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ARTICLE

Children's information-search strategies: Operationalizing efficiency and effectiveness

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Abstract

Research on the development of active learning and information search behaviors has been growing rapidly, drawing interest from multiple disciplines, from developmental psychology to cognitive science and artificial intelligence. These different perspectives can open pathways to understanding how preschool-age children grow into adaptive and efficient active learners. However, the lack of a shared vocabulary, operationalizations, and research paradigms has led to limited cross-talk and some conflicting findings. In this article, we advocate for using a shared operationalization of a "good" information-search strategy, as a function of its *efficiency* and *effectiveness* within a given ecology, based on the information-theoretic measure of expected information gain and observed behavioral outcomes, respectively. We also discuss factors that should be considered when designing experiments that examine children's information-search competence, specifically, using formal models as performance benchmarks and accounting for children's prior knowledge, assumptions, and self-generated goals.

KEYWORDS
development of search efficiency, information gain, information search

Research on the development of people's active learning and *information search* behaviors—either through exploring the environment or by asking questions—has been growing rapidly, drawing interest from multiple disciplines, from developmental psychology to cognitive science and artificial intelligence. This can be seen in the increasing number of experiments, reviews, and opinion pieces addressing the topic (Baer & Kidd, 2022; Brod, 2021; Coenen et al., 2019; Lapidow & Walker, 2022; Liquin & Lombrozo, 2020), which have contributed to our understanding of the developmental changes in active learning and their underlying processes, and have offered rich and fertile perspectives. However, research on when and how the information-seeking competences of young children emerge and develop has often led to inconclusive findings. In particular, research on decision making and education suggests that systematic, efficient, and effective information search and scientific reasoning emerge late in development, around age 10 or even later, in adolescence (e.g., Betsch et al., 2018; Davidson, 1996; Mata et al., 2011). In contrast, research from cognitive, developmental, and computational psychology has provided evidence that, when tested with age-appropriate methods, toddlers and preschoolers are capable of efficient and adaptive exploration and information search, and of designing informative interventions for causal learning (e.g., Cook et al., 2011; Pelz et al., 2022; Ruggeri et al., 2019; Swaboda et al., 2022). (For the sociodemographic characteristics of the studies reviewed herein, see Table S1.)

In our view, this tension is caused primarily by researchers' use of different experimental methods (some of which can be too complex for young children), concepts, and operationalizations, which lead

Abbreviations: EIG, expected stepwise information gain; IG, information gain; OED, optimal experiment design.

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them to measure different aspects of children's performance, not necessarily mapping onto each other in a linear way. Developmental researchers have mostly relied on behavioral outcome-based measures to quantify children's information-search skills, such as the number and type of questions used to reach a solution (Jirout & Klahr, 2020; Legare et al., 2013), the effect of experimental manipulations on binary exploration decisions (Lapidow et al., 2022), and the types of exploratory actions performed (Ronfard et al., 2021). However, a growing body of work is also using formal model-based approaches to quantify performance (e.g., Mousekids paradigm, Betsch et al., 2014; Schulz et al., 2019).

In this article, we propose a clear operationalization of the concepts of *effectiveness* and *efficiency* used in research on active learning in children from infancy to adolescence, with the goal of identifying common ground for evaluating learning strategies. We also emphasize that learning and information-search competence should be evaluated within the framework of *ecological active learning*, which assesses learners' ability to actively shape their exploration and learning process by recognizing and exploiting the specific characteristics and structure of the learning environment (Ruggeri, 2022). Finally, we highlight and discuss the crucial factors that should be considered when examining information search from a developmental perspective.

DEFINING AND QUANTIFYING EFFICIENCY AND EFFECTIVENESS

To understand information-seeking actions, researchers should adopt a framework that considers both the *outcomes* of the performed actions (e.g., whether the action succeeded at reaching a given goal) and the underlying *processes*. This approach is common in some lines of developmental work on information search, for example, in research on asking questions. In that field, researchers have traditionally measured children's competence by analyzing their success, along with their use of *constraint-seeking* questions, which target categories of objects (e.g., Is the object round?), versus *hypothesis-scanning* questions, which target individual hypotheses (e.g., Is it *this* object?) in versions of the 20 Questions paradigm (e.g., Jirout & Klahr, 2020; Legare et al., 2013; Mosher & Hornsby, 1966). The goal of the 20 Questions game is to identify a target object (e.g., the monster that activates a special machine; see Figure 1a) among several distractors by asking as few yes-or-no questions as possible. In this game, constraint-seeking questions were considered better than hypothesis-scanning questions for reaching a solution because they could rule out multiple hypotheses at each step of the search process.

In this literature on asking questions, efficiency and effectiveness have often been treated as interchangeable,

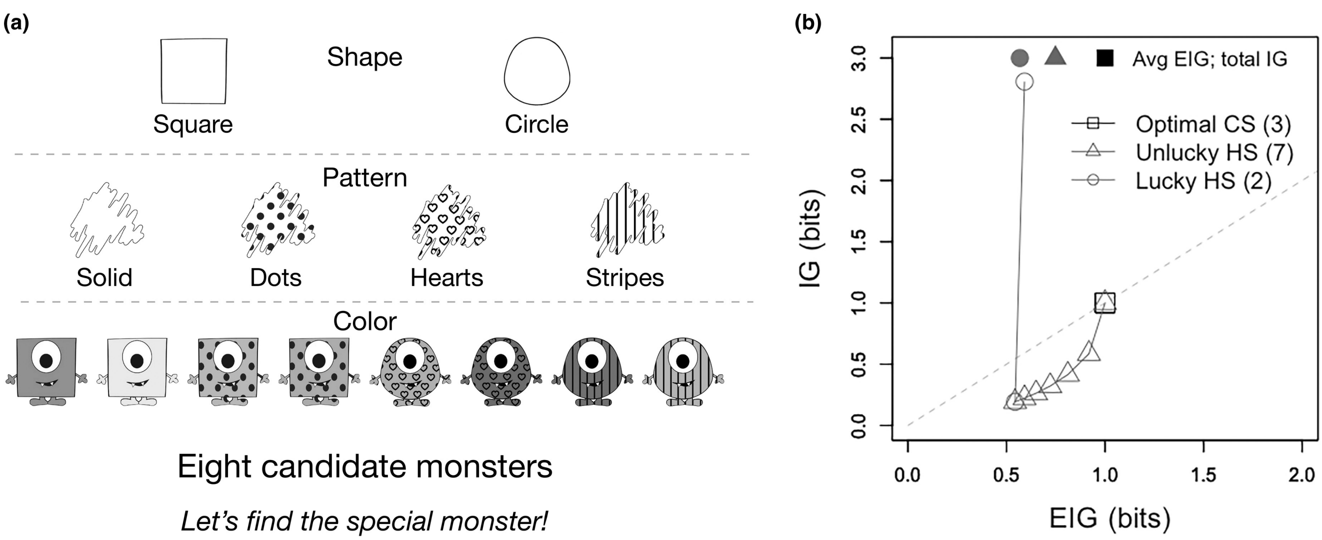

FIGURE 1 An example of a 20 Questions game and the strategies used to solve it. The illustration on the left (reproduced from Swaboda et al., 2022) shows stimuli used in a 20 Questions game and the questions that could be asked. The plot on the right depicts three question-asking agents following: an optimal constraint-seeking (CS) strategy (three steps taken to solution), a lucky hypothesis-scanning (HS) strategy (two steps taken to solution), and an unlucky hypothesis-scanning strategy (seven steps taken to solution). The *x*-axis shows a strategy's expected information gain, which defines efficiency in our framework; the *y*-axis shows the observed information gain yielded by a strategy, which we consider the effectiveness of the strategy and is reflected in the observed number of steps taken. For hypothesis-scanning questions, expected stepwise information gain (EIG) changes at each step of a multiple-question strategy. For the optimal constraint-seeking strategy that divides the hypothesis space into two at each step, EIG remains stable at 1, so all the queries overlap at [1,1]. The empty shapes denote each question asked. The filled-in shapes represent the average expected information gain for each strategy against the total information gain. Total information gain is equal for all strategies since they were all successful.

indistinguishable constructs. However, while the two constructs can be more or less related or even completely overlap depending on the task, from a theoretical perspective, they are independent.

We propose that research on active learning should clearly distinguish the *efficiency* of an information-search strategy (e.g., the informativeness of the queries/actions performed) from its *effectiveness* (e.g., the observed number of steps taken to solve a given problem) and *success* (e.g., whether or not the problem was eventually solved). This is necessary because successful outcomes of inquiry behaviors may at times be the result of luck, not the output of efficient search processes. Conversely, potentially efficient active-learning strategies may result in less effective or even unsuccessful outcomes due to unforeseen changes in the state of the environment that occur independently of the learner (cf. Schleihauf et al., 2023, in the domain of reasoning).

Nonformal approaches, such as the traditional analysis of question types mentioned earlier, have limitations in this respect. Take the 20 Questions scenario illustrated in Figure 1a: If only three equally likely candidate hypotheses (i.e., monsters) were left, hypothesis-scanning questions would be as informative as constraint-seeking questions. Moreover, if the alternative hypotheses considered were not all equally likely, a hypothesis-scanning question that targeted a single high-probability hypothesis (e.g., the monster that has a 70% probability of being the target) could be more informative than a constraint-seeking question targeting several hypotheses with a smaller summed probability. Furthermore, not all constraint-seeking questions are equally efficient: A constraint-seeking question that partitions the hypothesis space evenly is more informative than a constraint-seeking question that partitions the same space unevenly. These cases illustrate how relying on just the type of question might lead to incorrect conclusions about the efficiency and effectiveness of information-search strategies, failing to distinguish between them.

Instead, information-theoretic metrics applied to models of learning in the tradition of optimal experiment design (OED) can be used to explicitly and precisely quantify the different aspects of active-learning performance (see Coenen et al., 2019; Nelson, 2005). In the 20 Questions example, a learner is *successful* if they manage to identify the target hypothesis, and the *effectiveness* of a question-asking strategy is measured by observing the number of questions required to solve a given problem in a game.

In principle, multiple measures could operationalize the *efficiency* of a learning strategy in the OED framework (Nelson, 2005), and researchers are investigating which objective function best describes what drives active-learning behaviors (Liquin & Lombrozo, 2020). In the paradigms used in developmental and cognitive psychological research, these different measures (e.g., probability gain, information gain, utility gain) most often make identical predictions. Here, we consider an intuitive measure of the efficiency of a question that is widely used in developmental research and in studies of adults (Nelson, 2005; Steyvers et al., 2003): *expected stepwise information gain* (EIG; e.g., Eimas, 1970). EIG measures how much a question is expected to reduce the uncertainty about which hypothesis is correct, measured via Shannon (1948) entropy (SE). The computation of SE is based on the probabilities p associated with each of the candidate hypotheses h.[1]

$$\mathrm{SE}(H) = -\sum_{h \in H} p(h)\log_2 p(h). \tag{1}$$

Assuming a uniform prior (i.e., that all hypotheses are equally likely), the entropy at each step is log n, where n is the number of remaining hypotheses. The posterior entropy, that is, the entropy after a question Q was asked and an answer x was received, is

$$\mathrm{SE}(H \mid X = x) = -\sum_{h \in H} p(h \mid x)\log_2 p(h \mid x). \tag{2}$$

We can then distinguish the observed information gain (IG) of a question, computed as $\mathrm{SE}(H) - \mathrm{SE}(H|x)$, from its EIG, which weights the posterior entropy corresponding to each possible future answer with the probability of each answer x, $p(x) = \sum_{h \in H} p(x|h)p(h)$.

$$\mathrm{EIG}(q) = \mathrm{SE}(H) - \sum_{x \epsilon X} \mathrm{SE}(H \mid x) \cdot p(x). \tag{3}$$

Taken together, because in our example each question can yield two possible answers (yes/no) and we assumed a uniform prior, EIG is calculated as:

$$\mathrm{EIG}(q) = \log_2 n - \left[\frac{n_{\mathrm{no}}}{n}\log_2 n_{\mathrm{no}} + \frac{n_{\mathrm{yes}}}{n}\log_2 n_{\mathrm{yes}}\right], \tag{4}$$

where n_{yes} and n_{no} indicate the number of hypotheses that would remain under consideration if the answer were affirmative (i.e., if the target monster has the queried feature value, e.g., is green) and negative, respectively. Within this setup, the maximum stepwise EIG is 1, corresponding to a question that splits the hypothesis space in half. EIG decreases as the split induced by a query becomes less even (Nelson et al., 2014), with the minimum possible value being 0 (corresponding to confirmatory or irrelevant questions).

In an environment that has a symmetrical hierarchical structure—as in our example—the optimal, most efficient search strategy is a top-down approach, which first targets the highest-level category (i.e., the feature

[1]The choice of base for the logarithm is arbitrary. We use base 2, so the unit is the bit.

with two variants), then the middle-level category (i.e., the feature with four variants), and then the lowest-level category (i.e., the feature with eight variants). In this case, the optimal search strategy guarantees finding the solution with exactly the minimum possible number (three) of queries.[2] In contrast, the number of steps required to reach the target using a suboptimal strategy depends on *luck*. For instance, Figure 1b illustrates two inefficient learners who ask only hypothesis-scanning questions: a lucky one, who stumbled across the solution after only two questions, and an unlucky one, who found the target after seven questions. In this example, despite having used a less efficient strategy, the lucky learner achieves the solution with fewer steps (i.e., is more effective) than the optimal learner, who asks constraint-seeking questions. The probability of a hypothesis-scanning agent finding the correct solution is uniform over the number of steps (here, 12.5%), which means that the effectiveness of such agents—how many steps they actually take—does not predict their actual competence.

Therefore, what we call luck is the variability in effectiveness for a fixed EIG value (see Figure 1b). Because of luck, inferences about an agent's information-search competence are accurate only if they are based on the agent's efficiency rather than on their observed, luck-sensitive effectiveness (Török et al., 2023). Nevertheless, we acknowledge that tracking the effectiveness of queries may serve as a useful heuristic to infer question-asking competence. This is because the predicted behavioral outcomes based on efficiency and effectiveness often correlate, and observing cues to effectiveness may be less costly computationally and faster than computing and tracking efficiency based on EIG. Indeed, in one study (Török et al., 2023), children younger than 8 years old were more likely to use the difference in the number of questions asked by two agents to evaluate their competences, whereas older children relied more on EIG differences. More work is needed to investigate children's and adults' potential use of such heuristics, as well as their ability to go beyond them. Researchers should also explore whether children's assessment of their own competence can be formalized in this framework by asking whether they choose to perform tasks that are maximally informative for pinpointing their current level of competence.

In summary, within this framework, the most efficient questions are those that maximize EIG relative to the learner's model of the task. The efficiency of a strategy is then calculated as the average informativeness of the series of questions asked when solving the game. However, when comparing EIG averages across conditions or individuals, researchers should control for effectiveness (e.g., number of questions asked). For instance, in Figure 1a, the average EIG of the unlucky inefficient agent is higher than that of the lucky one, despite the fact that they used the same inefficient hypothesis-scanning strategy, simply because hypothesis-scanning questions have increasing EIG as the hypothesis space gets smaller.

BENCHMARKS FOR DEVELOPMENTAL PERFORMANCE: ADAPTIVENESS AND FORMAL MODELS

In our view, presenting children and adults with an identical paradigm and comparing their performance in absolute terms *only* (e.g., accuracy) is frequently not meaningful—although it may be a useful first step to describe the baseline developmental trajectory on a given task. To understand the developmental differences observed in performance and identify the underlying mechanisms, researchers need to use paradigms that are suitable for children (e.g., short, easy to understand, engaging) and shift from evaluating adults' and children's performance using absolute measures to using a twofold approach that focuses on children's *adaptiveness* and includes comparisons with computational models of behavior.

We define adaptiveness as the flexibility of the learner to maintain efficiency and effectiveness across different environments, which goes beyond being able to suitably adjust learning strategies within the context of one task. The OED framework, as we described, can be used not only to quantify efficiency but also to predict how different sets of beliefs and assumptions, as well as different stimulus structures, determine the most efficient strategy. One way to tap into children's adaptiveness is to compare their performance across conditions characterized by different probability distributions over the available hypotheses (e.g., uniform vs. skewed). For example, in a study (Ruggeri et al., 2017) that examined children's judgments of the informativeness of questions across dynamically changing hypothesis spaces, 4- and 5-year-olds were characterized as *ecological active learners*, that is, they relied on different types of questions (constraint-seeking or hypothesis-scanning) depending on their EIG in a given hypothesis space.

In another study (Ruggeri & Lombrozo, 2015), while the types of questions asked differed developmentally, 7- to 11-year-olds were just as likely as adults to adapt to differences in the prior probability distribution in the hypothesis space; this suggests that the observed developmental trends might not reflect age-related information-search differences per se, but other developing cognitive capacities. In line with this, in yet another study (Swaboda et al., 2022), even 3-year-olds adapted their exploratory strategies to the statistical structure

[2]For examples on how to calculate EIG values for the different question types, see appendix A in Ruggeri et al. (2017).

of a task when verbal requirements were minimized. Another way to assess adaptiveness is to contrast environments that differ in the dispersion of cue validity (high vs. low). When one cue strongly predicts outcomes and the others do not, the normative prediction for both decision-making and information search is prioritization of the high-value cue. In a study using this approach (Betsch et al., 2016), elementary-school-age children and adults, but not preschool-age children, were systematic in their probability weighting.

Formal quantification of the efficiency of information-search strategies enables comparisons against absolute benchmarks for random and optimal performance, which provide a more meaningful and objective basis for contrasting results across multiple studies and different populations. For example, it allows researchers to detect whether children, despite being generally less successful and efficient at information search than adults, still perform above chance or whether, despite displaying different default strategies, they may be as *adaptive* as adults (i.e., show a similar magnitude of sensitivity to different experimental conditions). Moreover, together with designs that manipulate the kinds of strategies required to solve the task optimally, formal models allow researchers to test alternative theoretical hypotheses about the *mechanisms and processes* underlying information search in children and adults (e.g., Betsch et al., 2018; Schulz et al., 2019).

Finally, formal models can and should consider developmentally realistic constraints on performance, following the framework of resource rationality (Gershman et al., 2015; Lieder & Griffiths, 2020). These constraints include children's prior knowledge, beliefs, and expectations about the task domain and stimuli, vocabulary, and general cognitive capacity (e.g., limits on the number of hypotheses considered at once). Experiments with adults have explored the role of factors such as sequential and biased hypothesis generation (Markant & Gureckis, 2014), the costs of information sampling (Petitet et al., 2021), and memory and processing constraints (Bramley et al., 2015).

MISSING PIECES IN THE ACTIVE-LEARNING PUZZLE

Developmental research on active learning and information search can address crucial factors. One important but understudied dimension is whether children engage in *planning* in temporally extended tasks. In the 20 Questions game, the split-half strategy is optimal both stepwise and globally, but this is generally not the case (Nelson et al., 2018). In one study (Meder et al., 2019), both children and adults searched myopically (i.e., taking only the immediate next step), likely due to the increased computational demands of global search. Researchers should investigate the factors that make participants more sensitive to stepwise versus global optimality and aim to understand how adults and children respond to environmental changes at different time scales: Do children adapt their strategies dynamically and if so, are they more flexible than adults?

Furthermore, while the OED framework is well-suited for designing and modeling controlled experiments on information search, it does not allow researchers to fully capture the richness of children's exploratory behaviors. In particular, children may seek to acquire information that is useful beyond the scope of the task in pursuit of rewards unanticipated by researchers. For instance, children might prioritize strategies that lead to improved generalization to new environments (Schulz et al., 2019) or enhanced memory recall of the items presented over strategies that ensure task efficiency (Stanciu et al., 2023). Alternatively, children may have motivations independent of the objectives of the task, such as socially engaging with the experimenter (Jaswal & Kondrad, 2016). How children represent their environment and understand experimental tasks, and the extent to which this diverges from researchers' assumptions, may be influenced directly or indirectly by multiple factors, including age (Jones et al., 2021); learning experiences; and interindividual differences in cognition or cultural, racial, and socioeconomic background. As a result, researchers can observe seemingly inefficient behaviors, despite the fact that children apply broadly efficient (or at least meaningful) strategies, when there is a mismatch between children's assumptions and the ground truth about the identity of the potential hypotheses and their relative likelihood. For instance, if children believe one hypothesis is very likely to be correct—even though from the researchers' perspective, all hypotheses are equally likely to be correct (Bramley et al., 2022; Ruggeri & Lombrozo, 2015)—they may rationally prefer targeted questioning (e.g., hypothesis-scanning).

Finally, if researchers' goal is to understand rich exploratory behaviors, they also need to adjust current experimental paradigms. We used the example of the 20 Questions game throughout this article to illustrate our arguments because of its simplicity and widespread use. However, the field will benefit from examining a much more varied range of paradigms (e.g., multi-arm bandit tasks converted into child-friendly spatial exploration tasks), potentially inspired by studies with adults. Nevertheless, it is unclear if and how the OED framework can be applied to exploration in completely new situations to explain how children set arbitrary rewards and costs to themselves, and to generate novel goals and ideas (Chu & Schulz, 2020; Davidson et al., 2022).

CONCLUSION

In this article, we recommended steps for determining what a "good" learning strategy is in developmental research on information search. We emphasized that competence should be evaluated through the lens of adaptiveness by using precise computational quantifications of *efficiency* and *effectiveness* and formal models as performance benchmarks. We find it encouraging that emerging research on information search across development is converging on these recommendations in various types of tasks, some outside the OED framework (e.g., probabilistic decision-making, Betsch et al., 2014; multi-armed bandits, Schulz et al., 2019; asking questions, Ruggeri et al., 2017), using different formal models.

Finally, we discussed crucial factors that should be considered when examining information search in children: the temporally extended aspect of learning and planning; the prior assumptions that children bring to an experiment, which may differ from researchers' assumptions; and the motivations and goals guiding children, which may not align with the learning-maximizing goals assumed by researchers. Without considering these factors, researchers may have the wrong intuitions about what their experimental measures capture, the designs may be confounded, and the results may be difficult to interpret unequivocally.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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