number of television advertisements for a car (generated by a 17-year-old). Table 3 lists cues that participants generated themselves but that were not included in the database: They are not considered in the analysis of frugality, because frugality is a measure of the usable cues for making an inference, and in these cases participants did not get any answer they could use to make the inferences.

Table 3

Study 1: Generated Cues That Were Not Included in the Database

Task	Participants asking for this cue	Cue
City population	1 younger child	Number of monuments
	1 younger child, 1 young adult	Number of shopping malls
	1 older child	Number of McDonald's
	1 older child	Number of streets
	1 young adult	Existence of a dialect
	2 young adults	First letter
Car price	1 older child	Kind of rims
	2 younger children, 2 older children	Color
	2 younger children, 1 older child, 2 young adults	The most recent
	1 young adult	Number of TV advertisements

At the beginning of the experiment, the participants received 60 tokens. For each correct inference they gained five tokens, whereas an incorrect inference left their number of tokens unchanged. Also, participants had to pay one token for each cue they asked for. The number of tokens was continually updated and appeared in the corner of the screen. The participants were told that, for each age group, the three participants with the highest number of tokens at the end of the experiment would be rewarded with bookstore vouchers of 45, 25, and 15 euros, respectively. We implemented this particular incentive system because we wanted to better model real decision making, where both the information and the process of acquiring it are often costly.

The experimenter tested each participant individually and all sessions were audio recorded. Participants took on average 25 min (ranging from 18 to 35 min) to go through the session, including reading the instructions. The experimenter read aloud the instructions, the two objects and criterion for each trial, and the values of the generated cues; this information was also displayed on the computer screen. To minimize potential effects of computer literacy, only the experimenter operated the computer.

Results

We compared the performances of the three age groups on four outcomes: (1) frugality, (2) accuracy, in terms of percentage of correct inferences, (3) specific cues generated, and (4) success of the generated cues.

Frugality. The *frugality* of a decision is indicated by the number of cues used to make an inference (Gigerenzer et al., 1999). The smaller this number is, the more frugal the decision is. As a proxy for frugality, we used the number of cues generated by participants. As shown in Table 4 (panel above) and confirmed by a Repeated Measures ANOVA with factors label (2 levels: names versus generic labels) and task (2 levels: cities versus cars), participants made more frugal decisions when objects had names, $F(1, 66) = 24.97$, $p < .001$, $\eta^2 = .28$, which makes sense because names can carry information. Moreover, the participants generated more cues in the car-price task, $F(1, 66) = 10.23$, $p = .002$, $\eta^2 = .14$.

All other main or interaction effects on frugality had $p > .1$; in particular, we did not find any effect of age on frugality.

The numbers in Table 4 (panel below) suggest that one-cue strategies were prevalent. As they had to pay one token for each cue they asked for, this result is not too surprising per se. Indeed, in most trials, only one cue was generated. For example, in 64 of the trials—that is, in 22 out of 34 trials—younger children generated one cue in the car-price task when the objects were presented with generic labels. If we consider only the generic-labels condition, to be sure that no prior knowledge was taken into account, we can observe that participants relied on one-cue strategies in more than 50% of the trials. Moreover, younger children seemed to rely on one-cue strategies a bit more than the other two age groups, and only for children was there an effect of task, children being more willing to ask for only one cue in the city-population task.

Table 4

Study 1: Frugality in Terms of Mean Number (and Standard Deviations) of Cues Generated by the Participants (Panel Above), and in Terms of Overall Number of Trials in Which One Cue Was Generated (Panel Below, Shown in Both Percentages and Natural Frequencies

Mean number of cues generated				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
Younger children	0.88 (SD 0.38)	1.24 (SD 0.44)	1.00 (SD 0.79)	1.53 (SD 0.93)
Older children	0.89 (SD 0.45)	1.15 (SD 0.52)	1.33 (SD 0.79)	1.44 (SD 0.76)
Young adults	1.00 (SD 0.65)	1.39 (SD 0.57)	1.18 (SD 0.66)	1.36 (SD 0.41)

Overall number of trials in which one cue was generated				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
Younger children	82 (28 out of 34)	82 (28 out of 34)	42 (14 out of 34)	64 (22 out of 34)
Older children	76 (38 out of 50)	72 (36 out of 50)	42 (21 out of 50)	52 (26 out of 50)
Young adults	57 (25 out of 44)	57 (25 out of 44)	50 (22 out of 44)	55 (24 out of 44)

Accuracy. Table 5 (panel above) presents the accuracy results for the trials where participants did not ask for any cues. We deemed these inferences made without generating cues in the generic-labels condition (in only 3 out of 256 trials) to be random guesses. The results of the names condition might indicate inferences based on prior knowledge, but we cannot exclude them to be random guesses, too. We are not interested in further investigating these results.

Table 5

Study 1: Accuracy (as Percentage of Correct Inferences) in Problems Where No Cues Were Generated (Panel Above), and in Problems Where at Least One Cue Was Generated (Panel Below). Number of Such Problems Out of the Total Number of Problems and Standard Deviations Are Given in Parentheses

Problems where no cues were generated				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
Younger children	60 (5 out of 34, SD 51)	--- (0 out of 34, SD ---)	91 (11 out of 34, SD 48)	--- (0 out of 34, SD ---)
Older children	50 (10 out of 54, SD 42)	100 (1 out of 54, SD ---)	71 (9 out of 54, SD 43)	100 (1 out of 54, SD ---)
Young adults	67 (9 out of 44, SD 46)	100 (1 out of 44, SD ---)	80 (10 out of 44, SD 40)	--- (0 out of 44, SD ---)
Problems where at least one cue was generated				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
Younger children	68 (29 out of 34, SD 42)	73 (34 out of 34, SD 31)	82 (23 out of 34, SD 35)	91 (34 out of 34, SD 20)
Older children	56 (44 out of 54, SD 40)	55 (53 out of 54, SD 40)	62 (45 out of 54, SD 38)	65 (53 out of 54, SD 40)
Young adults	73 (34 out of 44, SD 33)	53 (43 out of 44, SD 30)	77 (34 out of 44, SD 33)	86 (44 out of 44, SD 23)

Table 5 (panel below) shows the percentages of correct inferences for those problems where the participants generated at least one cue. A Repeated Measure ANOVA with factors label (2 levels: names versus generic labels) and task (2 levels: cities versus cars), showed that: First, there were no effects of labels on accuracy. Second, there was a main effect of age on accuracy, $F(2,66) = 8.40$, $p = .001$, $\eta^2 = .21$. All post-hoc analyses revealed no overall differences in terms of accuracy between younger children and young adults. Third, there was a main effect of task on accuracy, $F(1,66) = 10.79$, $p = .002$, $\eta^2 = .15$: All participants performed better in the car-price task.

Looking at Table 5 (panel below), we can see that in the names condition, younger children in the car-price task performed as well as young adults, and even slightly better, whereas in the city-population task young adults had an advantage. In the generic-labels condition, surprisingly, younger children outperformed young adults in both tasks. A possible explanation for our results is that younger children were able to generate more successful cues and so performed better in the generic-labels condition.

The cues generated. In the city-population task both older children and young adults generated more diverse cues than younger children (14, 21, and 6 cues, respectively). Even if we consider only the cues asked by at least two participants, older children and young adults still generated more diverse cues than younger children (10, 14, and 4 cues, respectively). In the car-price task, the participants generated a similar number of diverse cues (younger children: 16, older children: 21, young adults: 14). The number of cues generated by at least two older children, young adults, and younger children was 9, 12, and 9, respectively. Figure 1 shows the percentage of participants by age group who generated a certain cue in the city-population task and in the car-price task, taking into account only the cues generated by at least 10 of the participants of one age group.

In the city-population task (Figure 1A), more than 40% of all the participants ($M_{younger\_children}$= 41%, $M_{older\_children}$= 45%, M_{young_adults} = 43%) generated the cue "area." Almost half of the younger children (48%) generated the cue "number of buildings," a cue generated by only 13% of the older children and 4% of the young adults. The cues "tourism" and "density of population," the former generated by 11% of the older children and the latter by 10% of the young adults, were both generated by only a few of the younger children.

In the car-price task (Figure 1B), two cues predominated for the younger children, with 31% of the children generating "width" and 22% "length"; 31% of the young adults generated the cue "horsepower" and 22% generated "capacity". The other cues were generated by relatively few of the young adult participants. Older children, on the other hand, seemed not to have a strong preference for any one cue, even though many of them generated "length" (17%), "speed" (18%), "width" (12%), and "horsepower" (10%).

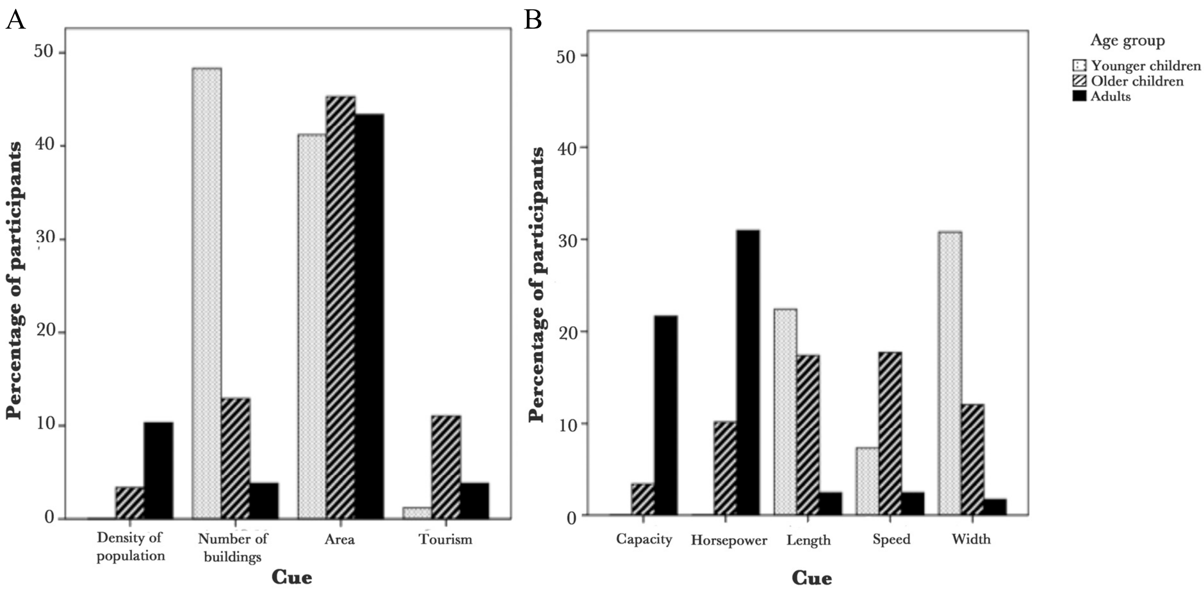

Figure 1. Study 1: Percentage of participants by group who generated a certain cue in (A) the city-population task and (B) the car-price task.

Success of generated cues. Table 6 displays the average success of the cues generated by the participants. A Repeated Measure ANOVA with factors label (2 levels: names versus generic labels) and task (2 levels: cities versus cars) showed a main effect of labels, $F(1,66)$ =6.32, p = .015, η^2 = .09: Overall, when the objects were presented by using their names, participants generated more successful cues. We found a main effect of age, $F(1,66)$ = 7.74, p = .001, η^2 = .2: All post-hoc analyses revealed overall no difference between younger children and adults in terms of success of the generated cues, whereas older children generated less successful cues. We also found a main effect of task, $F(1,66)$ = 17.22, p < .001, η^2 = .22, and an interaction between age group and task, $F(2,66)$ = 4.86, p = .011, η^2 = .13: In general, participants generated more successful cues in the car-price task. Though, in the generic-labels condition, younger children generated more successful cues in the city-population task. This fits with our finding of higher accuracy of younger children in the city-population task. But, as we saw, younger children performed better in the car-price task, as well. One reason for their better performance is that younger children always interpreted the cue in the right direction (i.e., the longer it is, the more expensive it should be), and they applied a cue only in those problems where it led to a correct inference. On the contrary, six different adults, in six trials, did not interpret correctly the direction where the cue pointed: After generating only one cue, in one trial they chose the slower car, in three trials the car with the lower power, in two cases the car with less horsepower.[4]

Table 6

Study 1: Average Success (and Standard Deviations) of the Cues Generated by the Participants

Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
Younger children	0.72 (0.18)	0.75 (0.19)	0.75 (0.13)	0.70 (0.12)

[4] We could not resist the temptation to ask some of the students we interviewed what horsepower is. One of them innocently replied: "Horsepower? I really have no clue. But I suppose it is something I should ask if I have to pick one of two cars, no?"

Older children	0.63 (0.15)	0.63 (0.15)	0.76 (0.11)	0.74 (0.10)
Young adults	0.69 (0.17)	0.63 (0.16)	0.78 (0.12)	0.80 (0.11)

Summary of the results of Study 1

In Study 1 we tested children and young adults on inference problems about real objects, by prompting them to generate their own cues. We focused on the frugality of the decisions (i.e., the number of cues asked), the accuracy of the participants, the specific cues generated, and their success (which is a measure of how often the cue points to the correct inference).

We found that (1) all participants and especially younger children mostly generated only one cue; (2) for problems where no names were given—only generic labels, such as Car 1 and Car 2—younger children outperformed the other two age groups in making cue-based inferences, in both tasks; (3) children and young adults generated different cues, and participants belonging to the same age group generated the same one or two cues more often; and (4) younger children overall generated cues that were as successful as those generated by the other two age groups, their cues being more successful than the ones generated by the older children and young adults in the city-population task.

In Study 2, we test if the results obtained in Study 1, leading to different conclusions than Mata et al. (2011), are due to the experimental designed adopted, as hypothesized.

Study 2: Fixed Set of Cues

Method

Participants. The experiment involved 75 participants: 24 children in the second and third grade (11 females, M_{age} = 8.4 years, *SD* = 0.72) and 15 children in the fifth grade (7 females, M_{age} = 10.3 years, *SD* = 0.46) of a primary school[5] in Livorno, Italy, and 36 young adults (7 females, M_{age} = 17.4 years, *SD* = 0.65) recruited from a high school[6] in Livorno. The participants were all born in Italy and belonged to various social classes.

Design and procedure. In this second experiment the design and the objects used were the same as in Study 1 (see Table 1), with one crucial difference: Participants were not allowed to generate their own cues but had to select them from a fixed set of five cues by clicking on a corresponding button on the screen.

There were two different sets of cues for each of the two inference tasks: One set comprised the five cues generated the most by the participants in Study 1 (as in Figure 1, with the addition of the cue "altitude" in the city-population task, not included in the Figure because generated by less than 10 of the participants). We will refer to this set of cues as the "new cues." The other set comprised, for the cities, five of the nine cues in the original city task of Gigerenzer et al. (1999): Number of universities, number of museums, number of soccer teams playing in the first league, number of train stations, whether the city is a regional capital or not (instead of the original cue state capital). We excluded four cues from the original task: three that were not applicable in Italy (the license plate, industrial belt, and East Germany cues) and the one that was the least successful of the original nine (national capital). Moreover, we modified some of the other cues ("Is the city on the Intercity line?" became "Number of train stations" and "Was the city once an exposition site?" became "Number of museums") mainly to have cues with continuous values instead of binary cues. For the cars, the second cue set comprised the first five cues shown in car descriptions on a

[5] Istituto Sacro Cuore, Livorno.

[6] Liceo Scientifico "F. Enriques", Livorno.

popular Italian website advertising and selling used cars.[7] We will refer to the set of cues taken from Gigerenzer et al. (1999) and the used car website as the "old cues", to indicate that these cues come from prior research stimuli. Some of the old cues coincide with the new cues, generated by the participants in Study 1. Because of the rationale that led us to the selection of the cues in both cue sets, we saw no reasons in excluding any of them. All cues and their relative success rates are presented in Table 7.

Table 7

Study 2: The Cues and Their Success in the Two Tasks, For the New-Cues and Old-Cues Manipulations

City-population task		Car-price task	
Cue	Success	Cue	Success
New-cues manipulation			
Buildings	0.92	Horsepower	0.88
Density of population	0.67	Capacity	0.84
Tourism	0.64	Speed	0.83
Altitude	0.56	Length	0.78
Area	0.52	Width	0.77
Old-cues manipulation			
Universities	0.76	Horsepower	0.88
Train stations	0.74	Capacity	0.84
Museums	0.70	Type of fuel	0.67
Soccer teams	0.66	Fuel consumption	0.62
Regional capital	0.52	Number of seats	0.58

Study 2 differed also in that participants faced in total 40 trials, divided in two rounds of 20 trials. In each round, we gave the participants either the old-cues set or the new-cues set, so that the cue-set manipulation (old versus new cues) is considered a within subject

[7] www.autosupermarket.it

variable. Each round consisted of five trials for each of the four blocks constituting the 2 × 2 matrix design, having as independent variables the task (city-population and car-price) and the objects' presentation (either by using their names or by using general labels). The order of the rounds and the four blocks within the rounds, as well as the order of the manipulations and the position of the cue buttons on the screen, was randomized.

Results

We compared the performance of the three age groups according to the same four criteria we used for analyzing the results in Study 1: (1) frugality, (2) accuracy, in terms of percentage of correct inferences, (3) specific cues selected, and (4) success of the selected cues.

Frugality. Regarding the average number of cues the participants consulted (Table 8, panel above), a Repeated Measures ANOVA with factors label (2 levels: names versus generic labels), task (2 levels: cities versus cars) and cue-set (2 levels: old versus new cues) revealed a main effect of the cue-set manipulation, $F(1,75) = 12.82$, $p = .001$, $\eta^2 = .15$: Participants selected more cues in the new-cues manipulation. We found no main effect of task, but we did find a main effect of age on the number of cues participants looked up: $F(1, 75) = 9.40$, $p < .001$, $\eta^2 = .21$. All post-hoc analyses revealed no difference in terms of number of cues looked up between young adults and older children, whereas younger children looked up more cues than the other two age groups.

The Repeated Measures ANOVA also showed that, as expected given that the names carry information, participants looked up more cues in the condition where the objects were presented with generic labels, $F(1,75) = 33.81$, $p < .001$, $\eta^2 = .32$. We also found an interaction effect between age and labels, $F(2,75) = 14.84$, $p < .001$, $\eta^2 = .29$, and an interaction between task and labels, $F(1,75) = 18.02$, $p < .001$, $\eta^2 = .20$.

The numbers in Table 8 (panel below) suggest that in Study 2, unlike in Study 1, one-cue strategies were used in less than 50% of the trials, except for the car-price trials of the old-cues manipulation, in the generic-labels condition. However, the incentive system was the same as in Study 1, that is, participants still had to pay one token for each cue they asked for. We did not find any consistent effect of age on the percentage of trials in which only one cue was selected.

Table 8

Study 2: Frugality in Terms of Mean Number (and Standard Deviations) of Cues Selected by the Participants (Panel Above), and in Terms of Overall Number of Trials in Which One Cue Was Selected (Panel Below, Shown in Both Percentages and Natural Frequencies), for the New-Cues and Old-Cues Manipulations

Mean Number of Cues Selected				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
New-cues manipulation				
Younger children	1.9 (1.6)	2.2 (1.5)	2.3 (1.5)	2.2 (1.3)
Older children	0.9 (1.0)	1.3 (1.4)	0.9 (0.8)	1.0 (0.9)
Young adults	0.9 (0.6)	1.7 (0.7)	1.3 (0.9)	1.6 (0.5)
Old-cues manipulation				
Younger children	1.9 (1.6)	1.9 (1.2)	1.8 (1.2)	1.7 (1.0)
Older children	0.5 (0.8)	1.0 (0.8)	0.7 (0.6)	0.9 (0.6)
Young adults	0.6 (0.5)	1.7 (0.6)	1.2 (0.5)	1.5 (0.6)
Overall Number of Trials in Which One Cue Was Selected				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
New-cues manipulation				
Younger children	35 (42 out of 120)	41 (49 out of 120)	29 (35 out of 120)	31 (37 out of 120)
Older children	37 (28 out of 75)	45 (34 out of 75)	39 (29 out of 75)	52 (39 out of 75)
Young adults	29 (52 out of 180)	32 (58 out of 180)	31 (56 out of 180)	44 (79 out of 180)
Old-cues manipulation				
Younger children	30 (36 out of 120)	43 (52 out of 120)	40 (48 out of 120)	57 (68 out of 120)

Older children	25 (19 out of 75)	49 (37 out of 75)	45 (34 out of 75)	55 (41 out of 75)
Young adults	29 (52 out of 180)	45 (81 out of 180)	44 (80 out of 180)	61 (109 out of 180)

Accuracy. As in Study 1, we first looked at the accuracy reached by the participants in the trials where they did not ask for any cues (Table 9, panel above). We found that in the generic-labels condition younger children and adults only in few trials made inferences without acquiring any information, whereas the number of trials in which older children randomly guessed is higher (20-24 trials out of 75). In the names condition, as already pointed out, the results might indicate inferences from prior knowledge, even though we cannot rule out that they were random guesses. Because we are mainly interested in the process of cue-selection, we do not report on these results.

Table 9

Study 2: Accuracy (as Percentage of Correct Inferences) in Problems Where No Cues Were Selected (Panel Above), and in Problems Where At Least One Cue Was Selected (Panel Below), for the New-Cues and Old-Cues Manipulations. Number of Such Problems Out of the Total Number of Problems Is Given in Parentheses

Problems where no cues were selected				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
New-cues manipulation				
Younger children	76 (21 out of 120, SD 18)	44 (9 out of 120, SD 19)	33 (12 out of 120, SD 18)	50 (8 out of 120, SD 19)
Older children	70 (33 out of 75, SD 25)	46 (24 out of 75, SD 21)	50 (32 out of 75, SD 27)	37 (24 out of 75, SD 23)
Young adults	79 (73 out of 180, SD 23)	60 (10 out of 180, SD 19)	71 (49 out of 180, SD 15)	29 (7 out of 180, SD 17)
Old-cues manipulation				
Younger children	62 (29 out of 120, SD 20)	33 (9 out of 120, SD 22)	37 (16 out of 120, SD 21)	33 (6 out of 120, SD 25)
Older children	75 (49 out of 75, SD 25)	38 (21 out of 75, SD 24)	70 (33 out of 75, SD 22)	60 (20 out of 75, SD 30)
Young adults	85 (101 out of 180, SD 18)	83 (6 out of 180, SD 18)	80 (40 out of 180, SD 16)	80 (5 out of 180, SD 15)
Problems where at least one cue was selected				
Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
New-cues manipulation				

Younger children	66 (99 out of 120, SD 23)	56 (111 out of 120, SD 26)	83 (108 out of 120, SD 21)	77 (112 out of 120, SD 25)
Older children	69 (42 out of 75, SD 25)	69 (51 out of 75, SD 25)	70 (43 out of 75, SD 30)	72 (51 out of 75, SD 27)
Young adults	78 (107 out of 180, SD 18)	78 (170 out of 180, SD 19)	90 (131 out of 180, SD 17)	88 (173 out of 180, SD 15)
		Old-cues manipulation		
Younger children	80 (91 out of 120, SD 19)	68 (111 out of 120, SD 24)	73 (104 out of 120, SD 22)	79 (114 out of 120, SD 20)
Older children	54 (26 out of 75, SD 22)	63 (54 out of 75,SD 23)	71 (42 out of 75, SD 15)	71 (55 out of 75,SD 22)
Young adults	66 (79 out of 180, SD 15)	83 (174 out of 180,SD 13)	84 (140 out of 180, SD 19)	86 (175 out of 180, SD 16)

The percentages of correct inferences for those problems where the participants looked up at least one cue are shown in Table 9 (panel below). A Repeated Measures ANOVA with factors label (2 levels: names versus generic labels), task (2 levels: cities versus cars) and cue-set (2 levels: old versus new cues) revealed no effect of the cue-set manipulation on accuracy. We also found no effects of labels, but a main effect of task on accuracy, $F(1,75) = 12.52$, $p = .001$, $\eta^2 = .15$: For the most part, participants performed better in the car-price task, the exception being that younger children performed better in the city-population task in the names condition with the old-cues manipulation.

We also found a main effect of age on accuracy, $F(2,75) = 26.68$, $p < .001$, $\eta^2 = .43$, and all post-hoc analyses confirmed that adults always performed overall better than children, and younger children better than older children. Moreover, there is an interaction effect between task and labels, $F(1,75) = 6.5$, $p = .013$, $\eta^2 = .08$, and between task, cue-set manipulation and age group, $F(2, 75) = 3.75$, $p = .028$, $\eta^2 = .09$.

The cues selected. Figures 2 and 3 show the percentages of participants by age group who selected particular cues in the two manipulations, for both tasks. In the city-population task with the new-cues manipulation (Figure 2A), young adults focused on three main cues: 44% of them selected the cue “density of population,” 23% the cue “area,” the least successful cues in the set, and only 29% the cue “number of buildings,” the most successful cue in the set. In contrast, younger and older children showed no preference for any particular cue, being very close to the random distribution of 20% per cue, even though fewer of them selected the cue “altitude.”

In the car-price task of this manipulation (Figure 2B), young adults showed a similar pattern, focusing on mainly two cues: “capacity” (41%) and “horsepower” (35%)—the most successful cues in the set. Children were a bit more selective in this task, focusing on the cues “horsepower” (29% of the younger and 26% of the older children) and “speed” (24% of the younger and 27% of the older children).

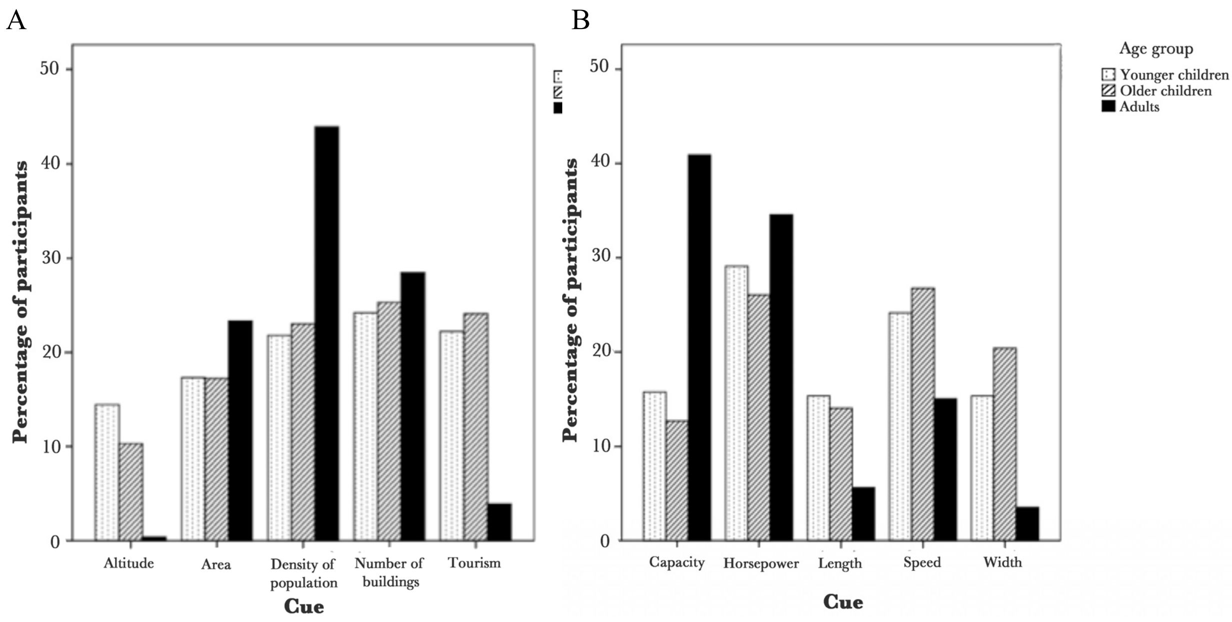

Figure 2. Study 2: Percentage of participants by group who selected particular cues in (A) the city-population task and (B) the car-price task with the new-cues manipulation.

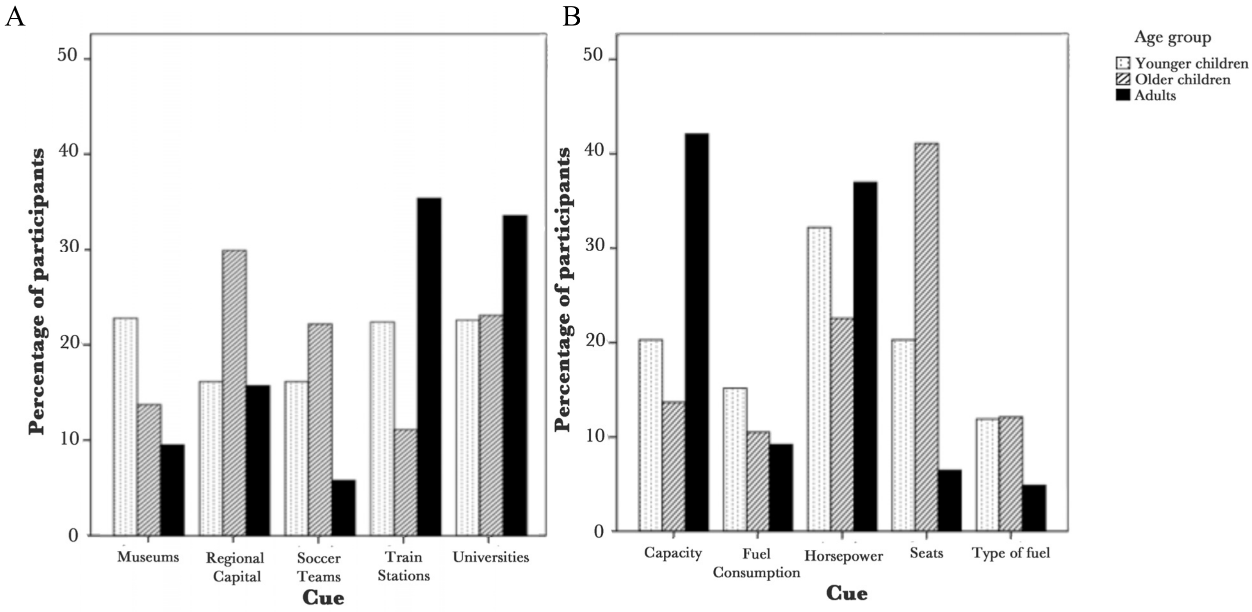

Figure 3. Study 2: Percentage of participants by group who selected particular cues in (A) the city-population task and (B) the car-price task with the old-cues manipulation.

In the city-population task of the old-cues manipulation (Figure 3A), young adults focused mainly on the cues "train stations" (35%) and "universities" (34%). Older children selected the cue "regional capital" a bit more often (29%), whereas younger children's selection of cues is close to the random distribution. In the car-price task (Figure 3B), all the age groups seemed to be more selective: Young adults chose mainly to look at the cues "capacity" (42%) and "horsepower" (37%), older children the cue "number of seats" (41%), and younger children the cue "horsepower" (32%).

Success of selected cues. In Table 10 we can see the average success of the cues selected by the participants. Overall, a Repeated Measures ANOVA with factors label (2 levels: names versus generic labels), task (2 levels: cities versus cars) and cue-set (2 levels: old versus new cues) revealed no differences between the two conditions (names versus generic labels). The quality of the cues selected in the car-price task was higher than in the city-population task, $F(1,55) = 130.03$, $p < .001$, $\eta^2 = .71$. This is not surprising, because of the more successful cues available in this task. The average success of the cues consulted in the new-cues manipulation was also higher, $F(1,55) = 32.12$, $p < .001$, $\eta^2 = .38$: Again, this is due to the fact that the cues available in this manipulation were, on average, more successful.

The analysis revealed a main effect of age on quality, $F(2, 55) = 17.53$, $p < .001$, $\eta^2 = .4$: All post-hoc analyses showed that young adults, overall, selected more successful cues than younger ad older children, and younger children selected more successful cues than older children.

We also found a interaction effect between task and the cue-set manipulation, $F(1, 55) = 17.74$, $p < .001$, $\eta^2 = .25$, and an interaction between age group and cue-set manipulation, $F(2, 55) = 8.84$, $p < .001$, $\eta^2 = .25$.

Table 10

Study 2: Average Success (and Standard Deviations) of the Cues Selected by the Participants, for the New-Cues and Old-Cues Manipulations

Group	City-population task		Car-price task	
	Names	Generic-labels	Names	Generic-labels
		New-cues manipulation		
Younger children	0.69 (0.08)	0.68 (0.06)	0.83 (0.02)	0.83 (0.02)
Older children	0.69 (0.12)	0.72 (0.08)	0.82 (0.03)	0.81 (0.03)
Young adults	0.69 (0.11)	0.71 (0.10)	0.86 (0.02)	0.85 (0.02)
		Old-cues manipulation		
Younger children	0.69 (0.03)	0.70 (0.03)	0.76 (0.06)	0.76 (0.07)
Older children	0.63 (0.08)	0.64 (0.06)	0.67 (0.08)	0.67 (0.06)
Young adults	0.71 (0.04)	0.72 (0.04)	0.82 (0.05)	0.82 (0.04)

Summary of the results of Study 2

In Study 2 we tested children and young adults on the same inference problems used in Study 1. In this experiment, however, we adopted an experimental design that has been predominantly used when testing cue-based inferences: Participants had to choose which cues to consult from a preliminarily defined fixed set. These five cues in the new-cues manipulation were the top five cues generated by the participants in Study 1; in the old-cues manipulation they were either five of the cues used in the original city-population task (Gigerenzer et al., 1999) or the first five cues shown in car descriptions on a popular Italian website advertising and selling used cars. As in the first experiment, we focused on the frugality and the accuracy of the inferences made, as well as on the specific cues generated, and on their success.

We found that (1) participants used one-cue strategies in less than 50% of the trials, in almost all the conditions; (2) young adults always outperformed the other two age groups in making cue-based inferences; (3) young adults always focused on some specific cues, even though they were not always the most successful ones (as in the city-population task), whereas children did not focus on any cues in particular; and (4) young adults selected more successful cues than children. Note that these results are different from those of Study 1, where participants were free to generate cues.

General Discussion

In this paper we tested children and young adults on the same inference problems by using both a new and an established experimental procedure: In Study 1 participants were prompted to generate their own cues, whereas in Study 2 they had to select from a list of available cues, either "old cues" that have been used in the previous literature (Gigerenzer et al., 1999) or "new cues" that were generated by other participants. This comparison allowed us to investigate whether and under what conditions children are capable of focusing on the most informative cues and, in general, to explore the generation of cues that people find informative, a so-far little-studied issue in cue-based inference.

First, we found that in Study 1 all participants and especially younger children mostly generated one cue, whereas in Study 2 they looked up more cues, even though in both experiments participants had to pay one token for each cue consulted. There are two possible explanations for this result, not mutually exclusive but compatible. On the one hand, it may have been that selecting cues from a given set was much less effortful than generating them from scratch. On the other hand, in Study 1, participants could only compare cues against others in their own cuebox, which we define as the set of cues available and usable for making an inference. Assuming that they had generated the most successful cue in their cue box first, participants might have been so confident in its predictive power that they thought the inference could be based on only that cue. In Study 2, in contrast, participants, presented with cues that they would not have considered otherwise, might have doubted the ranking of the most successful cues in their cuebox. This, together with the fact that the cues given to them were all informative cues, may have prompted participants to look up more cues to gain more confidence in which inference to make.

Second, in Study 1, for problems where objects were presented with generic labels instead of names, younger children outperformed the other two age groups in making cue-based inferences, in both tasks. On the other hand, in Study 2 young adults always outperformed children. We think the accuracy in cue-based inferences depends on the success of the cues generated/selected (see below) and on the ability of the participants to interpret the cues correctly, that is, to understand the direction in which the cues point.

Third, we found that in Study 1 children focused on one or two cues, generating them more frequently than other cues, whereas in Study 2, overall, they did not focus on any of the available cues in particular. Moreover, we found that in both experiments, young adults asked for task-specific cues that were somewhat “technical” and referred to hidden features of the objects—for example, horsepower or capacity in the car-price task, and density of population or area in the city-population task. In contrast, the cues on which younger children focused in Study 1 were more perceptual, observable cues, such as number of buildings in the city-population task, and length or height in the car-price task.

Indeed, children, being novices in most domains of inference, may first learn mostly perceptual cues, as young children are often “concrete” or “perceptually bound” (Flavell, 1985; Wartella, 1979), even though this limitation is less extensive than originally believed (Keil, 1989; Wellman & Gelman, 1988). As they grow up, children face new inference domains and deepen their knowledge of old domains, continually acquiring and reorganizing domain-specific knowledge (Carey, 1985). As children understand and grasp more concepts and terms, they also learn cues that go beyond appearances, cues related to hidden features and structures (horsepower, density of population) that are possibly more “technical.” This learning process leads to an update of cues in the cuebox that we argue is biased: The more technical cues are intuitively assumed to be more informative than the general, perceptual cues that were there before, because they are more elaborate and appropriate—even when we do not know exactly what they mean or how to interpret them. By bias we mean an asymmetrical tendency that is not good or bad per se: A bias that favors technical cues often leads to more accurate inferences, but these technical cues are not always the most informative.

Indeed, our fourth main result shows that in Study 1, children, somehow naturally biased towards perceptual cues, generated cues that were overall as successful as those generated by the young adults, and even better in the city-population task, where perceptual cues *happened* to be more successful.

In conclusion, we showed that “making your own kind of cues,” paraphrasing Mama Cass Elliot, matters. Compared to the set-up of Study 1, the set of cues presented in Study 2 indeed had a very different, if not opposite, effect on our participants. Having to compare cues they would not have considered otherwise might have been confusing for all the participants, who felt tempted to look up more cues to increase their confidence about their inference. However, young adults recognized that some of the cues offered were even more successful than any they would have thought of and selected them. Children, in contrast, probably unfamiliar with some of the cues presented, could not recognize which cues were the most successful. Thus, the procedure used in Study 2, by providing all the participants with a same cue box, *unbiased* them: Children were no longer biased toward perceptual cues, and young adults were no longer biased toward technical cues. Although this may result in an improvement for young adults, who are able to identify in a set of given cues those that are the most successful, it might be disadvantageous for children, who lose the advantage the “perceptual bias” gives them in some tasks without being able to compensate for the loss. In this first exploration of cue generation, though, a question our two studies cannot answer is whether the children and young adults in Study 1 generated the best cues they could, or the only ones they had available in their cue box. Moreover, if the children’s perceptual bias has been already thoroughly investigated, both as limit and advantage (John & Sujan, 1990; Springer, 2001), future research should investigate and test further the bias towards technical cues.

Finally, we find the generation paradigm a stimulating and promising methodology.

From a perspective of ecological rationality (Todd, Gigerenzer and the ABC Research Group, 2012), we believe that generating cues from scratch, more then choosing them from a catalogue, can be a crucial step in studying cue-based decision making and, in general, the process of searching for information that actually takes place when people make choices and decisions, assess preferences, generate hypotheses, and trace causes (see Mosher & Hornsby, 1966).

Author Note

Thanks to Uwe Czienskowski for programming the experiments, to Francesca Ricci, Eleonora Gilli, and Claudia Mazzeranghi for collecting the data, and to the teachers of the schools used for recruitment for their support, especially Maria Rosaria Angioni and Simona Preti. Thanks to Henrik Olsson, Nicolai Bodemer, Michaela Gummerum, Katherine McMahon, and Anita Todd for their useful comments.

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Chapter 4

Opening Up the Cuebox

Chapter 4

Opening Up the Cuebox

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Abstract

In this paper we open children's and young adults' *cuebox*, the set of the cues people have available for making an inference. We explore the importance of cues beyond content free representations, by examining the cues participants generate for a range of everyday inference tasks. Further, we investigate how objective informativeness of a cue and type of cue determine children's and young adult's ability to generate the most informative cue in their cuebox and to select the most informative between two given cues. Results show that children's cuebox contains more perceptual cues than young adults'. However, we found no difference between the two age groups in terms of informativeness of the cues generated.

Young adults showed the tendency to systematically consider non-perceptual cues more informative than visible cues, whereas children showed the same tendency only in a cue-selection task.

Introduction

What do we know about the cues children and adults use for making an inference, such as “which of two cars is more expensive”? Not much. The tasks and methods used by researchers on cue-base decision-making are well suited to investigate the research questions they address (e.g., what strategies people use when searching for information). However, there are at least three reasons why the same tasks and methods are less suited to investigate what type of cues people use for making an inference. Consider the following example, based on the literature (Rieskamp & Otto, 2006):

Imagine you are a geologist. You have to choose the most profitable out of three oil-drilling sites, on the basis of some test results. You can conduct six different tests (chemical analysis, geophones, gravimetry, ground water analysis, microscopic analysis, and seismic analysis), by clicking on corresponding icons on the computer screen, in a MouseLab-like task (Payne, Bettman, & Johnson, 1993). Each test has two possible outcomes (e.g., low/high, or strong/weak), one of them indicating more oil.

First, as in this example, cue-based decision-making research typically investigates the process of searching for information by using a cue-selection design. People have to select from among a set of available cues to get hints about the right inference to make. Pre-selecting the cues participants can consult for making inferences in an experimental setting, however, severely limits the conclusions that can be drawn about the cues people would spontaneously use for real-world inferences. Second, this line of research often tries to isolate the structure of the information of a certain decision problem, by handling the cue as a mere value, empty of content, often further reducing it to dichotomous values such as "low" and "high". Third, researchers use tasks with cover stories that minimize reliance on real-world knowledge as in the oil-drilling task, presenting a situation likely unfamiliar to most participants (e.g., Bröder & Schiffer, 2003; Gigerenzer, Todd and the ABC Research Group, 1999; Rakow, Newell, Fayers, & Hersby, 2005; Mata, von Helversen, & Rieskamp, 2011; but see Pachur, Bröder, & Marewski, 2008, for an exception). In this way, they aim at ruling out from the experimental design the experience people have with particular cues, the preferences they might have for some types of cues, and their intuition about the informativeness of a cue for an inference task

In this paper we open children's and young adults' *cuebox*, which we define as the set of the cues people have available for making an inference. We explore the importance of cues beyond the content-free representations, by examining the cues participants generate for a range of everyday inference tasks. Further, we investigate how objective informativeness of a cue and type of cue determine children's and young adult's ability to select the most informative cue available.

Because knowledge of cues develops across the life-span, we expect that children and young adults generate, and use, different types of cues. Presumably, children have less experience and knowledge than young adults. Thus, they will generate less cues than young adults. Moreover, we expect children, often described as "perceptually oriented" or "perceptually bound" (Flavell, 1985; John & Sujan, 1990; Springer, 2001; Wartella, 1979), to generate more *perceptual* cues than young adults. *Perceptual* cues refer to visible and countable features of the objects (such as the length of a car), whereas *non-perceptual* cues refer to the more underlying, potentially technical, features and structures of the objects (such as horsepower of a car).

Cues are not good or bad per se, but their efficacy depends on the inference task in which they are used. In some inference tasks, perceptual cues are more informative than non-perceptual cues, whereas in other inference tasks the opposite is true. For example, in the car-price inference task used by Ruggeri and Katsikopoulos (2012), non-perceptual cues (e.g., horsepower) were more informative than perceptual cues (e.g., length), whereas in the city-population task (i.e., which of two cities is more populous) perceptual cues (e.g., number of hotels) were more informative than non-perceptual cues (e.g., density of population). An intriguing possibility, then, is that children might actually generate more informative cues than adults for some inference tasks.

Study 1 explores the content of the cuebox by asking participants to generate and list all the cues they think could be relevant in 12 different inferences problems (for example, which of two cars is faster). Study 2 and 3 investigate whether children and adults can select the most informative cue available, and how the type of the cues—perceptual or non-perceptual—influences the selection process. Study 2 approaches this question by asking children and young adults to generate what they deem as the most informative cue for the same 12 inference tasks. Study 3 tackles the question by asking participants to select between two cues the one they think is more informative, for two different inference tasks.

Study 1

In Study 1 we expected children to have fewer cues available in their cuebox–therefore, to generate fewer cues–than young adults, because they have less experience and knowledge. Because we hypothesized that children generate more perceptual cues than young adults, they may have an advantage in some inference tasks, but not in others. Thus, overall, children may have in their cuebox cues that are just as informative as the ones young adults have.

Method

Participants. Participants in Study 1 were 47 children in the 4th and 5th grade (22 females, M_{age} = 9.3; SD = 0.62) and 51 young adults (44 females, M_{age} = 17.4; SD = 0.83) from two schools in Livorno, Italy.[8] The students were all Italian and belonging to various social classes.

Design and procedure. The experimental session consisted of a paper and pencil questionnaire, collectively administrated in class, composed of eight questions presented on separate sheets, all describing similar problems, such as: “There are two cars, Car 1 and Car 2, both currently produced by FIAT. Let’s suppose you have to guess which of these two cars is faster. What would you like to ask about them before making the decision?” For each inference, participants had five minutes to generate all the cues they could think of that could help them making that inference. At the end of the five minutes, participants were asked to move on to the next problem.

We had 12 problems in total, that differ in terms of the objects presented and the inference participants were asked to generate cues about (see Table 1). The problems were randomly assigned to the participants and presented in random order. Participants were repeatedly prompted to generate as many cues as they could and they were told that all the students completing the tasks ‘to the best of their abilities’ would be rewarded with a prize – a colored pencils’ box for the younger children and an USB-stick for the young adults.

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[8] The primary school “Istituto Sacro Cuore” and the high school “F. Cecioni”

Table 1

The inference tasks presented to the participants in Study 1 and 2

Abbreviation	Inference Task
City population	Which of these two cities is more populous?
Car price	Which of these two cars is more expensive?
Mobile price	Which of these two mobile phones is more expensive?
Actor earn	Which of these two actors earned more money last year?
Team results	Which of these two soccer teams will win the match?
Movie earn	Which of these two movies gained more money?
Player earn	Which of these two soccer players gains more money per month?
Animal speed	Which of these two animals is faster?
City temperature	Which of these two cities have on average the higher temperature?
Car speed	Which of these two cars is faster?
House price	Which of these two houses in Ardenza[9] is more expensive?
Book sales	Which of these two books sold more copies?

Results

Number of cues. In total, participants in Study 1 generated 3962 cues. Children generated on average 6.1 cues per trial (*SD* = 2.7), whereas young adults generated on average 4.5 cues per trial (*SD* = 1.8). From all the cues generated, we subsequently excluded: (a) the subjective cues, that is, cues which values (and therefore efficacy) could not be objectively assessed, such as “is the actor beautiful?”; (b) the cues which values were not assessable, such as “did one of the teams bribe the referee?”; and (c) the redundant cues, where the same participants asked the same information many times in different ways (for example, “are they heavy?” and “which one is heavier?”). Almost half of the cues were eliminated through this filtering, that left 2000 cues to be analyzed.

Because often participants did not generate any valid cue for a given inference task, we

[9] A neighborhood of Livorno

used a Mixed Models analysis that allowed all the available data to be considered. A Mixed Models analysis with inference task as repeated measure, and fixed effects age group and inference task showed a main effect of age group, $F(1,89) = 7.9$, $p = .006$: Children generated more cues per trial than young adults ($M_{children} = 2.8$; $SD = 1.9$; $M_{young\_adults} = 2.44$; $SD = 1.5$). We also found a main effect of the inference task, $F(11,60) = 42.2$, $p < .001$: For some inferences (for example, which of two houses is more expensive) participants generated more cues ($M = 5.5$; $SD = 1.8$) than for others (for example, which of two animals is faster, $M = 1.22$; $SD = 0.9$). The number of cues generated by the participants in the different inference tasks is shown in Table A1 of the Appendix.

Type of cues. We asked 4 adults, blind to the experimental hypotheses and to the tasks, to categorize all the cues generated as perceptual or non-perceptual. The reliance among the results of these 4 independent categorizations resulted to be very strong (Cronbach's alpha = 0.85). The cues together with the final categorization are shown in Table A2.

As expected, we found that overall, 53% of the cues generated by children are perceptual, whereas only 34% of the cues generated by young adults are perceptual. Children generated in every inference task a higher percentage of perceptual cues than young adults. For some inferences this difference is strong (Table A3). For example in the tasks "which of these two cars is more expensive" (Children: 62%; Young adults: 28%) and "which of these two cars is faster" (Children: 50%; Young adults: 8%).

Quality of the cues. The quality of the generated cues was measured in terms of success (Newell, Rakow, Weston & Shanks, 2004). The success of a cue in an inference task is the probability, in that particular inference task, that the cue will lead to a correct inference. For the calculation of success, it is assumed that if the cue has a higher value on one of the two objects, then this object will be picked, and if the cue has the same value on both objects, then an object will be picked randomly.

We ran a Mixed Models analysis with inference task as repeated measure and fixed effects age group and inference task. We found that, as hypothesized, the overall quality of the cues generated by the two age groups does not significantly differ ($M_{\text{children}} = 0.65$; $SD = 0.09$; $M_{\text{young\_adults}} = 0.65$; $SD = 0.09$). As for the number of questions generated, we also found a main effect of inference task on the quality of the cues, $F(11,31) = 263.7$, $p < .001$: For some inferences participants generated more successful cues (e.g., which of two cars is faster, $M = 0.76$; $SD = 0.08$) than for others (e.g., which of two actors earned more last year, $M = 0.54$; $SD = 0.02$). We also found an interaction effect between age group and inference task, $F(11,31) = 9.6$, $p = .03$: For some inferences children generated more successful cues than young adults (e.g., which of two cities is more populous, $M_{\text{children}} = 0.75$; $SD = 0.08$; $M_{\text{young\_adults}} = 0.64$; $SD = 0.08$), whereas in others young adults' cues were more successful (e.g., which of two cars is faster, $M_{\text{children}} = 0.72$; $SD = 0.05$; $M_{\text{young\_adults}} = 0.8$; $SD = 0.07$). The means related to the quality of the cues generated in each inference task by age group are shown in Table A4.

Discussion

We found that, surprisingly, children have more cues available in their cuebox, for all the inference tasks we tested, even after filtering the many subjective and not-assessable cues they generated. How is it possible, considering they have less experience and general knowledge than young adults? Our explanation is that children interpreted the inference tasks in Study 1 as free association problems, of the kind "tell me any feature you can recall related to this type of object (for example, to cars)". Indeed, children did not seem to have any strong a-priori filter, and they did not try too hard to separate the relevant and useful cues from the others. Another possible explanation is that children seemed to perceive more freely and to have fewer assumptions and expectations about what should be asked, because they are less bound to cues that become stereotypes or appropriate only through experience.

Children, as expected, generated a higher percentage of perceptual cues than young adults, for all inference tasks.

We found no difference between the two age groups in terms of quality of the cues generated. As in Ruggeri and Katsikopoulos (2012), in some inference tasks (as in the city-population task) perceptual cues *happen* to be more successful than non-perceptual cues, whereas in other inference tasks (as the car-price task) the opposite is true. In many other tasks (as in the mobile phone-price task), perceptual and non-perceptual cues are equally successful. Thus, being *biased* towards perceptual cues, as children are, can be both an advantage or a disadvantage in different inference tasks, according to an ecological rationality perspective (Todd, Gigerenzer & the ABC Research Group, 2012; Todd & Gigerenzer, 2007).

Knowing what is in people's cuebox does not tell us anything about which of the cues available they consider as the most informative. Study 2 and 3 investigate whether children and young adults can identify the most informative cue, when generating cues from their cuebox (Study 2) or when selecting between two given cues (Study 3). Moreover, in both studies we examine how the type of cues (i.e., perceptual or not-perceptual) influences the process of generation/selection.

Study 2

Consistently with the results of Study 1, in Study 2 we expected children to generate overall more perceptual cues than adults, who would generate more non-perceptual cues.

We assumed that, through experience, young adults are more familiar with the cues they have in their cuebox than children are. They should therefore be able to rank the efficiency of their own cues more accurately than children. Thus, we hypothesized young adults to generate more informative cues than children.

Method

Participants. Participants in Study 2 were 50 children in the 4th and 5th grade (26 females, M_{age} = 10.1; SD = 0.27) and 33 young adults (15 females, M_{age} = 17.6; SD = 0.86) from two schools in Livorno, Italy.[10] The students were all Italian and belonging to various social classes.

Design. In Study 2 participants were presented with a paper-and-pencil questionnaire collectively administrated in class. The questionnaire consisted of the same 12 inference tasks of Study 1 (see Table 1), presented in random order. Children and young adults were asked to generate only the cue they consider the most helpful in making the inference. They were given five minutes for each inference task.

We told the participants that the child and young adult generating the overall most successful cues, defined as the cues that would be most predictive of the correct inference, would be awarded with a 25-euro Amazon gift card.

Results

Type of cues. As in Study 1, children always generated more perceptual cues than adults (Children: 45%; Young adults: 26%), with strong differences between the inference tasks (see Table A5).

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[10] The primary school "Santa Maria Maddalena" and the high school "F. Enriques"

Quality of the cues. We ran a Mixed Models analysis with inference task as repeated measure and fixed effects age group and inference task, and we found no main effect of the age group, but an effect of the inference task, $F(11,92) = 278.8$; $p < .001$. For some inferences participants generated more successful cues (e.g., which of two cities has the highest average temperature, $M = 0.85$; $SD = 0.06$) than for others (e.g., which of two actors earned more last year, $M = 0.51$; $SD = 0.07$). Table A6 shows the average success of the cues generated by participants in the two age groups, for each inference task.

Discussion

As expected, we found that children generated overall more perceptual cues than young adults, who generated more non-perceptual cues.

Surprisingly, we found again no differences between children and young adults in terms of overall success of the cues generated. Even though young adults should be better than children at selecting the most informative cues from their cuebox due to their experience, they tend to generate non-perceptual cues even when they are less informative than perceptual cues. We interpret this behavior as indicative of a bias towards non-perceptual cues.

Study 3

In Study 3 we assumed young adults to be more experienced and familiar than children with the given cues. Thus, we expected that young adults would be better then children at selecting the most informative between the two cues, independently on their type. On the contrary, children might be able to select the most informative cue only when both the given cues are perceptual.

Method

Participants. Participants in Study 3 were 37 children in the 4th and 5th grade (20 females, M_{age} = 9.76; SD = 0.60) and 18 young adults (8 females, M_{age} = 17.22; SD = 0.43) from four schools in Livorno, Italy.[11] The students were all Italian and belonging to various social classes.

Design. Study 3 consisted of a computer experiment of 12 trials, presented in random order. In each trial, participants were presented with an inference task and had to select between two given cues the one they wanted to consult before making the inference.

Table 2

Cues Used in Study 3, and Their Success

	Mobile price			
	High Success		Low Success	
	Cue	Success	Cue	Success
Non-perceptual	Memory	0.89	Battery Length	0.52
Perceptual	Thickness	0.82	Camera	0.55
	Car price			
	High Success		Low Success	
	Cue	Success	Cue	Success
Non-perceptual	Capacity	0.76	Fuel Consumption	0.52
Perceptual	Length	0.77	Doors	0.63

There were two possible inferences: Which of two mobile phones is more expensive, and which of two cars is more expensive. Each inference was presented to the participants in 6 trials. In each trial, participants received one of the 6 possible different combinations of 2 cues taken from a set of 4 cues: A perceptual/high success cue (PH), a non-perceptual/high

[11] The primary schools "Fondazione Sacro Cuore", "Fondazione San Carlo Borromeo" and "Istituto Beata Rosa Venerini", and the high school "F. Enriques"

success cue (NH), a perceptual/low success cue (PL) and a non-perceptual/low success (NL) cue. Table 2 shows a list of the cues used for Study 3. We chose these two inferences, among the 12 used in the other two studies, because they satisfied two crucial conditions: (1) among the cues generated for these inferences in Study 1 we found examples of all the four cue categories mentioned above and (2) we could find two pairs of high success and low success cues which success was similar (see Table 2).

There was no time limit for completing the session. Participants were told that the child and young adult with the highest number of accurate inferences would be awarded with a 20-euro Amazon gift card.

Results

Two Repeated Measure ANOVAs, one for success and one for visibility, with inference task and trials as within-subject factors, and age group as between subject variable, revealed no difference between the two inference tasks. Thus, the data related to the two inference tasks are presented together. Figure 1A and Figure 1B show the percentages of children and young adults who selected respectively a high success cue and a perceptual cue, for the trials specified on the x-axis.

As we can observe, in trials where participants were given a perceptual/high success cue (PH) and a non-perceptual/high success cue (NH), both children and young adults selected only few times the perceptual cue (Children: 16%; Young adults: 28%). In the trials where participants were given a perceptual/low success (PL) cue or a non-perceptual/low success cue (NL), children again selected only few times the perceptual one (Children: 16%), whereas young adults selected the perceptual cue 52% of the times. In trials where participants were given a perceptual/high success cue (PH) or a perceptual/low success cue (PL), children selected the high success one slightly more often (58%) than young adults

(42%). In trials where participants were given a non-perceptual/high success cue (NH) or a non-perceptual/low success cue (NL), they selected more often the high success one (Children: 62%; Young adults: 86%).

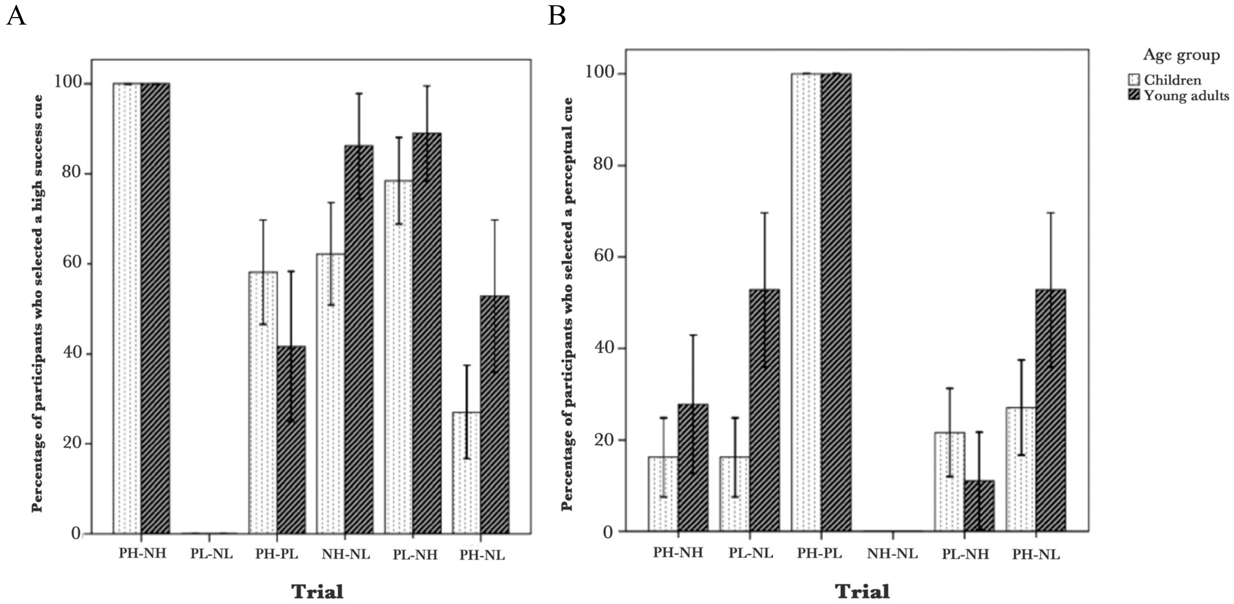

Figure 1: Percentage of children and young adults who selected a high success cue (Figure 1A) and a perceptual cue (Figure 1B), in the trials specified in the *x* axis. Bars indicate standard errors.

In trials where participants were given a perceptual/low success cue (PL) and a non-perceptual/high success cue (NH), they select more often the non-perceptual/high success one (Children: 78%; Young adults: 89%). Finally, in what we reckon as the crucial trial, where participants were given a perceptual/high success cue (PH) and a non-perceptual/low success cue (NL), children selected more often the non-perceptual/low success cue (73%), and young adults selected the perceptual/high success cue in only 52% of the trials.

Discussion

In Study 3 we found that when participants were given a perceptual and a non-perceptual cue, both being high or low success, they selected more often the non-perceptual one, especially the children. We also found that, in trials where the two cues presented were both perceptual or non-perceptual, the participants could not always identify the most successful one. In particular, it seemed to be hard for them to identify the most successful between two perceptual cues. This was especially true for the young adults, who maybe use these cues less often and are therefore less familiar with them.

In what we defined as the crucial trials, where participants had to trade between visibility and success, children selected the non-perceptual/low success cue more often, and adults selected the perceptual/high success cue only about half times.

These results suggest that the bias towards non-perceptual cues, observed in Study 2, is present also in a cue-selection design. Here, also children, besides the young adults, tend to select non-perceptual cues, assuming that they are more informative than perceptual cues.

General Discussion

In this paper we wanted to explore, from a developmental perspective, the interaction between the knowledge of cues useful for an inference, the type of cues and the ability to select the most informative cue available. To do so, we opened and compared children's and young adults' cuebox, by examining the amount, type and informativeness of the cues people have available, potentially, for making different kind of inferences (Study 1). Moreover, we tested whether children and adults can select the most informative cue available, and how this is influenced by the type of cues, in both a cue-generation (Study 2) and a traditional cue-selection (Study 3) task.

We found that children have in their cuebox more perceptual cues then adults. This fits with the definition of children as "perceptually oriented" (Flavell, 1985; John & Sujan, 1990; Springer, 2001; Wartella, 1979). Children have overall less knowledge and less experience of the objects and of their non-perceptual features. As they grow up, the process of updating their knowledge through experience leads also to an update of their cuebox: Some of the perceptual cues children used to base their inferences on are replaced by non-perceptual cues, assumed to be more appropriate, sophisticated and technical - *thus* more informative, as seen in Study 2. There is the rub: The informativeness of a cue is not a fixed feature, but it reflects a match between the cue and the task at hand. Therefore, in some inference tasks those non-perceptual cues, though more appropriate and sophisticated, are not more informative than perceptual cues. In these inference tasks, in a cue-generation design, children have an advantage, because they tend to generate perceptual cues (Study 2).

In a cue-selection design (Study 3), though, both adults and children show a bias, a tendency to deem non-perceptual cues as more informative than perceptual cues, even when they are not. Evidently, being presented with something that 'looks and sounds' more appropriate and sophisticated is enough for triggering this bias.

Our findings open the way and suggest further investigations, especially exploring the bias towards non-perceptual cues and testing possible interventions to make people aware of the situations where such tendency is not useful, learning from children.

Author Note

Thanks to Claudia Mazzeranghi, Selica Vicidomini, Riccardo Ruggeri, Marianna Sgherri and Chiara Chiellini for collecting the data, and to the teachers of the schools used for recruitment for their support. Thanks to Nicolai Bodemer and Katherine McMahon for their comments and suggestions.

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Appendix

Table A1

Study 1: Mean Number (and Standard Deviations) of Cues Generated by the Participants, Listed by Inference Task

Inference task	Children	SD	Young adults	SD	Mean	SD
City population	3.25	1.36	1.86	0.96	2.42	1.32
Car price	4.45	1.86	2.52	1.29	3.52	1.87
Mobile price	3.74	1.65	3.19	1.47	3.44	1.57
Actor earn	1.71	0.97	2.39	0.93	2.07	1.01
Team results	1.94	1.04	2.04	1.04	1.98	1.03
Movie earn	1.86	1.00	2.06	1.12	1.96	1.06
Player earn	1.63	1.25	2.21	1.22	1.94	1.26
Animal speed	1.36	0.99	1.10	0.89	1.22	0.94
City temperature	2.68	1.59	2.71	0.93	2.70	1.25
Car speed	3.76	2.01	2.50	1.27	3.00	1.70
House price	5.61	1.69	5.33	1.95	5.48	1.81
Book sales	1.69	1.05	1.30	0.95	1.51	1.02
Mean	2.79	1.91	2.44	1.54	2.61	1.74

Table A2:

Study 1: Cues (and their Type) Generated by Participants (Percentages Within Age Group), Listed by Inference Task

Inference task	Question	Type	Adults	Children
City population	Airport	Non-perceptual	4	4
	Altitude	Perceptual	2	10
	Area	Perceptual	41	36
	Capital	Non-perceptual	6	2
	Climate	Non-perceptual	18	2
	Density od Population	Non-perceptual	6	2
	Number of buildings	Perceptual	6	38
	Number of hotels	Perceptual	0	4
	Number of parks	Perceptual	2	21
	Number of restaurants	Perceptual	0	4
	Number of schools	Perceptual	8	15
	Number of monuments	Perceptual	12	6
	Number of Museums	Perceptual	2	4
	Seismic Risk	Non-perceptual	6	0
	Stadiums	Perceptual	0	2
	Tourism	Non-perceptual	10	11
	Train Stations	Perceptual	4	4
	Unemployment	Non-perceptual	12	11
Car price	AC	Non-perceptual	4	4
	Capacity	Non-perceptual	2	17
	Cylinders	Non-perceptual	20	13
	Doors	Perceptual	12	9
	Fuel consumption	Non-perceptual	0	9
	Gears	Perceptual	8	19
	Horsepower	Non-perceptual	43	49
	Length	Perceptual	0	23
	Parking Sensors	Perceptual	2	2
	Pollution level	Perceptual	2	0
	Seats	Perceptual	16	32
	Size	Perceptual	18	43
	Size of the trunk	Perceptual	2	17
	Speed	Non-perceptual	12	40
	Type of fuel	Non-perceptual	14	28
	Weight	Non-perceptual	2	2
	Width	Perceptual	0	11
Mobile price	Battery life	Non-perceptual	6	21
	Bluetooth	Non-perceptual	18	2
	Camera	Perceptual	51	38
	Dual sim	Perceptual	8	4

	Email	Perceptual	2	0
	Facebook	Non-perceptual	0	4
	Games	Perceptual	0	21
	GPS	Perceptual	4	0
	Internet	Perceptual	29	23
	Length	Perceptual	2	23
	Memory	Non-perceptual	41	23
	Screen resolution	Perceptual	6	11
	Screen size	Perceptual	4	13
	Size	Perceptual	4	9
	Thickness	Perceptual	2	4
	Touchpad	Perceptual	39	66
	Weight	Non-perceptual	0	4
	Width	Perceptual	0	2
	Wifi	Non-perceptual	12	2
	Years on the market	Non-perceptual	29	11
	Youtube	Non-perceptual	0	2
Actor earn	Age	Non-perceptual	12	30
	Awards	Non-perceptual	25	6
	Director	Non-perceptual	14	0
	Height	Perceptual	0	9
	Role	Non-perceptual	37	19
	TV series	Perceptual	14	11
	Years of Experience	Non-perceptual	114	66
Team results	Age	Non-perceptual	12	6
	Awards	Non-perceptual	10	15
	Fans	Perceptual	6	11
	Injured	Non-perceptual	14	4
	Number of players	Perceptual	57	83
	Size of the stadium	Perceptual	0	2
	Team ranking	Non-perceptual	47	66
Movie earn	3D	Perceptual	10	19
	Awards	Non-perceptual	27	9
	Book	Non-perceptual	6	2
	Length	Perceptual	6	34
	Number of actors	Perceptual	65	46
	Production costs	Non-perceptual	8	17
	Ranking	Non-perceptual	2	2
	Sequel	Non-perceptual	4	6
	Special effects	Non-perceptual	6	0
	Trailers	Non-perceptual	2	6
	Translations	Non-perceptual	10	2
Player earn	Age	Non-perceptual	29	13
	Awards	Non-perceptual	10	6
	Captain	Non-perceptual	4	9
	Height	Perceptual	0	2
	Nationality	Non-perceptual	2	4
	Position	Non-perceptual	29	57

	Team ranking	Non-perceptual	35	26
	Years of experience	Non-perceptual	51	19
Animal speed	Average age	Non-perceptual	8	15
	Height	Perceptual	4	6
	Herd	Non-perceptual	4	6
	Length	Perceptual	0	11
	Number of legs	Perceptual	27	28
	Size	Perceptual	0	2
	Strength	Non-perceptual	2	2
	Weight	Non-perceptual	2	2
City temperature	Altitude	Perceptual	24	23
	Area	Non-perceptual	10	21
	Cm of snow per year	Non-perceptual	0	2
	Cm rain per year	Perceptual	2	6
	Coast	Perceptual	51	30
	Humidity	Non-perceptual	10	6
	Island	Perceptual	2	4
	Latitude	Non-perceptual	71	57
	Northern Italy	Non-perceptual	14	17
	Population	Non-perceptual	6	17
	Tourism	Non-perceptual	4	9
Car speed	Acceleration	Non-perceptual	4	0
	Capacity	Non-perceptual	22	13
	Cylinders	Non-perceptual	29	17
	Doors	Perceptual	0	4
	Fuel consumption	Non-perceptual	4	2
	Gears	Perceptual	2	13
	Height	Perceptual	0	11
	Horsepower	Non-perceptual	59	23
	Length	Perceptual	0	17
	Price	Non-perceptual	16	15
	Seats	Perceptual	6	19
	Size	Perceptual	10	23
	Size of trunk	Perceptual	2	9
	Tank capacity	Non-perceptual	0	2
	Type of fuel	Non-perceptual	25	15
	Weight	Non-perceptual	16	11
	Width	Perceptual	0	11
House price	Area	Perceptual	49	87
	Attic	Perceptual	4	4
	Condo expenses	Perceptual	14	17
	Elevator	Non-perceptual	0	2
	Fireplace	Perceptual	2	9
	Furniture	Perceptual	20	23
	Garage	Perceptual	24	17
	Garden	Perceptual	45	47
	Height	Perceptual	33	51
	Kind of floor	Non-perceptual	0	6

	Length	Perceptual	0	4
	Light	Perceptual	6	19
	Number of rooms	Perceptual	37	64
	Pool	Perceptual	6	13
	Renewed	Non-perceptual	45	28
	Terrace	Perceptual	12	19
	View on the sea	Non-perceptual	18	30
	Width	Perceptual	0	4
Book sales	Author's other books	Non-perceptual	8	9
	Awards	Non-perceptual	6	0
	Illustrations	Perceptual	2	15
	Length	Perceptual	31	91
	Movie	Non-perceptual	4	4
	Nationality	Non-perceptual	2	9
	Price	Non-perceptual	16	23
	Ranking	Non-perceptual	6	0
	Sequel	Non-perceptual	4	0
	Width	Perceptual	0	4

Table A3

Study 1: Percentages of Perceptual Cues on The Total Amount of Cues Generated, Listed by Inference Task

Inference task	Children	SD	Young adults	SD	Mean	SD
City population	79	26	66	51	71	42
Car price	62	24	28	25	45	30
Mobile price	62	27	41	33	51	32
Actor earn	9	18	1	6	4	13
Team results	31	16	35	21	33	18
Movie earn	54	29	30	31	41	32
Player earn	11	20	2	9	6	15
Animal speed	63	32	56	45	60	38
City temperature	70	44	44	33	55	40
Car speed	50	28	8	14	26	29
House price	76	29	68	25	72	27
Book sales	56	29	31	27	45	31
Mean	53	35	34	37	43	37

Table A4

Study 1: Mean Success (and Standard Deviations) of the Cues Generated by the Participants, Listed by Inference Task

Inference task	Children	SD	Young adults	SD	Mean	SD
City population	0.75	0.08	0.65	0.08	0.69	0.09
Car price	0.73	0.03	0.75	0.04	0.74	0.03
Mobile price	0.69	0.06	0.68	0.08	0.68	0.07
Actor earn	0.54	0.03	0.53	0.02	0.54	0.03
Team results	0.70	0.10	0.69	0.08	0.70	0.09
Movie earn	0.60	0.03	0.58	0.02	0.59	0.03
Player earn	0.57	0.02	0.57	0.02	0.57	0.02
Animal speed	0.59	0.04	0.61	0.03	0.60	0.04
City temperature	0.66	0.08	0.71	0.05	0.69	0.07
Car speed	0.72	0.06	0.80	0.07	0.77	0.08
House price	0.66	0.05	0.66	0.05	0.66	0.05
Book sales	0.58	0.03	0.58	0.03	0.58	0.03
Mean	0.65	0.09	0.65	0.09	0.65	0.09

Table A5

Study 2: Percentages of Perceptual Cues on The Total Amount of Cues Generated, Listed by Inference Task

Inference task	Children	SD	Young adults	SD	Mean	SD
City population	38	49	35	49	37	49
Car price	56	50	15	37	43	50
Mobile price	76	44	63	50	71	46
Actor earn	00	00	04	20	02	13
Team results	29	47	00	00	14	35
Movie earn	73	46	07	27	41	50
Player earn	05	22	00	00	03	17
Animal speed	57	51	20	45	47	51
City temperature	12	33	08	28	10	32
Car speed	32	48	00	00	17	38
House price	98	15	96	20	97	17
Book sales	54	41	23	42	39	41
Mean	45	50	26	44	37	48

Table A6

Study 2: Mean Success (and Standard Deviations) of the Cues Generated by the Participants, Listed by Inference Task

Inference task	Children	SD	Young adults	SD	Mean	SD
City population	0.70	0.22	0.68	0.23	0.69	0.22
Car price	0.58	0.34	0.58	0.35	0.58	0.34
Mobile price	0.70	0.17	0.72	0.05	0.70	0.14
Actor earn	0.52	0.00	0.50	0.11	0.51	0.07
Team results	0.68	0.20	0.80	0.03	0.74	0.15
Movie earn	0.60	0.01	0.59	0.01	0.59	0.01
Player earn	0.55	0.03	0.55	0.04	0.55	0.03
Animal speed	0.62	0.03	0.62	0.05	0.62	0.04
City temperature	0.85	0.06	0.85	0.06	0.85	0.06
Car speed	0.81	0.12	0.82	0.16	0.82	0.14
House price	0.76	0.10	0.79	0.07	0.77	0.09
Book sales	0.62	0.07	0.54	0.05	0.58	0.06
Mean	0.69	0.20	0.70	0.19	0.69	0.19

Chapter 5

General Discussion

Chapter 5

General Discussion

This dissertation pioneers the exploration of people's intuitions about the importance of real cues in the real world and how those intuitions develop over the lifespan. We investigated if, and under which conditions, children and adults search and implement the most effective piece of information when categorizing (Chapter 2) or making inferences (Chapters 3 and 4).

My research makes three major contributions to psychology and cue-based decision-making. First, the results of Chapter 2 indicate the representation of objects can influence the efficacy of children's inquiring strategies; Different representations trigger different types of features. Specifically, the basic level of objects' representation facilitated children in generating questions based on higher-order features. Such features distinguish the objects within a same superordinate category and can therefore be used to ask effective questions. When children did not generate features to ask questions but instead selected among a set of given questions, the effect of domain and level of representation did not emerge. However, the developmental differences between younger children, older children and adults in identifying the most efficient questions from a given set remained.

As already mentioned in the conclusions of Chapter 2, the analysis of people's inquiring strategies in a sequential binary categorization task should be extended to situations where the set of potential alternatives is not given. In our everyday life there is rarely a well-defined set of alternatives, a catalogue to select among. Therefore, this design would be an extension to more ecological settings of the investigation presented in Chapter 2. Moreover, it could be used to explore how people dynamically construct and update the set of possible alternatives. Further, this investigation would allow us to examine at which level of abstraction and representation children and adults naturally think when building a set of alternatives from scratch.

Second, the results of Chapter 3 and 4 show that the cues children and young adults have in their cuebox differ, particularly in terms of type: Children have more perceptual cues and young adults have more non-perceptual cues. Despite this difference, across the tested inference tasks, we found no difference between the two age groups in terms of quality of the cues generated. Results of Chapter 4 also show that, surprisingly, children have more cues than young adults available in their cuebox, for all the inference tasks we tested. Moreover, we found that the type of cue influences children and adults' intuitions about its informativeness in a cue-selection design: The non-perceptual cues were considered more informative then perceptual ones.

These findings call for further investigations. First, the robustness of what we defined as a *bias* towards non-perceptual cues should be tested in other inference tasks and in other kinds of decision making situations, for example when choosing among consumer products. Second, it would be crucial to understand more precisely, from a developmental perspective, when and how children let go of the perceptual cues and start to fill their cuebox with non-perceptual cues. This could be done, for example, by monitoring this transition in a longitudinal study. Both these lines of research might also test and inform the design of possible interventions aimed at making children and adults aware of the situations where such tendency is detrimental. In this way, research could help them tune their cuebox to make it *adaptive* (Gigerenzer, Todd & the ABC Research Group 1999).

Third, the experimental design matters. In all three experimental papers composing this dissertation we compared two methodologies: A cue-generation paradigm, where children and adults are free to generate the cues they consider most relevant for the task at hand, and a cue-selection paradigm, where participants are asked to select among a set of given cues the ones they want to consult. We found substantial and interesting differences between these two methodologies. On the one hand, the effects of object domain and representation of (i.e., the facilitating effect of the basic-level condition, as well as the hindering effect of the subordinate-level and features-enriched conditions) emerge only in a cue-generation design. On the other hand, in a cue-generation design children have an advantage in the inference tasks for which the perceptual cues *happen* to be more informative. This advantage is lost in a cue-selection paradigm.

Even though the cue-selection paradigm is the one traditionally used to study cue-based decision-making, we argue that in many real world situations people are not provided with a set of cues they can look up. For this reason, I think that investigating further the process of generating cues is crucial to understanding the process that actually takes place when people search for information. In the next years, I plan to extend the cue-generation methodology I adopted in this dissertation. In particular, I started investigating the process of searching and identifying relevant cues when: a) tracing causes and generating hypotheses for an observed event (Ruggeri & Katsikopoulos, 2012; Ruggeri & Lombrozo, 2012); b) assessing own and other's preferences, such as for medical treatments or consumer products; c) assessing own and other's conditions (e.g., health condition or financial condition) and related risks. A nuanced understanding of how children and adults perceive the importance of environmental cues in different situations might be crucial to design better and more thoughtful interventions and intuitive communication strategies.

References

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Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation selbstständig und ohne die unzulässige Hilfe Dritter verfasst habe und die Dissertation auch in Teilen keine Kopie anderer Arbeiten darstellt. Die verwendeten Hilfsmittel sowie Literatur sind vollständig angegeben. Die Arbeit ist in keinem früheren Promotionsverfahren angenommen oder abgelehnt worden. Ich habe keinen Doktorgrad in dem Promotionsfach Psychologie, und die zugrunde liegende Promotionsordnung der Humboldt-Universität vom 03.08.2006 ist mir bekannt.

Berlin, den 20. Juni 2012

Azzurra Ruggeri