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The Development of Probability Learning and Repeated Choice Behavior in Childhood: An Ecological and Longitudinal Perspective

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Summary

From choosing which game to play to deciding how to most effectively delay bedtime—making repeated choices is a ubiquitous part of childhood. Two often contrasted paradigmatic choice behaviors are probability matching and maximizing. Maximizing, described as consistently choosing the option with the highest reward probability, has traditionally been considered economically rational. Probability matching, in contrast, described by proportionately matching choices to underlying reward probabilities, is debated whether it reflects a simple mistake or an adaptive mechanism overlearned in real-world environments.

Previous research on the development of probability learning and repeated choice revealed considerable change across childhood and reported the paradoxical finding that younger children are more likely to maximize—outperforming older children who are thought to be more likely to probability match (e.g., Jones & Liverant, 1960; Weir, 1964). However, this line of research largely disregarded the mind's ability to capitalize on the structure of the environment and that some cognitive constraints under which children operate may facilitate learning. In this dissertation, I investigate the inter- and intra-individual development of probability learning and repeated choice behavior in childhood under consideration of ecological, cognitive, and methodological aspects. In four empirical chapters, analyzing almost 70.000 choices from over 600 children and more than 200 adults, I demonstrate that the interaction between the maturing mind and characteristics of the learning and choice environment shapes the development of adaptive choice behavior.

Chapter 2 compares how children and adults learn to adapt to an ecologically plausible statistical structure and provides a benchmark in relation to previous work. Behavioral and computational modeling results showed emerging adaptivity from school-age onward and indicated that younger children were more persistent in their choices but showed less sensitivity to the environment. Chapter 3 builds on this finding and longitudinally examines the intra-individual development of probability learning and repeated choice behavior in relation to executive functions from 3.5 to 6.5 years. Behavioral analyses revealed that children became more likely to probability match with increasing age but that probability maximizing was related to age differences in the cohort. Moreover, improving executive functions were associated with choice diversification as children grew older. Motivated by a recent rise in online data collection methods in developmental research, Chapter 4 takes a methodological view on the development of probability learning from 3–4 years. Results demonstrated a decline in performance toward the end of the task and the adoption of qualitatively different strategies when tested online via video chat. Connecting research on risky choice and probabilistic inference in childhood, Chapter 5 investigates how children make repeated choices when learning probabilistic information from description. Whereas younger children performed below chance, school-aged children demonstrated a high propensity for switching behavior, suggesting that descriptive learning formats amplify developmental differences.

In conclusion, the present research proposes that the development of probability learning and repeated choice behavior in childhood progresses from high persistence but also high inter-individual

variability to emerging adaptivity marked by increased diversification and exploration. This process is shaped by the development of cognitive capacities and growing experience with environmental structures, highlighting the benefit of taking an ecological rationality view in research on the development of decision making abilities. In particular, this dissertation emphasizes the importance of ecologically plausible study designs (e.g., ecologically valid statistical structures, experience-based learning formats) for revealing the young mind's ability to capitalize on the structure of the environment.

Zusammenfassung

Von der Entscheidung welches Spiel gespielt werden soll bis zur Wahl einer Taktik, wie man die Schlafenszeit am besten hinauszögert - ein allgegenwärtiger Aspekt in der Kindheit ist es, wiederholt Entscheidungen zu treffen. Zwei paradigmatische Verhaltensweisen, die oft miteinander verglichen werden, sind *probability matching* (dt. Angleichen der Wahrscheinlichkeit) und *Maximieren*. Um Belohnungen zu maximieren, muss eine Person ausschließlich die Option mit der höchsten Wahrscheinlichkeit auswählen. Dies wird ökonomisch als rationales Verhalten angesehen. Probability matching beschreibt, dass eine Person jede Option mit der gleichen Wahrscheinlichkeit auswählt, wie deren zugrunde liegende Wahrscheinlichkeit einer Belohnung ist. Es gibt Argumente, dass es sich bei probability matching um einen Fehlschluss handelt, aber auch, dass es adaptiver Mechanismus sein könnte, der in der realen Welt erlernt wurde.

Frühere Forschung zu probabilistischem Lernen deckte erhebliche Entwicklungen im Laufe der Kindheit auf und berichtete über das paradoxe Ergebnis, dass jüngere Kinder eher maximieren als ältere Kinder. Von älteren Kindern nimmt man hingegen an, dass sie probability matchen (z. B. Jones & Liverant, 1960; Weir, 1964). In früherer Forschung wurde jedoch kaum berücksichtigt, dass Menschen die Struktur der Umwelt zu ihrem Vorteil nutzen können. In dieser Dissertation untersuche ich die inter- und intraindividuelle Entwicklung des probabilistischen Lernens und der wiederholten Entscheidungen in der Kindheit unter ökologischen und kognitiven Gesichtspunkten. In vier empirischen Kapiteln, in denen ich fast 70.000 Entscheidungen von über 600 Kindern und mehr als 200 Erwachsenen analysiere, zeige ich, dass die Interaktion zwischen heranreifenden kognitiven Funktionen, sowie Merkmalen der Lern- und Entscheidungsumgebung die Entwicklung des adaptiven Entscheidungsverhaltens prägt.

In Kapitel 2 vergleiche ich, wie Kinder und Erwachsene lernen, Entscheidungen an eine ökologisch plausible statistische Struktur anzupassen. Die Anpassungsfähigkeit nimmt ab dem Schulalter zu und jüngere Kinder sind zwar persistenter in ihren Entscheidungen, reagieren aber weniger sensibel auf die Umwelt. Kapitel 3 baut auf diesen Ergebnissen auf und untersucht die intraindividuelle Entwicklung des probabilistischen Lernens im Kontext von exekutiven Funktionen im Alter von 3,5 bis 6,5 Jahren. Verhaltensanalysen ergaben, dass Kinder mit zunehmendem Alter eher probability matchen. Altersunterschiede in der Kohorte sagen Maximieren von Wahrscheinlichkeiten vorher. Darüber hinaus zeigt sich mit zunehmendem Alter der Kinder ein positiver Zusammenhang zwischen exekutiven Funktionen und Diversifizierung von Entscheidungen (d.h., wechseln zwischen Option). Angeregt durch die jüngste Zunahme von Online-Datenerhebungsmethoden in der frühkindlichen Entwicklungsforschung, nimmt Kapitel 4 eine methodische Perspektive ein. Ergebnisse zeigen, dass die Leistung gegen Ende der Lernaufgabe abnimmt und 3- bis 4-Jährige qualitativ andere Strategien anwenden, wenn sie online per Videochat teilnehmen statt offline in Person. Kapitel 5 stellt eine Verbindung zwischen der Forschung zu Entscheidungen unter Risiko und statistischen Intuitionen in der Kindheit her und untersucht, wie Kinder wiederholte Entscheidungen treffen, wenn Wahrscheinlichkeiten beschrieben sind. Während die Entscheidungen jüngerer Kinder zufällig schienen, zeigten Kinder im Schulalter die Tendenz zwischen

Optionen zu wechseln und Erwachsene maximierten Wahrscheinlichkeiten. Dies deutet darauf hin, dass beschreibende Lernformate Entwicklungsunterschiede verstärken können.

Zusammenfassend lässt sich sagen, dass die Entwicklung des probabilistischen Lernens und der wiederholten Entscheidungen in der Kindheit mehrere Phasen durchlaufen: von hoher Persistenz, aber auch hoher interindividueller Variabilität bei jüngeren Kindern zu wachsender Anpassungsfähigkeit durch zunehmende Diversifizierung und Exploration bei älteren Kindern. Die Forschung in dieser Dissertation unterstreicht insbesondere den Nutzen einer ökologischen Rationalitätsperspektive und die Bedeutung ökologisch plausibler Studiendesigns (z. B. ökologisch plausible statistische Strukturen, erfahrungsbasierte Lernformate, etc.), um die Fähigkeiten von Kindern, Strukturen der Umwelt zum eigenen Vorteil zu nutzen, besser erfassen zu können.

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1 | General Introduction

"With great power, there must also come great responsibility."

—Stan Lee, Amazing Fantasy #15

Becoming an independent person is an important process across childhood and beyond. But with increasing independence and power comes the need to make sound choices. How do children grow into adaptive decision-makers? Considering the types of decisions that children make in their everyday life, one might realize two aspects inherent to many choice situations: First, living in a complex and changing world, children usually do not know if a choice will result in a desired outcome with certainty or only with a higher or lower probability. Second, children are rarely required to make a decision only once, but choice situations often repeat over time (e.g., choosing a game, book, with whom to play, what route to take to school, etc.). By making repeated choices and experiencing their outcomes across numerous everyday situations, children can learn about the probability of events and the structure of real-world environments. For example, a child may have learned from previous experience that asking their grandparents for ice cream is typically more successful than asking their parents. Despite its real-world and developmental relevance, we still know little about how children learn to capitalize on the probabilistic structure of the environment when making repeated choices.

The process of learning about choice-outcome probabilities and applying this knowledge to consecutive choices is known as probability learning (Estes, 1964). Originating in classical conditioning and statistical learning, probability learning has been studied in both children and adults for more than half a century (e.g., Atkinson, 1956; Derks & Paclisanu, 1967; Estes, 1950; Estes & Straughan, 1954; Siegel & Goldstein, 1959; Weir, 1964). Experimental tasks typically require participants to make repeated choices between two or more options and learn about their outcome probabilities from feedback (e.g., predicting which light bulb will turn on; Gardner, 1957). Imagine the following real-world example of a paradigmatic probability learning task: A person lives between two subway lines—one is new and the other one rather old—and has to pick a route to work in the morning. The person learned from experience that when choosing the new line, they will arrive on time approximately 7 out of 10 times, and choosing the old line, they will arrive punctually only 3 out of 10 times. When faced with repeated choices between options, adults and older children often probability match: They select an option with the same probability that this option yields a desired outcome. In this example, the person would take the new line on 70% of the days and the old line only on 30% of the days. Suppose the likelihood of punctual or delayed trains remains constant over time (e.g., due to two independent railway switches that malfunction 70% or 30% of the time, respectively). Probability matching would result in the person arriving at work on time with a lower average probability (i.e., $p = 70\% \times 70\% + 30\% \times 30\% = 58\%$) than when consistently choosing the new line (i.e., p = 100% x 70% = 70%). In other words, probability matching results in a obtaining a desired outcome at a lower rate than probability maximizing (i.e., by exclusively choosing the option with the highest outcome probability) and, hence, represents a striking violation of rational economic choice.

There are two perspectives on probability matching that differ in their optimism about human rationality. One perspective suggests that people fall prey to their cognitive limitations and, consequently, fail to identify the superiority of a maximizing strategy (James & Koehler, 2011; Koehler & James, 2014; Shanks et al., 2002; Vulkan, 2000). This perspective resonates with research showing that some non-human animals also probability match in reinforcement learning paradigms. However, there is increasing evidence that behavior close to probability maximizing is common across a large variety of species (for a review of the animal literature, see Montag, 2021). Similarly, probability matching does not seem to be an innate behavior in humans. Research on the development of probability learning in childhood has demonstrated that younger children under 5 years tend to maximize probability by persistently choosing the option with the highest outcome probability (Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Weir, 1964). In contrast, only older children from 6 to 11 years are reported to be more likely to probability match (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Plate et al., 2018). It would seem surprising that rats, baboons, pigeons, or fish indeed outperform older children and adults in a simple repeated choice task. However, opposing the idea of a sophisticated or superior strategy that can only be achieved by deliberation (Koehler & James, 2010), probability maximizing may require only little implementation effort (Saldana et al., 2022) and can serve as a satisficing strategy (Schulze et al., 2020). Thus, different choice behaviors can result from different processes—some may be misleading, but it is also conceivable that some of them are adaptive (for reviews, see Koehler & James, 2014; Newell & Schulze, 2017).

The adaptive perspective on probability matching takes up an *ecologically* rational position. The framework of *ecological rationality* assumes that people adaptively use a set of search and decision strategies that enables them to capitalize on the structure of the environment despite only having finite cognitive resources (Gigerenzer & Goldstein, 1996; Pleskac & Hertwig, 2014; Simon, 1956, 1990a; Todd & Gigerenzer, 2007). Advocates of an ecologically rational perspective on probability matching argue for an overlearned behavior from the real world that people inappropriately apply in experimental environments (i.e., a mismatch between the experimental and natural environments; Gaissmaier & Schooler, 2008; Green et al., 2010; Schulze et al., 2017, 2020). People may have evolved strategies suited to probabilistic structures they experience regularly—yet, behavioral experiments often differ in these key statistical properties. For example, in real-world environments, autocorrelation between outcomes in a sequence or clumped resources may rather be the norm than an exception (Koenig, 1999; Reimers & Harvey, 2011; Scheibehenne et al., 2011; Wilke & Barrett, 2009). In such environments, probability matching may be more profitable than strict probability maximizing (Schulze et al., 2017). The idea of a mismatch between stationary probability learning tasks and real-world environments is not new in the debate on probability matching (e.g., Jones & Liverant, 1960). Yet until today, it received surprisingly little consideration, particularly in research on the development of probability learning in childhood.

Taking an ecological rationality perspective, my dissertation investigates how probability learning and repeated choice behavior develop in childhood, considering ecological, cognitive, and methodological aspects. What characterizes children's choice behavior in different age groups? If probability matching is indeed an ecologically rational strategy, how much life experience is needed to use it adaptively? What underlying cognitive mechanisms guide repeated choice behavior in childhood, and what is the role of intra-individual development? How do the learning format and other methodological factors shape adaptive choice behavior? To address these questions, I will integrate research on decision-making and cognitive development, previously operating in parallel, and use both cross-sectional and longitudinal study designs to map developmental trajectories of repeated choice behavior from early childhood to pre-adolescence between 3 and 11 years.

The empirical chapters (Chapters 2–5) in this dissertation discuss theoretical introductions tailored to their specific research questions and stand alone as research articles. In the following sections of this chapter, I will provide a general overview of the theoretical foundations of my work. First, I will describe the ecological rationality framework in more detail and how it can inform research on cognitive development. I will then discuss previous literature on probability learning in adults, focusing on probability matching. Afterwards, I will review work on the development of probability learning in childhood and how cognitive building blocks, in particular executive functions, may shape this process. Following, I will discuss the relationship between probability learning and early probabilistic inferences and, lastly, provide an overview of the comparability between developmental online and offline studies as a recent methodological concern in research on cognitive development. To conclude the general introduction, I will provide an outlook on the empirical research chapters.

1.1 An Ecologically Rational View on the Development of Judgment and Decision-Making

Consider a person living in a remote place where bus service is only provided once an hour, waiting for a friend to arrive by public transport. How likely is it that the person checks every other minute if their friend has already arrived? Given the lower probability that a bus will arrive farther away from the scheduled time, it seems unlikely that a person ignores this information completely. That people adapt their information search or decision strategies in some way or another to the structure of an everyday situation can be hardly contested. Yet, one of the most influential psychological research streams, the heuristics-and-biases program originating in the 1970s (Tversky & Kahneman, 1974), systematically discounted the ability of the human mind to capitalize on the structure of the environment in behavioral experiments (see Lejarraga & Hertwig, 2021). The *ecological rationality* framework, in contrast, explicitly considers the fit between the human mind and the structure of the environment (Todd &

Gigerenzer, 2007). Inspired by Herbert Simon's scissors metaphor—that the mind and the environment represent two blades of a pair of scissors working together (Simon, 1990)—the framework assumes that a set of domain-specific search and choice strategies enable people to exploit environmental characteristics, even though only investing limited cognitive resources. A growing body of evidence demonstrates how people succeed in myriad situations by using simple heuristics adapted to the features of the environment (e.g., see Hertwig et al., 2022; Spiliopoulos & Hertwig, 2020; Todd & Gigerenzer, 2012). The ecological rationality framework has been successfully applied to a lifespan perspective for the aging decision maker (Mata et al., 2012)—but how do children grow into ecologically rational decision-makers?

There is some evidence that children are using ecologically rational search and choice strategies in an increasingly systematic and adaptive manner across development (Horn et al., 2016; Lang, 2021; J. D. Nelson et al., 2014). Assume a hypothetical scenario in which a child is presented with the names of two TV shows—Peppa Pig and Friends—and asked which TV show they believe has more episodes. Using the recognition heuristic (see Goldstein & Gigerenzer, 2002), the child could infer that the TV show they recognize, Peppa Pig, must have more episodes than the other show they have never heard of. Children from 9 years onward have been found to use this heuristic systematically. However, only older adolescents have been reported to correctly use the predictive validity of the recognition cue to learn in which situations the heuristic is adaptive and in which not (Horn et al., 2016). For example, recognizing the TV show Peppa Pig may not be beneficial but misleading when not the number of episodes but the number of seasons was the criterion to be judged (Peppa Pig has more episodes, but yet fewer seasons than Friends; *IMDb*, n.d.). Relying on the same strategy may hold advantages in one environment but not in another. Apart from basic cognitive processes—such as memory encoding, retrieval, and discrimination between a known and novel item—other experiential factors related to the environment, for instance, domain knowledge, play an important role in learning to use the recognition heuristic adaptively (Horn et al., 2016).

Likewise, each decision strategy requires the interplay between a set of underlying cognitive skills and environmental knowledge or experience (to a greater or lesser extent). Thus, when asking how children become adaptive decision-makers, one needs to consider at least two aspects that develop with increasing age: cognitive processes that mature alongside the developing brain and experience with different environments or task structures. In the domain of repeated choices, this means that different choice behaviors may emerge as a result of increasing cognitive functions as well as increasing experience with real-world structures. But because scientists often only theorize about either the mind or the environment, but rarely in concert, the development of ecological rationality still needs to be better understood.

1.1.1 An Evolutionary Perspective on Adaptive Behavior: The Life History Framework

Ecological rationality can provide a useful framework to study how the foundations of adaptive decision-making develop in childhood. However, the concept is not yet widely adopted in other domains of cognitive development (but see Ruggeri, 2022). In recent years, however, a similar conceptualization originating in evolutionary psychology gained significance as a framework for studying adaptive behavior in childhood (Gopnik, 2020). The life history framework suggests that people allocate resources differently across development to maximize fitness and that evolved capacities increase the chance of survival (Kaplan & Gangestad, 2015). In this framework, childhood serves its unique purposes: developing an immune system, growing a large brain, and, most of all, learning as much as possible (Kaplan & Gangestad, 2015). Indeed, during the first years of life, one developmental milestone is chasing the next: learning how to speak, walk, count, or read happens during a time frame that some adult person needs to write a dissertation. But how can children learn so many elementary skills in a short period despite the fact that their brains have not yet fully developed and yet less cognitive capacities than in adulthood are available?

A growing body of research suggests that cognitive limitations characteristic of childhood—or in other words, cognitive immaturity—are not only necessary consequences of a not yet fully-developed brain or a mere obstacle to overcome but that these limitations are beneficial for learning (e.g., Bjorklund & Green, 1992; Gopnik, 2020; Gopnik et al., 2017). For instance, young children's over-optimism in their own abilities may help them to continue practicing a difficult task (Bjorklund & Green, 1992). In particular, childhood is thought to serve as a developmental phase adapted to wide exploration, which may be especially useful in changing environments (Gopnik, 2020). For example, young children have been found to outperform older children and adults in inferring an unusual hypothesis (Gopnik et al., 2015, 2017) or to detect environmental structures (Liquin & Gopnik, 2022). Exploration tendencies progress from less systematic to more goal-directed information search across childhood (e.g., Giron et al., 2022; Meder et al., 2021; Schulz et al., 2019). In a world where technological, societal, and climatic changes are occurring with increased frequency, it may be highly relevant on a societal level that young learners have the capacity to adopt new hypotheses quickly—even if they seem unlikely at first. Research inspired by the life history framework further argues that early experience of environmental structures can serve as a cue for future conditions that a person must adapt to (Fawcett & Frankenhuis, 2015; Nettle et al., 2013). For instance, if a person experiences early on in life that cues have high reliability in predicting outcomes in the environment, they may adapt their information search process accordingly and sample less information than when cues are unreliable (see Frankenhuis et al., 2019). From an evolutionary perspective, it seems plausible that being highly sensitive to environmental structures, particularly in childhood, is an adaptive capacity of the brain that increases fitness.

Although the life history and ecological rationality frameworks both argue for an interplay between mind and environment, they approach this topic from different angles. Research rooted in the life history framework typically explores how the interplay between environment and mind has shaped the evolution of a flexible cognitive system on an extensive timescale (Kaplan & Gangestad, 2015) and how this evolved flexibility is beneficial in learning environments (Gopnik, 2020). Yet, this stream of research is often mute about specific underlying cognitive processes that allow children to be particularly explorative or flexible learners and *how* they adapt to environmental characteristics. In contrast, the framework of ecological rationality is designed to investigate the specific fit between a search or choice strategy and a particular environmental structure beyond addressing questions about survival and fitness. Combining the two approaches, thus, provides an interesting perspective on studying the development of search and choice behavior in childhood and its underlying cognitive processes: How do characteristics of the developing brain and the experiences made in the environment interact in the development of ecologically rational decision making, for instance when making repeated choices? This overarching question is addressed in several empirical chapters of this dissertation.

1.1.2 Characteristics of Real-World Environments

Now, the elephant in the room is certainly what kind of environmental structures children experience in their everyday life and, thus, may have individually learned to adapt strategies to. Ahead of influential theories on the development of probabilistic inferences, Tolman and Brunswik (1935) argued that even young children already hold the (misleading) expectation that laboratory tasks reflect the probabilistic structure of actions and outcomes experienced in their everyday lives. Characterizing these features is arguably a challenging endeavor, and a thorough analysis of statistical structures in real-world environments marks a current gap in the literature (see also Frankenhuis et al., 2019). In the following sections, I will attempt to offer an overview of which real-world properties may, in particular, shape the development of children's choice behavior when making repeated choices. A basic but helpful first step is distinguishing between certain, uncertain, and risky environments.

1.1.2.1 Risk and Uncertainty

Many everyday life environments are not certain (i.e., they do not unequivocally lead to the same outcome; Luce & Raiffa, 1989), but events occur probabilistically: for instance, since the Covid-19 pandemic, we learned that a supermarket having all items on stock is sometimes unlikely and whether our favorite sports team will win the next match is yet to be determined. There are different ways to conceptualize the space that is not fully certain (for a review, see Kozyreva et al., 2019). Two key concepts taken up by several definitions of this space are *uncertainty* and *risk.* Different conceptualizations pertain, for instance, to the source of uncertainty (e.g., epistemic or aleatory; Hacking, 2006), to the degree of knowledge, or to the measurability of probabilities (Knight, 1921). In this dissertation, when speaking of uncertainty and risk, I am following the definition by Luce and Raiffa (1989). In decisions under *uncertainty,* a person must choose between multiple actions without precisely knowing the probability with which an action will result in a set of possible outcomes (Luce & Raiffa, 1989). In contrast to not knowing outcome probabilities in decisions under uncertainty, the concept of *risk* describes a situation in which the decision-maker does know the probabilities associated with each outcome before making a choice (Luce & Raiffa, 1989). Although less common than decisions under uncertainty, some life situations are, indeed, risky based on this definition. For instance, the probability of a person suffering from a side effect after vaccination is approximated based on the frequency of previous side effects in a vaccinated population, or the likelihood of rain is typically communicated in terms of explicit probabilities.

Both concepts play a role in the probability learning and repeated choice tasks investigated in the empirical chapters in this dissertation. Probability learning tasks are typically viewed as making decisions under uncertainty (see Chapters 2–4): at the beginning of the task, participants do not have any information about the outcome probabilities. Over the course of the task, participants could use the information from previous outcomes to compute approximate probabilities. As the measurability of uncertainty increases, it may be arguable if the end of a probability learning task is better characterized by decisions under uncertainty or risk. In contrast, Chapter 5 describes a task where participants make decisions under risk: All probabilistic information is provided before making a choice. In the present dissertation, decisions under risk and uncertainty are associated with different learning formats where outcome probabilities are either learned from feedback while making choices or from description before making a choice.

1.1.2.2 Learning From Experience and Description

How do people learn about the probabilities of choices resulting in desired outcomes in the real world? When deciding whether or not to take an umbrella, a person can interpret the probability of rain given in the weather forecast (i.e., learning from a description). An alternative possibility would be to infer the likelihood of rain from experiences over the last days, weeks, or months (i.e., learning from experience). Indeed, learning from experience is often the only way to acquire probabilistic information in uncertain real-world environments when probabilities are unknown at first. In decisions from description, a decision-maker typically receives outcome information verbally or graphically before making a choice; decisions from experience usually require the decision-maker to learn about outcome probabilities from feedback or to draw samples of information before making a choice (Wulff et al., 2018).

The learning format is an important but often discounted task characteristic, leading to possibly contradictory findings about people's statistical reasoning abilities when not explicitly accounted for (see the intuitive statistician vs. heuristics-and-biases program; Lejarraga & Hertwig, 2021). Literature on the *description–experience gap* has shown that people's choices differ systematically depending on whether they learned about probabilities from experience or description (e.g., Hertwig & Erev, 2009; Newell & Rakow, 2007; Teoderescu et al., 2013; Wulff et al., 2018). For instance, people tend to give rare events less weight than their objective probability when they learn from experience and tend to overweight rare events when learning from description (Hertwig & Erev, 2009; Wulff et al., 2018).

In a developmental investigation of the description–experience gap, older children from 9 years have been found to weigh probabilities similarly to adults (Rakow & Rahim, 2010). But even beyond risky choice and gambles, addressing the learning format is essential when comparing cognitive abilities across a wider age range. As a consequence of adapting task demands to the abilities of the target sample, probabilistic tasks for children often rely on experiential formats or graphical descriptive representations (Denison & Xu, 2019; Schulze & Hertwig, 2021). When mistakenly contrasted with adults', sometimes poorer, performance in verbally descriptive tasks, children may seem more capable of probabilistic reasoning than they actually are (Schulze & Hertwig, 2021). For instance, Schulze and Hertwig (2022) demonstrated that children seemingly outperform adults in conjunctive and Bayesian reasoning problems, but only when children learn from experience and adults from description. In contrast to descriptive learning formats, which may increase in importance with age and formal education, young children's everyday learning opportunities about probabilistic structures are more likely to be experiential. Nevertheless, only few studies have explicitly addressed the impact of learning formats on (young) children's decision-making abilities, and there is yet much to be discovered. Comparing findings from experiential probability learning tasks (Chapters 2–4) and a descriptive risky choice task (Chapter 5), this dissertation provides new insights into the role of the learning format for repeated choices in childhood.

1.1.2.3 Statistical Characteristics of Real-World Environments

Coming back to the example of a person deciding to take an umbrella with them or not when going outside. In this scenario, it seems unlikely that the probability of rain is the same every single day. However, some influential research streams in judgment and decision-making, like probability learning (for a review, see Vulkan, 2000), constructed theories of human choice under the assumption that outcome probabilities are independent and identically distributed and do not change over time. That said, many natural or social environments in everyday life are, indeed, subject to frequent change. In non-stationary environments, perceiving events closer together in time and space as part of a group or sequence could serve as a cue to predict future environmental states; perceiving events as more distant could disrupt this process.

In the domain of weather and other naturally occurring events, autocorrelation across space and time seems to be a useful statistical measure to characterize change as underlying physical processes arise and decrease gradually (e.g., Chopin & Blazy, 2013; Fawcett et al., 2014; Koenig, 1999; Ping et al., 2004; Trenberth, 1984). Nevertheless, autocorrelated processes are not restricted to naturally occurring environments. In an ecological analysis of real-world economic datasets, Lejarraga and Lejarraga (2023) show that autocorrelation and non-stationarity are key statistical characteristics underlying variables that inform managerial decision making. For instance, when predicting the cost of goods or sales, experiences from the recent past have a higher predictive value than those from longer ago.

Autocorrelation is closely related to locally or temporarily clumped resource distributions. Another mechanism that may contribute to the emergence of clumped resources in real-world environments is how rewards are retained or decay over time (e.g., Jensen & Neuringer, 2008). Whereas in laboratory environments, a person can regularly only collect a reward at one specific instance (e.g., a monetary incentive for making a correct prediction or placing a bet), resources in the real world often do not immediately disappear if not instantaneously collected: for instance, when harvesting fruit or vegetables much of the produce will remain available while maturing slowly, money remains in a bank account even if not withdrawn immediately, and water in a rainwater tank will only slowly evaporate if not used. Although some retained resources will eventually disappear due to naturally decaying processes, the availability of resources may also depend on previous actions by oneself or other people. In such situations, sequential dependencies between choices and outcomes can be used as a cue to make predictions about future outcomes and help people to adapt to the environmental structure (Schulze et al., 2017).

Under the assumption that autocorrelation, non-stationarity, or sequential dependencies are prevalent in many real-world environments, it may be plausible that people evolved strategies adapted to capitalize on these statistical structures (Fawcett et al., 2014; Haselton et al., 2009; Reimers & Harvey, 2011; Scheibehenne et al., 2011). However, in environments that do not possess these characteristics, it may seem like a mistake, for instance, when a person anticipates that recent outcomes are predictive of following outcomes.

1.1.3 From Fallacies to Phenomena

Considering that people's decision strategies may be particularly adapted to features of real-world environments, some previously deemed fallacies may instead reflect simple but adaptive responses to environments where people learned to make choices in. Two prominently discussed choice fallacies are the gambler's (Kahneman & Tversky, 1972) and the hot-hand fallacy (Gilovich et al., 1985). The gambler's fallacy describes that people show negative recency when predicting sequential events—for instance, when tossing a coin, they expect a streak of heads to stop with increasing streak length. Kahneman and Tversky (1972) concluded that people mistakenly expect a subset of a local sequence to hold the same characteristics of the global sequence (e.g., that a coin toss will always reflect the underlying probability of heads or tails with $p = .5$). The same argument of misperceived *local representativeness* has been used to explain why people fall prey to the hot-hand fallacy (the opposite of the gambler's fallacy) and why people probability match (e.g., James & Koehler, 2011). A hot hand describes the assumption that an outcome streak will continue with increasing length (e.g., a basketball player becomes increasingly likely to score with increasing streak length of past successful throws; Gilovich et al., 1985). Whereas it has been suggested that the hot-hand fallacy is a cognitive illusion (Gilovich et al., 1985), correcting for previously biased estimations of a hot hand has shown that positive recency in streaks may not be a pure illusion (Miller & Sanjurjo, 2018). Moreover, it has been shown that the statistical assumptions rendering these behaviors a fallacy often do not hold in the subset of events that people are able to monitor with their finite cognitive capacities (Hahn & Warren, 2009).

Indeed, there is a growing body of evidence showing that these "fallacies" may not arise due to cognitive limitations or misperceptions of randomness but from a mismatch between the experimental and real-world environments (Oskarsson et al., 2009). For example, Ayton and Fischer (2004) suggested that the gambler's and hot-hand fallacy may be adaptive responses learned in real-world environments where positive and negative recency are regularly encountered. Consistently, people across cultures seem to anticipate streaks or clumped resources (Blanchard et al., 2014; Wilke & Barrett, 2009). Moreover, it has been demonstrated that people make forecasts as if data points were positively autocorrelated even when they are objectively not (Reimers & Harvey, 2011) and make more accurate predictions when sequences are positively compared to negatively autocorrelated (Kareev, 1995).

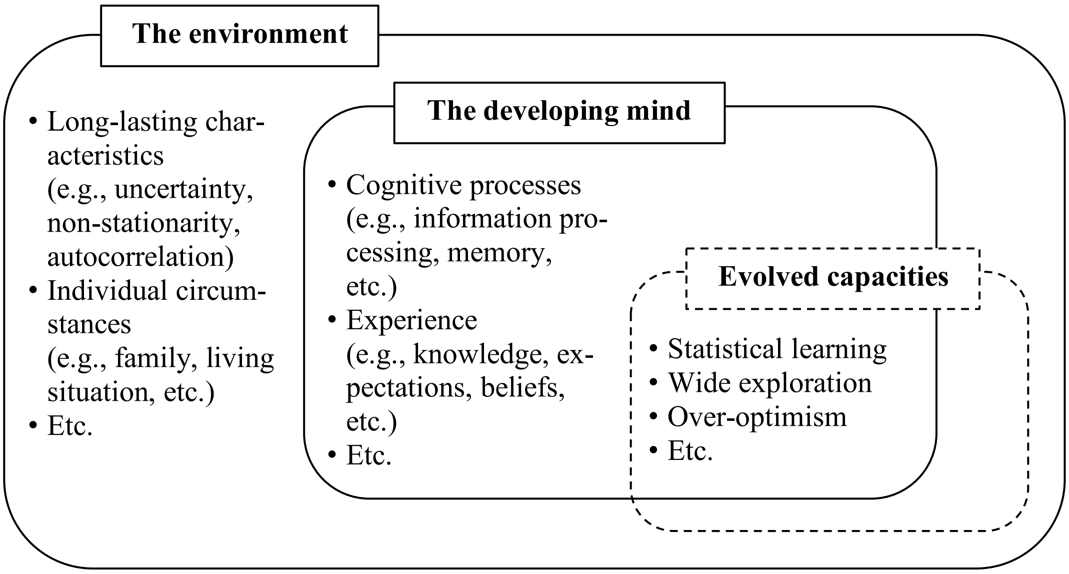
The lessons learned from apparently "irrational" inferences in adults can facilitate an alternative perspective in research on the development of decision-making. Even though children are sometimes viewed as a proxy for an adult model with deficient cognitive capacities (more common from a heuristics-and-biases perspective; e.g., Baron et al., 1993; Ivan et al., 2018; Kokis et al., 2002), seemingly irrational behavior may reflect an adaptive response to a child's environment.

1.1.4 Studying the Development of Ecological Rationality: Many Moving Parts

Summarizing the previous section, it becomes apparent that the development of ecological rationality is shaped by different processes that interact on different timescales over evolution and ontogenesis. A schematic high-level overview of involved processes relevant to this dissertation is presented in Figure 1.1. Taken together, the development of ecological rationality involves multiple interdependent sources. Inter-individual variability can arise from both mind and environment components. When evaluating how developing cognitive functions contribute to the development of ecologically rational choice behavior, it needs to be considered that these developments take place within and in interaction with the environment, as the cornerstone for plasticity in brain development (Greenough et al., 1987; Oakes, 2017). Moreover, there are individual-independent factors like evolved functions of cognitive immaturity and environmental characteristics that most children will experience while growing up. Building on this framework, my dissertation investigates how the interaction between environment and developing mind shapes adaptive probability learning and repeated choice behavior in childhood.

Figure 1.1

Schematic Overview of Processes Involved in the Development of Ecological Rationality



1.2 Probability Learning in Adulthood

Probability learning describes the process of learning how likely a choice will result in a desired outcome and applying this knowledge to subsequent choices (Estes, 1964). With increasing interest in statistical models, probability learning has been studied since the early 1950s (e.g., Atkinson, 1956; Estes, 1950; Estes & Straughan, 1954). Classic probability learning paradigms are experience-based tasks that require a person to make repeated choices between two or more probabilistically rewarded options, for example, predicting which of two light bulbs will turn on next (e.g., Estes & Straughan, 1954; Siegel & Goldstein, 1959). People typically do not obtain information about the probabilities associated with each choice option beforehand but need to learn this relationship from trial-wise feedback. Suppose a green light turns on in 70% of the trials and a red light in 30% of the trials, and a person receives an incentive for every correct prediction. An economic approach to human rationality would suggest that a person should maximize the probability of making a correct prediction. If outcome probabilities are independent and identically distributed, probability maximizing entails exclusively predicting the option associated with the highest outcome probability (the green light), obtaining an average reward rate of $p_{maximizing} = .70$. Yet, numerous studies suggest that adults do not always maximize probability but instead probability match (for reviews see Koehler & James, 2014; Vulkan, 2000). A probability matching person would predict each option according to its corresponding outcome probability. Consequently, in 70% of the trials, the person would predict the green light, and in 30% of the trials, the red light. This choice behavior violates economic views on rationality as it yields a lower average reward rate than probability maximizing with $p_{matching} = .70 \times .70 + .30 \times .30 = .58$.

Although sometimes mistaken for Herrnstein's *matching law* (e.g., Lo et al., 2021), probability matching and the matching law differ in their predictions about how people allocate choices to the alternative options (e.g., Houston et al., 2021; Houston & Sumida, 1987; Schulze et al., 2017). Herrnstein's matching law (Herrnstein, 1961) assumes that a person matches choices to the rate of the *obtained* reward from an option compared to the obtained reward from an alternative option—not the programmed outcome probability integrating both *obtained and forgone* rewards in the case of probability matching. Counterintuitive to its name, the matching law, thus, predicts asymptotic probability maximizing. This dissertation focuses on probability matching, not the matching law.

1.2.1 From Aggregate to Individual Probability Matching

Previous work on probability matching from the early stages of probability learning research has been reviewed elsewhere (e.g., Montag, 2021; Myers, 2014; Vulkan, 2000), yet one aspect may have received less attention than deserved: Much of the earlier work analyzed probability learning as a function of aggregated choices over trials *and* people (e.g., Estes & Straughan, 1954; Gardner, 1957; Goodnow, 1955; Grant et al., 1951; Humphreys, 1939; Jarvik, 1951; Morse & Runquist, 1960; Neimark & Shuford, 1959). However, these aggregate statistics do not allow determining if probability matching is, indeed, a choice behavior that individual people regularly pursue (Derks, 1962; Shanks et al., 2002; but see Estes, 1964 for an argument on the statistical benefit of group data). Probability matching on a group level could arise from heterogenous choice behavior across people: For instance, if half of the participants predict the green light at chance level and the other half predicts the green light on 90% of the trials, a researcher might find that participants, on average, approximate the underlying outcome probability of $p = .70$. Similarly, often reported aggregate *overshooting* (i.e., choosing the high-probability option at a higher rate than its objective outcome probability but not exclusively) cannot be viewed as evidence against individual probability matching (see Montag, 2021), but could indicate a bimodal distribution where some people probability match and others maximize.

Only a few studies from the earlier probability learning wave analyzed probability matching on an individual level (for adults, see Derks, 1962; for children, see Derks & Paclisanu, 1967; Jones & Liverant, 1960). But how is probability matching measured on an individual level beyond visually inspecting graphical choice curves? Derks (1962) suggested quantifying a reasonable deviation from the underlying outcome probabilities, conditioned on the number of trials (i.e., the square root of the average reward probability when probability matching, multiplied by the number of trials). The probability of the more frequently reward option plus and minus the quantified deviation then serves as the upper and lower boundary, respectively, to classify probability matching behavior. Returning to the previous example of predicting a green and red light turning on with probabilities $p_1 = .7$ and $p_2 = .3$, respectively: The estimated deviation over N = 100 choice trials would be $\hat{\sigma} = 4.58$. Based on a criterion of plus and minus twice the estimated deviation around the base rate of a green light turning on (i.e., the high-probability option), a person would be categorized as a probability matcher if they predicted the green light on 61–79 out of 100 trials.

Individual repeated choice behavior and probability matching has become the focus of more recent research since the early 2000s. Some of this later work moved away from experience-based probability learning paradigms and instead studied probability matching in descriptive tasks where outcome probabilities were known beforehand or where participants indicated a strategy for several (hypothetical) trials rather than making trial-by-trial predictions (e.g., Gal & Baron, 1996; James & Koehler, 2011; West & Stanovich, 2003). Several definitions of individual probability matching are reported in the more recent literature: choosing the high-probability option according to its precise, objective frequency (James & Koehler, 2011; Koehler & James, 2010; West & Stanovich, 2003); choosing the high-probability option according to an individually varying frequency (Koehler & James, 2009); choosing the high-probability option within a binomial proportion 95% confidence interval (Saldana et al., 2022); comparison of probability matching model fits (Feher Da Silva et al., 2017; Plate et al., 2018); or choosing the high-probability option according to its objective outcome probability plus or minus a fixed error margin, e.g., between 3–10% (Gaissmaier et al., 2016; Koehler & James, 2010; Newell & Rakow, 2007; Schulze et al., 2015; Schulze & Newell, 2016a, 2016b). In a nutshell, there is no gold standard for defining probability matching as an individual choice behavior. Thus, it is important to keep in mind that classification rules depend on researchers' choices (both for probability matching and maximizing). Without being aware of possible (and sometimes considerable) differences in the definition and aggregation level, comparing probability matching across studies may unintentionally result in a comparison of apples and oranges.

Table A1 (experience-based paradigms) and A2 (descriptive paradigms) in Appendix A provide an overview of research reporting numeric proportions of participants who individually probability matched, alongside the respective task characteristics, sample size, and classification criteria for probability matching. Summing up this previous evidence, there are two main takeaways: First, probability matching is reported across a variety of tasks irrespective of whether people learn about outcome probabilities from experience or description. Yet, not every person is best described by probability matching, and there are considerable differences across task implementations. Across different studies that either investigated the prevalence of probability matching contingent on task characteristics or actively tried to reduce this behavior, between 3–90% of participants are reported to probability match—leaving room for other choice behaviors such as random choice, overshooting, and maximizing. Second, the large variance in reported proportions of participants who probability match demonstrates the importance of contextual and methodological factors: for instance, definition criteria, if people perceived outcomes to be (in-) dependent, incentivization, time pressure, or number of trials. Particularly the length of an experiment seems to affect probability matching behavior. People probability match less and make more maximizing responses as they become more experienced with the task and the number of trials increases (e.g., Newell & Rakow, 2007; Otto, Taylor, et al., 2011; Schulze & Newell, 2016b; Shanks et al., 2002). What do these findings imply for why people probability match in the first place?

1.2.2 Probability Matching: Fallacy or Phenomenon?

Probability matching can arise from different underlying processes—some may be a mistake and others an adaptive response. In the following, I will describe two alternative views on probability matching that either favor the view of a fallacy or a phenomenon.

1.2.2.1 Fallacy

The majority of research in favor of viewing probability matching as a shortcoming of the human mind is based on the dual-system account of cognitive processes (for a review, see Koehler & James, 2014). The dual-system perspective argues that an automatic but error-prone response (i.e., probability matching) needs to be overcome by a slower, deliberate process to achieve optimal behavior (i.e., probability maximizing; for a review on the dual-system account, see Evans, 2008). Indeed, there is evidence that a higher proportion of maximizing responses is related to larger cognitive capacities, either on an individual level (Rakow et al., 2010; West & Stanovich, 2003) or as a result of pooled resources in groups (Schulze & Newell, 2016a). From a dual-process perspective, people have an initial tendency to probability match because this strategy comes to mind more readily (Koehler & James, 2009, 2010) but will eventually shift to probability maximizing with sufficient deliberation (Koehler & James, 2010; Newell et al., 2013). Higher strategy availability of matching compared to maximizing has been suggested to result from people's misperception of randomness and, specifically, their expectation of local representativeness (see previous section; Kahneman & Tversky, 1972). Recall that local representativeness describes the expectancy that any sub-sequence will hold the properties of the underlying generating mechanism (e.g., representative outcome probabilities or alternation rate of events in the sequence; see Bar-Hillel & Wagenaar, 1991; Reimers et al., 2018). In a coin tossing scenario, people would fail to consider that a higher number of coin tosses will increase the likelihood of heads and tails more closely approximating the underlying outcome probabilities. Consequently, they would instead expect even small samples to be representative of a long sequence (the *law of small numbers;* Tversky & Kahneman, 1971). James and Koehler (2011) tested the hypothesis that people expect the frequency of outcomes in a short sequence (e.g., equally many heads and tails) to match their underlying probabilities in a descriptive repeated choice task. They facilitated or inhibited sequence-wide expectations by introducing individuating features (e.g., framing the task as the same or different guessing games or asking participants to focus on the entire sequence instead of individual outcomes). Consistently with their hypothesis, they found that more people probability matched when the generation of sequence-wide expectations was promoted and concluded that probability matching is a mistake resulting from cognitive limitations and misperception of randomness (James & Koehler, 2011). But are sequence-wide expectations always a mistake?

1.2.2.2 Phenomenon

Perceiving repeatedly occurring events as dependent could help to detect regularities in an outcome sequence. Autocorrelation or clumped resources in real-world environments may facilitate this process. Consider the following example: every fall, numerous people from Berlin collect mushrooms in the city's outskirts. Next to a long road in a forested area, sometimes more and sometimes fewer cars are parked on the road bank. Perceiving these parked cars as dependent outcomes in a sequence (e.g., they belong to people collecting mushrooms and accumulate in areas with many mushrooms) could serve as a cue for where to search for mushrooms to maximize return. In other words, generating expectations about events in a sequence, either in space or time, could provide benefits when there are, in fact, patterns to detect or dependencies to exploit.

When making repeated choices, people may misapply adaptive expectations and strategies overlearned from everyday life to laboratory environments where they are no longer appropriate (e.g., Green et al., 2010). This mismatch between theoretically adaptive behavior and the laboratory environment is the central argument for an ecologically rational approach to studying probability matching (Gaissmaier & Schooler, 2008; Green et al., 2010; Schulze et al., 2017; Seth, 2007). For instance, it has been argued that probability matching is related to people's tendency to look for patterns in outcome sequences (Feher Da Silva et al., 2017; Gaissmaier et al., 2006; Gaissmaier & Schooler, 2008; Peterson & Ulehla, 1965; Saldana et al., 2022; Schulze et al., 2020; Wolford et al., 2004). Participants who probability match in the absence of a pattern in a probabilistic outcome sequence have been found to be more likely to detect a pattern when there actually is one (Gaissmaier & Schooler, 2008; Schulze et al., 2020); in contrast, probability matching was observed to decrease in task environments when pattern search was more effortful (Saldana et al., 2022). Moreover, choice diversification close to probability matching has been found to provide an advantage over exclusively choosing one option in repeated choice tasks simulating characteristics of real-world choice ecologies, for instance, sequential dependencies (Schulze et al., 2017) or competition (Schulze et al., 2015; Seth, 2007). As uncertainty is inherent to many real-world environments, probability matching could be related to people's incomplete knowledge about the true nature of the generating process in an outcome sequence (Green et al., 2010). In particular, when outcome probabilities change over time or people do not receive full information about all options' outcomes, exclusively selecting one option may prevent them from obtaining useful information (Feher Da Silva et al., 2017; Schulze et al., 2017). As a specific form of diversifying choices across options, probability matching facilitates exploration (Feher Da Silva et al., 2017) and has been linked to the use of a win-stay lose-shift heuristic (WSLS; Ellerby & Tunney, 2019; Otto et al., 2011; Schulze et al., 2017). WSLS is a simple reward-sensitive choice rule that requires relatively few cognitive resources but entails exploratory benefits under uncertainty and is used by children, adults, and myriad animal species from albatrosses to bumblebees (Berman et al., 1970; Bonawitz et al., 2014; Bonnet-Lebrun et al., 2021; Maboudi et al., 2020; Scheibehenne et al., 2011; Spiliopoulos & Hertwig, 2020; Worthy et al., 2012).

Taken together, previous research on repeated choices shows that probability matching depends on both cognitive and contextual factors. It is safe to say that there is no single reason why a person will or will not probability match in a repeated choice scenario. Instead of being a strategy per se, probability matching can arise from different underlying (mal-) adaptive processes. However, the difficulty in defining the circumstances under which people probability match also reflects an advantage. As a flexible behavior, matching outcome probabilities can guide repeated choices across numerous uncertain situations, allowing for exploration and exploitation of environmental structures. If probability matching is, indeed, a lesson learned from life, how early do children learn this lesson? In the next section, I will introduce previous research on the development of probability learning and repeated choice behavior across childhood.

1.3 Probability Learning in Childhood

Children are known to be capable statistical learners (e.g., Forest et al., 2023; Saffran & Kirkham, 2018), but how do they learn to apply this knowledge to repeated choices? Most research on the development of probability learning and repeated choice behavior dates back to the 1960s (e.g., Craig & Myers, 1963; Derks & Paclisanu, 1967; Jones & Liverant, 1960; Kessen & Kessen, 1961; Offenbach, 1964; Rabinowitz & Cantor, 1967; Schusterman, 1963; Siegel & Andrews, 1962; Stevenson & Hoving, 1964; Stevenson & Weir, 1959; Weir, 1964; Weir & Gruen, 1965). There are several parallels to the adult literature, for instance, frequent neglect of different aggregation levels (Lewis, 1966; Messick & Solley, 1957; Siegel & Andrews, 1962), but also the use of similar experience-based probability learning paradigms (e.g., predicting which light bulb will turn on; e.g., Derks & Paclisanu, 1967). Other earlier probability learning tasks designed for children typically relied on physical objects: token delivery machines in which children decide between two or three buttons and receive a token for a correct choice (e.g., Kreitler et al., 1983; Stevenson & Weir, 1959; Sullivan & Ross, 1970; Weir, 1964), a deck of cards showing different colors or objects (e.g., Messick & Solley, 1957; Offenbach, 1964), or boxes that probabilistically contain objects (e.g., Moran & McCullers, 1979; Siegel & Andrews, 1962). Newer studies, in contrast, tend to rely on computerized versions of similar tasks (Plate et al., 2018; Starling et al., 2018). In the following, I will provide an overview of the previous literature on the development of probability learning in childhood (aggregate and individual levels) and underlying strategies that children have been suggested to rely on when making repeated choices (for more detailed reviews of the earlier literature, see Fischbein, 1975a; M. R. Jones, 1971). It is crucial to keep in mind that all previous work on the development of probability learning and repeated choice behavior relied on tasks where outcomes were independent and identically distributed. In these tasks, probability matching is a mistake, and exclusively choosing the high-probability option yields maximum rewards.

1.3.1 Probability Learning: A U-Shaped Function Across Development?

A somewhat surprising finding in the developmental probability learning literature, on an aggregate level, is that younger children have been reported to make more high-probability choices than older children, claiming a U-shaped function between the rate of high-probability choices and age from early childhood to adulthood (Derks & Paclisanu, 1967; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980). The problem with this finding arises when asking what exactly *younger* and *older* children means. Some researchers reported that 3- to 4-year-olds are more likely than older children to choose the high-probability option (similar to adults; Derks & Paclisanu, 1967; Weir, 1964); others found 3- to 4-year-olds to be less likely to make high-probability choices than older children (Lewis, 1966; Messick & Solley, 1957); and again, other researchers reported no difference (Offenbach, 1964). Moreover, it remains inconclusive if 5- and 6-year-olds are particularly likely or unlikely to make high-probability choices (Craig & Myers, 1963; Lewis, 1966; Messick & Solley, 1957; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980). However, some evidence shows that (pre-) adolescent children between 11 and 13 years choose the high-probability option at a relatively low rate (Sullivan & Ross, 1970; Weir, 1962, 1964).

Summarizing these findings, the developmental pattern between high-probability choices in probability learning tasks is somewhat inconclusive. Despite mixed findings, there is more evidence in favor of young children being highly likely to make favorable high-probability choices than for the opposite assumption. However, it remains unclear when young children potentially transition from more to fewer maximizing responses. It is noteworthy that the tasks across these studies differed in some aspects, for instance, in the number of choice options or probability levels (e.g., $p_1 = 75\%$ vs. $p_2 = 25\%$, or $p_1 = 66\%$ vs. $p_2 = 0\%$ vs. $p_3 = 0\%$). Nonetheless, only considering the most similar tasks does not fully reconcile findings (for an attempt at reviewing systematic differences between studies, see Jones, 1971).

1.3.2 Of Maximizing Preschoolers and Matching Kids

Much like in the adult literature, only few studies investigated the development of probability matching on an individual level (for an overview see Table A3 in Appendix A). Allowing for a 10% error margin around the outcome probability of the high-probability option ($p = .70$), Jones and Liverant (1960) found that by the end of 100 trials, 20% of children aged 4–6 years, in contrast to 70% of children aged 9–11 years probability matched. Comparing choice behavior over the first and second half of a 200-trial choice task, Derks and Paclisanu (1967) reported that 38% of 3- to 4-year-olds probability matched over the first half of the task but only 3% in the second half. For older children between 8–10 years, more than half of the children probability matched, and the proportion of probability matchers remained comparable across the experiment (Derks & Paclisanu, 1967). Children from 5–8 years were mostly undermatching or, in other words, choosing the high-probability option less than its objective probability (Derks & Paclisanu, 1967). In a probability learning task with eight different choice options, Plate et al. (2018) found that 74% of children aged 6–8 years were best described by a model that assumed initial probability matching before transitioning to overshooting or maximizing (over 200 trials); a probability-matching-only model better described 26% of children. This proportion of strict probability matchers rose to 69% when outcome probabilities across options were less discriminable (Plate et al., 2018). Taken together, probability matching behavior in repeated choices tasks is already prevalent in childhood. However, the evidence is less robust for younger children below 5 years.

Compared to probability matching, there is more research on probability maximizing across childhood. Maximizing is typically defined as either exclusively choosing the option with the highest outcome probability (Stevenson & Weir, 1959) or choosing the high-probability option on at least 90% of the trials by the end of a task (e.g., Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Weir, 1964). Evidence from several studies suggests that probability maximizing is more common in earlier than in later childhood: Across studies, approximately 50% and 70% of children between 3 and 6 years have been reported to maximize (Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Sullivan & Ross, 1970; Weir, 1964). The variability across children and studies might explain some of the inconsistencies on an aggregate level discussed before.

Nevertheless, it may seem counterintuitive at first that young children regularly rely on behavior considered rational from an economic perspective, even though older children do not. It has been suggested that younger children profit from lacking older children's experience. For instance, older children may expect that there is a perfect solution to a probability learning task that allows to predict all outcomes correctly (Baltes, 1987; Stevenson & Weir, 1963; Weir, 1962, 1964). To test if believing in a perfect solution affects children's choice behavior, Weir (1962) instructed children either that a perfect solution exists or that the outcome sequence is random. Children, who were instructed that a perfect solution exists, gave more patterned responses (e.g., repeating left, middle, right choices) but were equally likely to make high-probability choices as other children. Although these findings cannot explain differences in maximizing behavior, they suggest that children's expectations may influence strategy use. An alternative perspective argues that children younger than 5 years rely on associative learning strategies but that their yet poorer response inhibition prevents them from switching between options (Derks & Paclisanu, 1967; S. J. Jones, 1970). Although the proposed relationship between response inhibition and maximizing in early childhood has not been tested, a large body of research on learning and executive function demonstrates considerable improvements across childhood compatible with this hypothesis (Garon et al., 2008; Tamm et al., 2002; White, 1965). Thus, probability maximizing in early childhood is rather viewed as a behavior requiring low-implementation effort, whereas probability matching in older children is thought to require more knowledge or experience with other task structures. Taken together, it seems that brain development and increasing real-world experiences may be equally important for the development of probability learning and repeated choice behavior, but researchers know yet very little about how these processes act in concert.

1.3.3 Roads to Diversification: Children's Underlying Choice Processes

Many roads lead to probability matching or choice diversification more broadly. What do we know about the choice processes underlying this behavior in childhood? Bogartz (1966) proposed that young children tend to apply simple rules to the single last choice or outcome (depending on what they still hold in memory), resulting in repetition or alternation behavior. In a probability learning task reinforcing every choice, 3-year-olds tended to persist with one option but 4- and 5-year-olds tended to alternate (Jeffrey & Cohen, 1965). Indeed, there is ample evidence that alternation tendencies increase in early childhood and are particularly strong for children between 5 and 6 years old (Craig & Myers, 1963; Derks & Paclisanu, 1967; S. J. Jones, 1970; Kessen & Kessen, 1961; Schusterman, 1963). Similarly, in the case of more than two choice options, circular behavior (e.g., choosing left, middle, right) is an often observed behavioral pattern in younger children (Gruen & Weir, 1964; Rabinowitz & Cantor, 1967) and has been suggested to be related to lower memory capacity (Kreitler et al., 1983). Indeed, a memory aid helped children to apply more complex alternation responses, such as double alternation (e.g., left, left, right; Balling & Myers, 1971).

These simple rule-based strategies seem to evolve into reward-sensitive strategies with increasing age, for instance, win-stay lose-shift (Craig & Myers, 1963). This strategy entails choosing the same option again after a win and switching to the other option after a loss. Despite the simplicity of the rule, children differ in its implementation. For instance, Weir (1964) suggested that the ability to switch after a loss, in particular, improves with age (see also van den Bos et al., 2009). This finding, however, is not undebated. On the contrary, it has been argued that lose-shift serves as a default strategy in childhood that is overcome by better executive control (Berman et al., 1970; Ivan et al., 2018). In any case, the common ground of this research is that the use of a win-stay lose-shift heuristic improves with age. This is particularly evident when considering that younger children use this rule, but only older children from 5 years adapt the strategy more optimally to the task (Schusterman, 1963). Investigating the fine-tuning of a win-stay lose-shift heuristic across development using computational modeling techniques that have proven useful in studying adult choice behavior (Otto, Taylor, et al., 2011; Schulze et al., 2017; Worthy et al., 2012) could provide new insights into how children use wins and losses to guide repeated choices.

In sum, research on children's choice processes in probability learning tasks suggests that they persist less with one option and diversify their choices more around preschool age. Maximizing less and diversifying more may benefit increasingly systematic exploration in childhood (Gopnik, 2020; Meder et al., 2021). Beyond cognitive development, there is evidence that task factors further drive increased exploration in probability learning tasks. For instance, Wittig and Weir (1971) found that 4- and 5-year-old children chose the high-probability option less and diversified more when only partial feedback was provided or they had to select between more than two choice alternatives. In the case of more than two choice alternatives it seems to be a crucial factor for diversification that all options are probabilistically rewarded: Several studies reporting maximizing behavior in young children included three choice options of which only one was probabilistically rewarded (and the other two never; e.g., Stevenson & Weir, 1959; Weir, 1962, 1964). In sum, numerous unanswered questions remain about what kind of exploration and choice strategies children rely on in probability learning across development, and how these strategies are influenced by environmental characteristics. Two chapters in this dissertation aim to fill this gap by using behavioral and computational modeling analyses to shed light on differences in strategy use contingent on age, statistical structure of the environment, and testing modality (Chapters 2 and 4).

1.3.4 Limitations to Cross-Sectional Findings on the Development of Probability Learning

It is important to consider a few limitations to previous research on the development of probability learning. So far, virtually all studies on the development of probability learning relied on cross-sectional study designs as a proxy for intra-individual change. More broadly, there are very few longitudinal investigations on the development of decision-making (but see Levin et al., 2007), and the field still needs to take advantage of the opportunity to disentangle between-person and within-person change. Under the assumption that gaining experience with statistical structures alongside improving cognitive abilities is important for adaptive decisions, a longitudinal analysis would be more appropriate to address the question of developmental trajectories. Baltes (1987) suggested that a multidirectional process of concurrent gains and losses often characterizes ontogenetic development. Reviewing probability learning in early childhood as an example, he proposes that increasing experience with task structures (i.e., gain) can prevent older children and adults from performing at the same level as naïve younger children who probability maximize (i.e., loss; Baltes, 1987). When do young children, reported to maximize, develop the ability to diversify their choices? Does the transition from probability maximizing to matching in early childhood occur unidirectionally, or do children switch back and forth between strategies?

Moreover, considering that most research on this topic was conducted about 60 years ago, cohort effects might play a role compared to young children today. Indeed, the environment in which ontogenetic development takes place changes over time and can lead to considerable variability between persons (i.e., history-graded influences; Baltes et al., 1980). Whereas the view on environmental influences on cognitive development became more popular over the years (e.g., Bronfenbrenner, 1979; Sameroff, 2009), a thorough characterization of choice ecologies representative of children's environments is yet missing (both then and now). Significant advancements in many areas of everyday life, from better nutrition to improved education in families and the schooling system (Lynn, 2009), provide the grounds to believe that environmental changes may have affected children's everyday learning environments directly and cognitive development indirectly since the greater part of probability learning studies were conducted.

In this dissertation, I investigate the intra-individual development of probability learning and repeated choice behavior in a two-year accelerated longitudinal study spanning the age ranges from 3.5 to

6.5 years (see Chapter 3). To advance the understanding of how individual differences in cognitive development interact in this process, I furthermore explore the relation between children's choice behavior and developing executive functions.

1.4 Individual Differences in the Development of Probability Learning: Executive Functions

Previous research on the development of probability learning and repeated choice behavior suggests considerable individual differences across childhood (for a review, see M. R. Jones, 1971). But how do individual differences arise? What are the cognitive building blocks underlying age-related changes in probability learning and repeated choice behavior? Whereas several cognitive factors, like working memory capacity, are regularly discussed as contributing to children's flexibility in learning on a conceptual or theoretical level (e.g., Gualtieri & Finn, 2022), empirical analyses of such relationships are yet largely missing. Previous findings on how cognitive resources relate to adults' choice processes can aid hypothesis generation on this topic, for instance, how cognitive capacities influence pattern search, choice diversification, or maximizing (e.g., Gaissmaier et al., 2006; Rakow et al., 2010; Schulze et al., 2019). From an adaptive perspective on cognitive immaturity, it is crucial to keep in mind that cognitive constraints, facilitating exploration or learning in childhood, may lead to suboptimal behavior in adulthood. Consequently, the same constructs may not necessarily serve the same purpose across development.

Cognitive functions that have been suggested to impact the development of repeated choice behavior mostly relate to executive functions (EF). EF are viewed as a set of cognitive processes involved in performing complex tasks. Miyake and colleagues (2000) identify three intercorrelated components in their influential model: "[…] (a) shifting between tasks or mental sets, (b) updating and monitoring of working memory representations, and (c) inhibition of dominant or prepotent responses (p. 54)". In the present research, I am focusing on working memory and response inhibition. There is an ongoing debate to what extent these components map to discriminable processes in childhood—yet, achieving a consensus in increased differentiation across childhood and adolescence (Hartung et al., 2020; Huizinga et al., 2017; Lerner & Lonigan, 2014; McKenna et al., 2017; Reilly et al., 2022; Shing et al., 2010; Xu et al., 2013). Brain regions associated with EF are typically located in the prefrontal cortex (Delgado Reyes et al., 2020; Kwon et al., 2002; McKay et al., 2022; Tamm et al., 2002; Thompson-Schill et al., 2009) and adult-like structural brain networks are thought to be recruited from middle childhood on (Engelhardt et al., 2019; Kharitonova et al., 2012). Performance in tasks tapping into different EF processes rapidly increases in preschool years, reflecting important developments of neural underpinnings (for reviews, see Fiske & Holmboe, 2019; Garon et al., 2008; Zelazo & Müller, 2002). Now, how can the development of EF in childhood help to explain behavioral differences in probability learning tasks?

1.4.1 Response Inhibition

It has been suggested that the ability to inhibit a prepotent response contributes to more maximizing and persistence in young children's repeated choice behavior (S. J. Jones, 1970). In the EF literature, response inhibition refers to a mechanism that suppresses an overlearned or dominant response (Zelazo et al., 2003). Improving significantly in early childhood (Garon et al., 2008), inhibitory mechanisms do not fully mature until late childhood or adolescence (Shing et al., 2010). Inhibiting prepotent responses has been linked to other constructs that may be relevant for early decision-making abilities, for instance, theory-of-mind (i.e., developing belief concepts; Carlson & Moses, 2001), search strategies (Baker et al., 2011; Ruggeri et al., 2019) and counterfactual reasoning (Beck et al., 2009; Kominsky, Gerstenberg, et al., 2021; but see, Buchsbaum et al., 2012). Evidence from adults' reinforcement learning mechanisms suggests that better inhibition of prepotent responses may be related to model-based choice (Otto, Skatova, et al., 2011)—a more sophisticated reinforcement learning formalization that has been reported to increase across childhood and adolescence (for a review, see Bolenz et al., 2017). In sum, inhibitory control may be important for several processes affecting choice behavior in childhood.

The cognitive demands associated with suppressing a prepotent response are thought to differ in complexity across tasks (Carlson & Moses, 2001; Hendry et al., 2022): For instance, delay-of-gratification tasks (e.g., refraining from taking a marshmallow; Mischel et al., 1988) may require less control than interference-control tasks in which a person needs to suppress a prepotent response in favor of giving an alternative response instead (e.g., Stroop-like tasks; Stroop, 1935). However, the increased complexity of interference tasks often comes at the cost of requiring multiple EF processes simultaneously, leading to difficulties in measuring distinct components (discussed as task impurity; e.g., Miyake et al., 2000). The Stroop-like day–night task is an example of a child-friendly inhibitory task requiring different EF processes (Gerstadt et al., 1994). In this task, a child is presented with cards showing either a sun representing the day or a moon and stars representing the night. Under the assumption that children have the correct association with each card, the inhibition task requires children to say "day" when presented with the night-card and "night" when presented with the day-card. This task is thought to require inhibiting a prepotent response (i.e., the correct association), memorizing a new rule, and acting on a conflicting response (i.e., saying the opposite of the initial association).

This more complex form of response inhibition may play a significant role in probability learning tasks. Whereas an immature mechanism could facilitate the repetition of choices—potentially beneficial in static repeated choice environments—more mature abilities could help to suppress the prepotent in favor of an alternative response—yielding an adaptive benefit in changing environments. Depending on the suppressed response tendency (e.g., repetition or alternation), improved inhibition may gradually allow for a larger set of possible strategies in probability learning tasks[1]. However, factor analyses

[1] Response inhibition and impulsivity are sometimes interchangeably used. Whereas impulsivity has been linked to probability matching behavior in habitual gamblers (Gaissmaier et al., 2016), impulsivity is not thought to be equivalent to motoric response inhibition in risky choice in childhood (Rosenbaum et al., 2019), and it is advisable to view these distinct two distinct concepts.

showing that inhibition and memory tasks sometimes only load on a single EF factor in childhood (e.g., Shing et al., 2010; Xu et al., 2013) seem to suggest that response inhibition acts jointly with other processes in shaping choice behavior.

1.4.2 Working Memory

There is yet less evidence for the role of working memory capacity in developing probability learning abilities, and it likewise remains a controversial topic in the adult literature. Children's working memory capacity and development thereof are often evaluated in terms of Baddeley and Hitch's influential model (Baddeley, 2000; Baddeley & Hitch, 1974). The model comprises a central executive, coordinating and integrating information, and three systems storing a limited amount of information: the visuospatial sketchpad (primarily visual and spatial information), the phonological loop (verbal information), and the episodic buffer (multidimensional information and interface to long-term memory; Baddeley, 2000). Performance in working memory tasks improves through childhood and adolescence (Best & Miller, 2010; Garon et al., 2008; Huizinga et al., 2017) and shows a robust relationship to fluid intelligence (Engel et al., 2010; Rosenberg et al., 2020).

Increasing working memory capacity could enable children to become better decision-makers in two ways: first, improving storage for temporary information, and second, integrating this information more efficiently. For instance, higher working memory capacity has been positively related to 7- and 10-year-olds' performance in a proportional reasoning task (Ruggeri et al., 2018), suggesting a relationship between working memory and evaluating frequencies. Moreover, increasing working memory capacity may be important for probabilistic feedback processing (van Duijvenvoorde et al., 2008) and efficiency in strategy use (Mata et al., 2011). Specifically, it has been suggested that working memory capacity and selective attention are closely related in childhood, allowing to differentiate between task-relevant and irrelevant information (Plebanek & Sloutsky, 2019). The causality in this relationship is yet less clear.

So far, there is only limited research on the role of working memory capacity and probability learning. Kreitler and colleagues (1983) investigated the association between 6- and 7-year-olds' performance in a serial recall task and choice behavior in a probability learning task. The authors found that children performing more poorly in the memory task were more likely to systematically alternate between options (i.e., a fixed response pattern like left, right, left, etc.). However, memory span was unrelated to high-probability choices. Kreitler and colleagues (1983) concluded that better memory of past outcomes is important for children to overcome simple response tendencies in favor of more effective strategies. Similarly, a memory aid has been reported to help children to adopt a more complex diversifying strategy than simple alternation (Balling & Myers, 1971). Apart from working memory, other cognitive maturation processes may further enable children to diversify their choices and exploit environmental structures. Recall that working memory capacity and fluid reasoning abilities show a robust association in childhood (e.g., Engel et al., 2010). General cognitive capacities measured in intelligence tests revealed a negative relationship with high-probability choices in a standard probability learning task[2] and a positive relationship in a repeated choice task with patterned outcome sequences in children aged 5–15 years (Goldman & Denny, 1963). Taken together, previous research indicates that improved information storage and integration capacity leads older children to diversify their choices more than younger children–potentially by testing new strategies and exploring hypotheses about the task.

These findings relate to the idea that better working memory capacity enables adults to search for patterns in an outcome sequence (Gaissmaier et al., 2006; Wolford et al., 2004). If people search for patterns in a probability learning task (but fail to find one), they may choose the high-probability option less consistently than people who do not engage in pattern search (e.g., Gaissmaier et al., 2006; Gaissmaier & Schooler, 2008; Schulze et al., 2020). That said, evidence in favor of the relationship between working memory capacity and probability maximizing and probability matching remains inconclusive. Gaissmaier and colleagues (2006) found evidence for an association between memory span and high-probability choices in one experiment but a follow-up experiment showed somewhat different results. Similarly, Wolford and colleagues (2004) reported that performing a secondary task, simulating cognitive load, increases people's likelihood to adopt a maximizing strategy. Yet, this result failed to replicate in a study with a larger sample size than in the original experiment, suggesting that probability matching is a robust choice behavior even under taxing conditions (Schulze et al., 2019). Consistently, another study found that adults were equally likely to probability match, irrespective of whether cognitive resources were compromised or not (Otto, Taylor, et al., 2011). Again, many roads may lead to probability matching, but the underlying process may differ depending on the availability of cognitive resources (Otto, Taylor, et al., 2011).

In sum, it seems plausible to assume that as working memory capacity increases, children improve in remembering and integrating outcome information more efficiently in a probability learning task. Although increased memory capacity is not robustly related to adults' pattern search, the interaction of immature capacities unique to childhood may nevertheless favor exploratory tendencies. However, there are still several open questions. How are working memory capacity and probability learning related in children younger than 6 or 7 years? Does higher capacity create an advantage for early choice diversification? And more generally, regarding the role of executive function—do working memory capacity and response inhibition have a distinguishable effect on young children's choice behavior beyond being a proxy for better information processing and cognitive control? These questions will be discussed as part of a longitudinal investigation on the intra-individual development of probability learning and repeated choice behavior in Chapter 3.

[2] This is the opposite of the relationship between general reasoning abilities and probability maximizing reported by other researchers for adult participants (Gal & Baron, 1996; Rakow et al., 2010; West & Stanovich, 2003). However, it has been suggested that these contrasting findings are related to differences in the task format, specifically whether trial-by-trial outcome feedback was provided (Rakow et al., 2010).

Although developing executive functions have been related to probabilistic reasoning in descriptive tasks (Ruggeri et al., 2018), even very young children and infants are known to have probabilistic intuitions early on in ontogenetic development (Denison & Xu, 2019; Schulze & Hertwig, 2021). These early intuitions may be important building blocks underlying the development of repeated choice strategies. Although the two research streams have yet largely acted in parallel, both fields may profit from drawing connections between them.

1.5 Probabilistic Reasoning in Childhood: A Precursor of Probability Learning?

A central assumption underlying the development of probability learning and repeated choice behavior is that children are able to draw inferences based on probabilistic information. Consider the following task: An experimenter explicitly counts the number of blue and red marbles before putting them in a bag and shaking them thoroughly. The experimenter then asks the child to predict the color of a randomly drawn marble based on the known color distribution. This describes the basic procedure in one of the tasks that Piaget and Inhelder (1951) used in their seminal work on children's probabilistic intuitions. From children's verbal responses in this and other tasks, Piaget and Inhelder (1951) determined three stages of probabilistic reasoning abilities (in a nutshell): little to no understanding of chance and probability from 4 to 7 years, emerging probabilistic concepts from 8 to 10 years, and matured probabilistic reasoning abilities from 11 to 13 years. However, assessing probabilistic reasoning based on verbal protocols may systematically discount younger children's preverbal abilities—one of the major criticisms of Piaget and Inhelder's work (see, e.g., Davies, 1965; Fischbein, 1975; Schlottmann & Wilkening, 2011). Indeed, there is robust evidence showing that infants are remarkable implicit statistical learners. For instance, statistical learning enables infants to extract structures in continuous linguistic input and infer the meaning of a new word (e.g., Romberg & Saffran, 2010; Saffran & Kirkham, 2018; Thiessen et al., 2019). This implicit statistical learning ability has been suggested to be fundamental for young children's capabilities to make probabilistic inferences, and it is by now undisputed that preverbal probabilistic reasoning precedes verbal competencies (for reviews, see Denison & Xu, 2019; Forest et al., 2023; Schulze & Hertwig, 2021).

As noted before, classic probability learning tasks typically employ a learning-from-experience format that does not require abstract statistical knowledge and allows for incremental updating of new information (for reviews, see Fischbein, 1975a; Vulkan, 2000). However, this causes the constraint that there is no clear separation between learning and choice. Consequently, numerous trials are necessary to provide sufficient opportunity to learn about the underlying probabilistic structure. This leads to the question of whether younger children behave differently than older children or adults because of differences in learning or the choice process. For instance, their limited attention span and smaller memory capacity may make it more difficult for children to remember previous outcomes and infer probabilistic information from feedback.

In research on probabilistic inferences in early childhood, in contrast, probabilistic information is often provided before requiring a response, as in the marble guessing task described above (see Denison & Xu, 2019; Schulze & Hertwig, 2021). Tasks regularly incorporate features from both descriptive and experiential learning formats (Schulze & Hertwig, 2021), for instance, sequential presentation of information before the entire distribution is visible (Denison et al., 2013; Schulze & Hertwig, 2022) or randomization processes emphasizing the probabilistic nature of a task (e.g., Girotto & Gonzalez, 2008; Téglás et al., 2007). Whereas a large body of research suggests that infants and young children are able to make predictions based on visually presented proportions and probabilities (e.g., Denison et al., 2013; Denison & Xu, 2010; Téglás et al., 2007), other researchers failed to find further supporting evidence and report that children use simple shortcuts rather than making sophisticated use of probabilities (e.g., Girotto et al., 2016; Lang & Betsch, 2018; Levin & Hart, 2003). However, there seems to be a consensus that reducing the cognitive demands inherent to a task facilitates children's probabilistic reasoning, for instance, by using icon arrays instead of numerical descriptions (Gigerenzer et al., 2021; Ruggeri et al., 2018; Schulze & Hertwig, 2022) or providing a memory aid (van Duijvenvoorde et al., 2012; but see Girotto et al., 2016).

Until now, research on probability learning and in other developmental domains that require some form of probabilistic reasoning have largely acted in parallel despite sharing commonalities. For instance, the concept of probability matching has been discussed in relation to language acquisition (for a review, see Montag, 2021) and to causal learning (Denison et al., 2013). Specifically, Denison and colleagues suggested that children sample outcomes from a possibility space according to their probability of being correct when inferring causal relationships. Consider the following example: there are 80% red marbles and 20% blue marbles in a bag. The authors' sampling hypothesis suggests that either 80% of children will predict a randomly drawn marble to be red in a one-shot scenario or that children will predict red in 80% of repeated trials (Denison et al., 2013). Although there is some evidence for this hypothesis in one-shot scenarios, it still needs to be tested if the sampling hypothesis also holds true for repeated choices when outcome probabilities are known to children before making a choice.

Many open questions at the intersection between children's probabilistic inferences from known probabilities and risky choices still need to be addressed. When learning and choice are more clearly separated (e.g., either because probabilities are described or there is a dedicated information sampling phase; see observe-or-bet-task; Rakow et al., 2010; Tversky & Edwards, 1966), how do young children make repeated choices? Can child-friendly visually descriptive formats that keep some experiential features (e.g., sequential presentation) improve young children's repeated choice behavior, or does reduced experience disrupt their choice processes? Bridging research on probabilistic reasoning in other domains of cognitive development and probability learning might provide new insights into how children harness described probabilities to guide choice behavior. To address this gap, Chapter 5 will connect the sampling hypothesis, probability matching, and repeated risky choices.

So far, I have discussed *what* still needs to be better understood in the development of probability learning and repeated choice behavior from a theoretical perspective. Nevertheless, the Covid-19 pandemic and its restrictions have shown that *how* this research is conducted is standing at a (virtual) crossroads and deserves a closer look from a methodological perspective. In the following section, I will provide an overview of recently increasing online data collection methods in developmental research and discuss how validation studies can provide new insights into child cognition beyond aiming to replicate offline evidence.

1.6 The Same but Different? Online and Offline Developmental Data Collection

What may be considered standard in psychological research with adult participants is rather new when investigating cognitive development with child participants: Over the past few years, interest in remote data collection via the internet increased in developmental science (e.g., Scott & Schulz, 2017; Sheskin et al., 2020; Sheskin & Keil, 2018; Venkatesh, 2021). There is little doubt that this process was accelerated by the challenges the Covid-19 pandemic posed to researchers, for instance, closed laboratories and public testing locations like schools or museums. But beyond being a makeshift solution as a response to a pandemic, remote data collection has the potential to combat critical issues that the field is facing. For instance, a recent study using a machine learning approach to estimate replicability in psychology found that developmental psychology ranked lowest relative to selected other disciplines in their publications' likelihood to replicate (Youyou et al., 2023). Indeed, it has been argued that developmental research needs to overcome underpowered studies to improve replicability (e.g., Byers-Heinlein et al., 2022; Davis-Kean & Ellis, 2019). Using online data collection methods could help to solve this issue, in particular when using a design that does not rely on real-time interaction between a researcher and the participating family (asynchronous or unmoderated studies; Sheskin et al., 2020). As of January 2023, more than 5 billion people in the world are estimated to use the internet (which corresponds to more than 60% of the current world population; DataReportal, 2023), offering the opportunity to reach more children and families than in-person testing might allow. Apart from increasing sample size, sampling bias towards western and industrialized populations has been recognized as a further limitation in developmental psychology (Nielsen et al., 2017). With well-planned recruitment schemes, online data collection could increase the diversity in samples on a smaller scale within cultures (e.g., social groups not regularly visiting museums or research-institution adjacent schools; see Bacon et al., 2021) or on a larger scale across cultures to extend the potential implications of theories in developmental research (e.g., Zaadnoordijk et al., 2021).

The technological opportunities seem endless, but we find ourselves yet at the very beginning. Before exploiting the benefits of online data collection, it is essential to validate its use in developmental research. Do results from offline conducted studies replicate in online studies, even with young children? There is, of course, great interest in proving that offline and online data collection methods are equivalent in the data quality and results they produce. Several best-practice papers, published within a short time, are guiding researchers in their implementation choices for online studies with young children to achieve replicability of results (e.g., Gijbels et al., 2021; Kominsky et al., 2021; Segal & Moulson, 2021; Shields et al., 2021). Evidence from studies addressing the validity of online collected data compared to offline studies is somewhat mixed. Several studies reproduced the overall developmental pattern, but young children's performance in online tasks seemed to be slightly worse than in offline tasks (Chuey et al., 2021; P. M. Nelson et al., 2021; Schidelko et al., 2021; Scott et al., 2017; Sheskin & Keil, 2018). On the one hand, it has been reported that infants in an online violation-of-expectation paradigm (Bacon et al., 2021) and children in verbal comprehension and matrix reasoning tasks (P. M. Nelson et al., 2021) performed better than children tested offline. On the other hand, some researchers found worse performance in a shape discrimination task in an online compared to an offline sample (Bochynska & Dillon, 2021) or performance at chance level in the online version of a second-order inference task (Lapidow et al., 2021). In sum, it seems that some paradigms or tasks may be better suitable for online testing with children than others.

A preprint using a meta-analytic approach to evaluate the replicability of offline data in online studies reports a trend, yet non-significant, for effect sizes in online studies to be smaller than offline and concludes that online and offline data collection are comparable in child research (Chuey et al., 2022). However, several critical issues have not yet been addressed that would improve a meta-analysis' explanatory power[3]. For instance, the inclusion criteria for papers allowed a replication study to differ in their dependent measure across testing methodologies (e.g., preferential look instead of preferential touch; Chuey et al., 2022). Yet, it has been suggested that these different dependent measures may contribute to discrepant findings in infant research and, thus, should not be used interchangeably (Denison & Xu, 2019). Moreover, previous evidence showing that online replicability seems to be contingent on the cognitive process studied or paradigm used was discounted but could provide stronger conclusions if integrated.

Taken together, it still needs to be better understood how children differ across online and offline testing methodologies and how characteristics of each format may shape cognitive processes and behavior. In fact, it has not yet been investigated whether or how online and offline testing may affect children's cognitive processes differently, contingent on characteristics of each format (e.g., social cues, temporal dynamics of feedback, etc.). In research on the development of imitation behavior, it is a well-known finding that younger children show a deficit in learning from videos instead of in-person observation but that the quality of video learning improves with age (Guellai et al., 2022; Strouse & Samson, 2021). This effect has been recently extended to the domain of spatial recall, showing that young children are better searchers in a physical than in a digital task (Kirkorian & Simmering, 2023). It seems rather likely that the prevalence of online instruction and testing methods in developmental psychology

[3] For a recent comment on general concerns of interpretability in meta-analytic reviews, see Simonsohn et al. (2022).

will not decrease but increase in the foreseeable future (Sheskin et al., 2020). But instead of viewing failed online replications as a risk or threat to developmental science, it may rather be a chance to take a closer look at task or methodological characteristics and their interaction with children's cognitive processes across development. How is children's cognition affected by the characteristics of online and offline data collection? What (unintended) obstacles may arise for young children in online data collection? Chapter 4 takes a first step in this direction and explores how performance and strategy use differ when children participate in a probability learning task online via video chat or offline in person.

1.7 Overview of the Dissertation

In this dissertation, I examine the development of probability learning and repeated choice behavior in early childhood, considering ecological, cognitive, and methodological aspects. In four empirical chapters, I approach this topic from different angles concerning the interplay between the mind and the environment: the probabilistic structure of the environment, intra-individual developmental trajectories, executive functions, effects of the data collection method, and learning format. Each of the empirical chapters is written as a self-contained scientific article.

Chapter 2 investigates how children from 3 to 11 years adapt their choice behavior to an ecologically plausible environment. To this end, I created a child-friendly probability learning task in which probabilities change as a function of prior choices. Compared to classic probability learning paradigms with static outcome probabilities, children from 6 years on showed signs of emerging adaptivity and benefitted from but were also constrained by their tendency to explore. Younger children, in contrast, showed yet less sensitivity to the environmental structure. Chapter 3 adds the unique perspective of intra-individual development to probability learning in early childhood. Using an accelerated longitudinal design spanning the age ranges from 3.5 to 6.5 years, this chapter investigates the intra-individual development of probability matching and maximizing. Chapter 3 also explores the relationship between choice behavior and developing working memory capacity or response inhibition. Results demonstrate that between-person and within-person age variability play key roles in probability maximizing and matching, respectively. Moreover, developing executive functions seem to facilitate increasing choice diversification in middle childhood. Chapter 4 addresses how a recent shift toward online data collection in developmental research may affect 3- and 4-year-olds' cognitive processes when performing a probability learning task. Observed decreases in performance toward the end of the task and qualitative differences in the underlying cognitive process emphasize that the testing modality holds important implications for online conducted research. Chapter 5 examines how children between 3 and 7 years make repeated choices when learning outcome probabilities from description before making a choice, without additional trial-wise feedback. Results suggest that descriptive risky choice amplifies developmental differences observed in experiential probability learning tasks. Lastly, Chapter 6 provides a summary of key findings and a general discussion of the main empirical contributions, carving out theoretical and practical implications for future research.

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2 | Emerging Adaptivity in Probability Learning: How Young Minds and the Environment Interact

Abstract. Learning to make choices based on probabilistically occurring outcomes is an important challenge in early childhood, and children's repeated choice behavior has long been studied in static probability learning paradigms. Yet in failing to take the statistical structures of real-world choice ecologies into account, previous studies may have underestimated children's competencies. Taking an ecologically rational perspective, we investigated the development of adaptive choice diversification and probability matching over childhood. We compared the performance of children aged from 3 to 11 years (N = 362) with that of adults (N = 121) in a child-friendly probability learning task, implementing three different statistical environments as between-subjects conditions (one ecologically plausible dynamic condition and two static conditions). Although probability matching was already seen in the 3–4-year age group, children only adaptively diversified choices in the ecologically plausible condition from age 6 years onward. Children showed a stronger tendency for exploration, whereas adults were better able to overcome this tendency in favor of exploitation. Moreover, in line with previous work, we found that young children were highly persistent in their choices, irrespective of whether they maximized reward or not. Computational modeling results revealed that children adapted *which* strategy they used to the environment but that adults held an advantage in *how* they fine-tuned a strategy. Our findings have implications for future research on the development of ecologically rational decision-making and contribute to the discussion on the adaptive functions of cognitive immaturity.

2.1 Introduction

Putting all of one's eggs in one basket is not generally considered wise: It is simply too risky to commit all available resources to a single option. In the context of repeated choices, however, choice diversification—that is, putting one's eggs in different baskets—has long been viewed as irrational behavior resulting from cognitive limitations (for reviews, see Koehler & James, 2014; Newell & Schulze, 2017; Vulkan, 2000). Consider the following scenario: A wheel of fortune has seven blue and three red segments. A person receives a fixed payment for correctly predicting the color of the next spin. To maximize the probability of making correct predictions over many consecutive spins, the person should predict blue every time. When making repeated choices, however, people often *probability match,* predicting each color according to its underlying probability of being drawn (i.e., predicting blue in seven and red in three out of ten spins; e.g., James & Koehler, 2011; Newell & Rakow, 2007; Schulze et al., 2017; Shanks et al., 2002; West & Stanovich, 2003). In this scenario, the expected payoffs of probability matching are lower than those of *probability maximizing*, that is, choosing the option with the highest outcome probability every time. In other words, when making repeated bets on a wheel of fortune, it makes sense to put all of one's eggs in one basket.

There is, however, a striking mismatch between spinning a wheel of fortune and everyday choice situations. Whereas many established repeated choice paradigms assume stationary probabilities throughout a task (for a review, see Vulkan, 2000), the probabilities of outcomes in real-world situations may be clumped, autocorrelated, or sequentially dependent—and they are often learned from feedback rather than description (e.g., Ayton & Fischer, 2004; Fawcett et al., 2014; Groß et al., 2008; Scheibehenne et al., 2011). Choice diversification strategies—like probability matching—can reflect an adaptive response to these statistical structures in real-world, dynamic environments (Schulze et al., 2017).

2.1.1 Ecologically Rational Probability Matching

The mismatch between laboratory and real-world environments is a central critique of *ecologically rational* perspectives on probability matching (e.g., Feher Da Silva et al., 2017; Gaissmaier & Schooler, 2008; Schulze et al., 2015, 2017, 2020; Seth, 2007). Ecological rationality emphasizes the fit between the human mind and the environment, providing a framework for studying the mind's ability to adapt to the statistical structures of the environment (e.g., Hertwig et al., 2022; Todd & Gigerenzer, 2007, 2012). From this perspective, probability matching may not be good or bad per se but can deliver adaptive benefits under certain conditions. For instance, studies have shown that probability matching may be particularly profitable in environments where people, animals, or artificial agents compete for resources (e.g., Schulze et al., 2015; Seth, 2007), that it evolves in noncompetitive environments as a result of near-optimal reinforcement learning (Niv et al., 2002), and that it facilitates the detection of patterns in outcome sequences (Gaissmaier et al., 2016; Gaissmaier & Schooler, 2008; Schulze et al., 2020).

Indeed, statistical regularities in outcome sequences may play a key role in shaping the learning and choice processes underlying probability matching. For instance, a Bayesian learning model incorporating beliefs about the temporal dependency of outcomes approximates probability matching when aiming to maximize outcomes (Green et al., 2010). Similarly, choice diversification strategies close to probability matching may be adaptive in exploiting sequential dependencies between choices and outcomes (Schulze et al., 2017). Such sequential dependencies can arise, for instance, when rewards that are not collected remain available over multiple trials in an outcome sequence, which simulates an ecologically plausible resource depletion mechanism (see Jensen & Neuringer, 2008). Creating an analogous task structure, Schulze et al. (2017) showed that people learned to adaptively diversify their choices in response to the dependencies in the environment. That people bring expectations about choice–outcome dependencies learned in the real world to laboratory environments was suggested in the early stages of probability learning research (Tolman & Brunswik, 1935). However, surprisingly little is yet known about how and when people develop strategies adapted to the statistical structure of real-world environments. If adaptive choice diversification strategies like probability matching are habits learned in everyday life, then how much life experience is needed for them to emerge?

2.1.2 Development of Probability Learning

Learning to make choices based on probabilistically occurring outcomes is an important competence for children to acquire—for instance, which book will be most fun to read or which sibling will be more likely to share their candy. However, the task structures implemented in previous studies on the development of probability learning may misrepresent children's experience with typical choice ecologies and, consequently, systematically underestimate their competencies (for a similar argument in the domain of active learning, see Ruggeri, 2022).

The development of repeated choice behavior has been studied in children from about 3 years of age across numerous standard probability learning paradigms with stationary outcome probabilities: predicting which light will turn on next (Craig & Myers, 1963; Derks & Paclisanu, 1967), which button will deliver a token (Gruen & Weir, 1964; Stevenson & Hoving, 1964; Stevenson & Weir, 1959; Sullivan & Ross, 1970), or under which rock in a computerized task a coin is hidden (Plate et al., 2018). Typically, these tasks require children to learn about outcome probabilities from feedback rather than description. For instance, one light turns on in 75% of the trials (i.e., the high-probability option) and the other in the remaining 25% of trials (i.e., the low-probability option; Derks & Paclisanu, 1967).

To date, research investigating the development of probability learning and repeated choice behavior reveals mixed findings, with some developmental patterns supported by stronger evidence than others. First, children under 5 years are regularly found to maximize probability (e.g., Derks & Paclisanu, 1967; Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Weir, 1964). However, the proportion of young children persisting with this behavior varies across tasks, leading to inconsistencies on an aggregate level. The developmental literature suggests that instead of arriving at maximization by deliberation—as reported for adults (Koehler & James, 2010; Newell et al., 2013)—young children, in whom cognitive control and response inhibition are not yet developed, use maximizing as a low implementation-effort strategy (Derks & Paclisanu, 1967; S. J. Jones, 1970). Second, school-aged and preadolescent children commonly diversify choices by probability matching (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Plate et al., 2018), leading some researchers to assume a U-shaped function between high-probability choices and age (e.g., Derks & Paclisanu, 1967; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980). The width and turning point of this U-function are debated, however: It remains somewhat unclear at what age the transition from probability maximizing to probability matching occurs. It has been suggested that this transition represents a trade-off between gains and losses in cognitive development (Baltes, 1987): With increasing cognitive capacities and experience, children pursue new optimization strategies that may occasionally prove a poor fit to the environmental structure.

From the perspective of ecological rationality, the increase in choice diversification over childhood might reflect children's growing experience with the statistical structures of a world in which it is often not advisable to put all one's eggs in one basket. It has been suggested that human childhood, with its extended period of immaturity relative to other mammals, accommodates significant brain changes and facilitates the development of a diverse set of search and inference strategies (Gopnik, 2020; Gopnik et al., 2017; Ruggeri, 2022). Indeed, some cognitive limitations inherent to childhood have been suggested to enhance learning (e.g., Bjorklund, 2018; Bjorklund & Green, 1992; Gopnik et al., 2017). Moreover, childhood is seen as a period of exploration during which children are particularly flexible learners, gathering and testing new information about the environment (e.g., Blanco & Sloutsky, 2020; Giron et al., 2022; Gopnik et al., 2017; Nussenbaum et al., 2022; Schulz et al., 2019). This could equip them to uncover features of the environment (Gopnik, 2020; Liquin & Gopnik, 2022) and to use environmental conditions as cues for adaptive strategies (Fawcett & Frankenhuis, 2015; Frankenhuis et al., 2019). How children learn to adapt their choice strategies to the specifics of the environment and how much experience with typical choice ecologies is required to shape this process remains incompletely understood. In this article, we provide new insights into these questions by testing how children adapt to a dynamic probability learning task that simulates an ecologically plausible environment. Additionally, we compare children's choices in this dynamic environment to their choices in a static environment under different outcome probabilities, and we use computational cognitive modeling to investigate the development of the cognitive mechanisms underlying adaptive probability learning.

2.1.3 The Present Study

Drawing a connection between research on ecologically rational probability matching in adulthood and research on the benefits of cognitive immaturity in childhood (see Bjorklund & Green, 1992; Gaissmaier & Schooler, 2008; Gopnik, 2020; Green et al., 2010; Schulze et al., 2017), we investigated the development of adaptive probability matching and choice diversification from early childhood to adulthood. To this end, we contrasted an ecologically plausible dynamic choice environment with classic stationary probability learning paradigms. On the basis of previous research investigating probability learning and exploration strategies (e.g., Derks & Paclisanu, 1967; Gopnik et al., 2015, 2017; Schulz et al., 2019; Weir, 1964), we identified the age range between 3 and 11 years as a critical period for the development from persistent to more diversified choice behavior. To compare probability learning in early, mid-, and late childhood, we examined the age groups 3–4 years, 6–7 years, and 9–11 years (see, e.g., Gopnik et al., 2017).

In the context of a child-friendly task requiring repeated choices between two options, we implemented three different statistical environments as between-subjects conditions. The *static high* condition reflected classic probability learning paradigms (e.g., Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Siegel & Andrews, 1962). In this condition, the high-probability option yielded a reward in 70% of trials; the low-probability option in 30% of trials. One way in which this statistical structure differs from many real-world environments is that rewards that are not immediately collected disappear. In everyday life, in contrast, resources often remain available for some time before disappearing due to maturation, competition, or other decay processes (see Jensen & Neuringer, 2008). For instance, parents will keep on offering food to a child for some time before removing it; a child can choose to go on the swing at the playground until another child occupies it; and the more a toy is used the sooner it will run out of battery. Consequently, the probability of obtaining a desired outcome may change over time and as a function of prior decisions. As children gain more experience with environments in which resources remain available for some but not all of the time, they may become more efficient in exploiting this structure. The *ecologically dynamic* condition in our study simulated dynamically changing probabilities as a function of prior decisions. In this condition, outcomes were initially scheduled to occur with probabilities of 70% and 30% for the high- and low-probability option, respectively, but rewards remained available over subsequent trials until collected (Ellerby & Tunney, 2019; Schulze et al., 2017). A side-effect of this dynamic reward-hold mechanism is that the options' reward probabilities can converge—or even flip—over time, making the options less discriminable. In the *static random* condition, both choice options were equally likely to yield a reward. This condition allowed us to compare choice behavior in two conditions with less discriminable outcome probabilities and to explore whether young children persist in their choices even in the absence of a favorable option.

Given previous research indicating that young children are more likely to probability maximize than older children (e.g., Derks & Paclisanu, 1967; Weir, 1964), we might expect the youngest age group to maximize more than 6- to 11-year-olds, irrespective of the environment and at a similar rate as adults. If 3- to 4-year-olds engage in probability maximizing as a satisficing, low implementation-effort strategy, we can expect the proportion who persist with this behavior to remain constant over conditions. Yet it is also conceivable that even young children can adapt to a dynamic environment. Indeed, infants show sometimes surprising capabilities for statistical learning and inference (for reviews, see Denison & Xu, 2019; Forest et al., 2023; Schulze & Hertwig, 2021), enabling them to extract patterns from sequential input and thus to master key developmental milestones, such as language acquisition (Romberg & Saffran, 2010). From this perspective, even a small amount of experience with environments in which sequential dependencies are regularly encountered may suffice to help young children adaptively diversify their choices, which would be reflected in probability matching in the ecologically dynamic condition.

We expected that—as they grow older and gain more experience with real-world environments, and as continued brain development allows them to become more directed explorers—children become more effective in adapting their choice behavior to an ecologically plausible environment. We therefore hypothesized that older children (i.e., 6- to 7- and 9- to 11-year-olds) mainly diversify their choices in line with probability matching—particularly in the ecologically dynamic condition, where expectations about dynamic probabilistic structures learned in the real world are beneficial and not misleading. Lastly, we expected to replicate findings from a similar study with adult participants showing adaptive diversification in response to a reward-hold condition (Schulze et al., 2017).

Because choice diversification and probability matching can result from different cognitive processes, we complemented our behavioral analyses with a computational modeling approach that made it possible to explore the development of the cognitive processes underlying repeated choice behavior. Specifically, this approach allowed us to pinpoint the cognitive mechanisms on which children and adults differ, and to investigate whether they use different diversification strategies depending on the statistical structure of the environment.

2.2 Method

2.2.1 Participants

We recruited 381 children from three age groups (3–4 years, 6–7 years, and 9–11 years) and 121 adults to participate in the experiment. The sample size was determined before recruitment via a power analysis based on the effect sizes reported in studies examining adult behavior in similar tasks (e.g., Schulze et al., 2017).[4] A total of 18 3- to 4-year-olds and one 6-year-old terminated the experiment prematurely and were excluded from data analysis. The final sample consisted of 120 children aged 3–4 years (*M* = 4.07 years, *SD* = 0.56 years, 48% female), 121 children aged 6–7 years (*M* = 6.92 years, *SD* = 0.56 years, 58% female), 121 children aged 9–11 years (*M* = 10.15 years, *SD* = 0.78 years, 55% female), and 121 adults (*M* = 26.23 years, *SD* = 5.99 years, range 18–51 years, 52% female; see Table B1 in Appendix B for age distribution per experimental condition).

The experiment and procedure were reviewed and approved by the institutional review board of the Max Planck Institute for Human Development. Data collection took place from December 2019 to April 2022, with interruptions because of the Covid-19 pandemic. Most participants were tested at the Museum für Naturkunde and Zoo Berlin; due to Covid-19 restrictions, some participants had to be tested in the behavioral lab at the Max Planck Institute for Human Development. The two static conditions were run simultaneously, with participants being randomly assigned to a condition. Data for the dynamic condition were collected subsequently. Adult participants and parents of minor participants gave written consent prior to the study. Children were additionally asked for verbal consent at the beginning of the task. Every session was recorded on video.[5] Adults received a performance-based payment of 1 EUR for every 10 correct choices; children received one sticker for every 10 correct choices. Parents of children tested at the behavioral lab additionally received 15 EUR as an expense allowance.

2.2.2 Design

We implemented three probabilistic task structures as between-subjects conditions in a probability-learning task in which participants made repeated choices between two options. The options' reward probabilities were not explicitly stated but needed to be learned from trial-wise feedback. In the *static high* condition, one option delivered a reward in 70% of trials and the other in 30%; the placement of

[4] Specifically, we entered the results reported in Schulze et al. (2017) as proportions in a Fisher's Exact Test between two independent groups in G*Power (Faul et al., 2007) to compute the sample size necessary to detect effects with a power of .8 and significance criterion $\alpha = .05$. Anticipating somewhat noisier behavior in children, we rounded up the required 34 participants per condition and age group to 40 participants.

[5] Sessions were recorded for child protection reasons; the video data will not be evaluated here. To protect participants' privacy, the recording showed only their hands and the tablet. Participants gave explicit consent for the video data to be collected.

the high-probability option (left or right) was randomized across participants. In the *static random* condition, each option delivered a reward in 50% of trials. In both static conditions, rewards at each option were mutually exclusive and had to be collected immediately.

To create an ecologically plausible environment, we implemented a reward-hold mechanism (see also Ellerby & Tunney, 2019; Schulze et al., 2017). This mechanism mimics choice situations in which an uncollected reward is not lost immediately. For instance, a parent may offer their child a snack of carrot sticks. A child who prefers orange slices may ask for these instead, knowing that this request will only occasionally be successful. But even if it is denied, the carrot sticks will remain available. And even if orange slices are provided, the child may still get the carrot sticks afterwards too. Thus, in the *ecologically dynamic* condition, rewards were initially scheduled to occur at one option in 70% of trials and at the other option in 30% of trials, but were not mutually exclusive: one option, both options, or no option could deliver a reward at any trial.[6] However, a reward that was scheduled to occur but was not collected immediately remained available over the following trials until collected (see Figure 2.1), but rewards did not accumulate (in the same way as the number of carrot sticks available does not increase while a child campaigns for orange slices). Hence, the actual outcome probability at any trial depended on both the programmed probabilities and participants' prior choices. Consequently, an option's outcome probability could increase over trials while it was not selected (see Jensen & Neuringer, 2008; Schulze et al., 2017).

In this environment, a strategy that approximates probability matching (e.g., several high-probability choices followed by a single low-probability choice) outperforms persistent choice (for exact computations, see Table 1 in Schulze et al., 2017).

2.2.3 Material and Procedure

We developed a tablet-based[7] and child-friendly repeated choice task with 100 trials in which escaped zoo animals were hiding behind two houses (i.e., the choice options). The experiment was implemented in the jsPsych framework (Leeuw, 2015) with custom-built functions. At the beginning of the task, an experimenter showed one of two laminated sheets displaying 50 out of 100 escaped zoo animals. This procedure ensured that all participants understood that many animals needed to be found without revealing the total number of trials. Adults completed the task by themselves, reading the instructions on the tablet; children were instead instructed verbally. The experimenter presented the child with the tablet showing two identical drawings of houses side by side (Figure 2.1A) and explained that they needed to find as many escaped animals as possible by guessing behind which of the houses an animal

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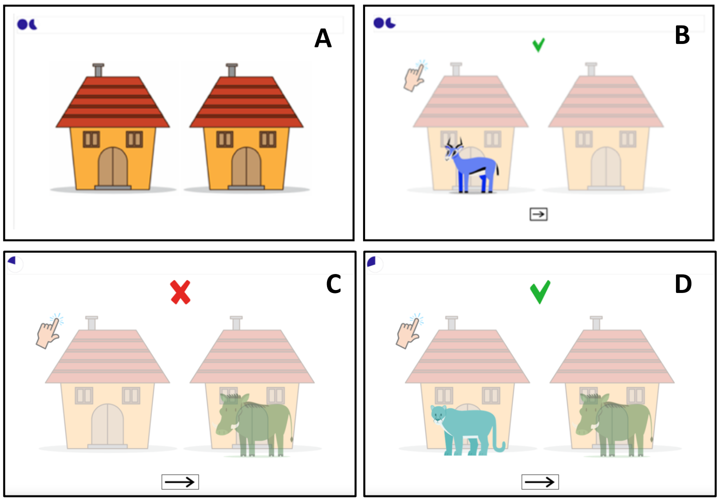
[6] We simulated different choice behaviors (e.g., win-stay lose-shift, ratios of choosing the high- and low-probability option) in the ecologically dynamic condition with and without mutual exclusivity. Because some diversification strategies did not outperform persistent choice under mutual exclusivity, we implemented the condition without mutually exclusive rewards to increase the profitability of diversification.

[7] We used Lenovo Tab2 A10-30 tablets with a screen resolution of 1280 × 800 px.

was hiding. Children were familiarized with the symbols displayed in two practice trials—one programmed to show a correct choice (Figure 2.1B); the other to show an incorrect choice (Figure 2.1C). In the ecologically dynamic condition, children completed a third practice trial in which there was an animal hiding behind each house (Figure 2.1D). Here, the experimenter explained that only one animal can be found per trial, even when two animals are later revealed on the screen. After children had made a choice by tapping on the tablet, a feedback screen showed where the animal was hiding, a hand symbol indicated the chosen option, and a checkmark or cross at the top of the screen marked whether the choice was correct or incorrect. Both houses were rendered transparent to provide full feedback about the outcomes of both the option chosen and the other option. At the top left of the screen, one-tenth of a blue circle was added for every correct choice. For every full circle, children received a blue token that they could later exchange for stickers. Before the task, children were encouraged to look through the sticker box for stickers they liked.

Figure 2.1

Repeated Choice Task: Choice and Feedback Screens



Note. (A) Choice screen in all three conditions; (B) Feedback screen for a correct choice in all three conditions; (C) Feedback screen for an incorrect choice in all three conditions; in the ecologically dynamic condition, the reward remains on hold; (D) Feedback screen in the ecologically dynamic condition; the animal on the right is on hold.

Following the practice trials, participants completed 100 trials. To keep children interested in the task, the experimenter announced the name of each animal in a neutral tone and handed out a blue token after every ten correct choices. To gauge how well participants understood the task, we subsequently asked participants to indicate behind which of the two houses more animals were hiding and to use a response slider to give a numerical estimate of how many animals were hiding behind each house. The slider restricted numerical estimates to add up to a total of 100. Participants were then asked to explain how they made their choices and to provide information about their age, gender, and education level.[8] Lastly, children were encouraged to exchange their blue tokens for stickers, and parents of minors tested in the laboratory as well as adult participants were paid in cash.

2.3 Results

2.3.1 Behavioral Results

We first analyzed general persistence in terms of choices of the participant's preferred option across our three experimental conditions—irrespective of whether that option maximized probability or not—to investigate general persistence. We then investigated whether this choice behavior implied probability learning in the static high and ecologically dynamic conditions. Finally, we classified individual participants' responses as either probability matching or probability maximizing and report their ability to identify the high-probability option after completing all trials. All behavioral analyses were conducted in R (R Core Team, 2023). We used the afex package to estimate mixed models (Singmann et al., 2022) and the emmeans package for follow-up tests (Lenth, 2022).

2.3.1.1 Aggregate Choice Behavior

Persistence. To compare behavior across the three conditions, we calculated how many times a participant chose each option and defined the option they chose more frequently as their preferred option. This measure allowed us to investigate persistence irrespective of the reward structure and to compare behavior in the ecologically dynamic condition to the static random condition where probabilities (could) converge. Table 2.1 shows the proportion of participants whose preferred option was also the high-probability option in the static high and ecologically dynamic conditions.

Table 2.1

Proportion of Participants Whose Preferred Option Was Also the High-Probability Option by Condition and Age Group

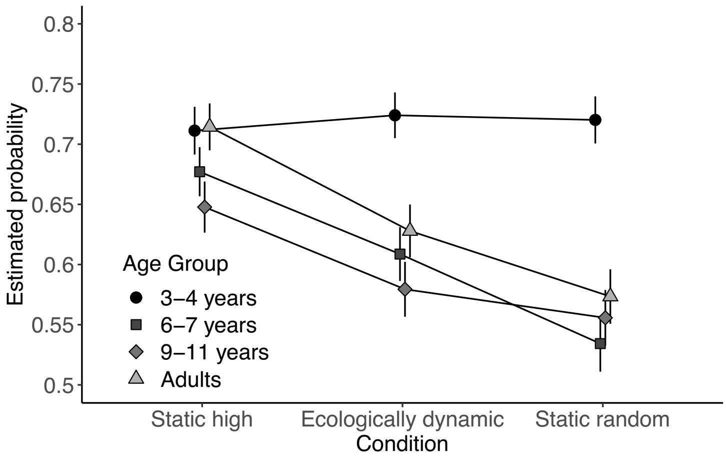
	Condition	
Age group	Static high	Ecologically dynamic
3–4 years	.77	.66
6–7 years	.95	.90
9–11 years	.95	.95
Adults	.90	.90

[8] Because young children had difficulties with using the slider to give a numerical estimate and answering the strategy question, we do not analyze these data here.

To examine if children and adults prefer one option irrespective of whether this option maximizes reward, we estimated a mixed model to investigate participants' likelihood to choose their preferred option as a function of trial block (five blocks of 20 trials), condition (static high vs. static random vs. ecologically dynamic), age group (3- to 4-year-olds, 6- to 7-year-olds, 9- to 11-year-olds, adults), and the interactions between age group and condition as well as age group and trial block (all included as fixed effects). We used a logit link function accounting for the binary nature of the dependent variable (choosing the preferred option or not). Individually varying intercepts reflected the random effects structure, capturing that each participant made 100 choices. Figure 2.2 shows the fitted means and 95% confidence intervals derived from the mixed model for each age group and condition, averaged across trial blocks.

Figure 2.2

Preferred Option Choices by Age Group and Condition



Note. Estimated probability of a participant choosing their preferred option by condition and age group averaged across trial blocks based on the mixed-model analysis. Error bars represent the 95% confidence interval.

First, we found a main effect of trial block, $\chi^2(4) = 132.56$, $p < .001$, as well as an interaction between age group and trial block, $\chi^2(12) = 24.72$, $p < .05$, indicating that, on average, participants increasingly tended to choose their preferred option over time. However, this effect was strongest for the youngest age group.

Indeed, age played an important role in general persistence. Averaging across conditions and trial blocks, we found that the likelihood of a participant choosing their preferred option differed as a function of age group, $\chi^2(3) = 59.48$, $p < .001$. Tukey-corrected pairwise contrasts between age groups showed that 3- to 4-year-olds were more likely than any other age group to choose their preferred option: Averaged across trial block and condition, 3- to 4-year-olds chose their preferred option more often than 6-

to 7-year-olds ($z = 6.45$, $p < .001$), 9- to 11-year-olds ($z = 7.16$, $p < .001$), or adults ($z = 4.64$, $p < .001$). Older children (6+ years) and adults did not differ in terms of choice of their preferred option (all *p*s > .05).

Furthermore, we found a significant main effect of condition, $\chi^2(2) = 32.96$, $p < .001$, reflecting that, across trial blocks and age groups, participants were not equally likely in every condition to choose their preferred option. Tukey-corrected pairwise contrasts between conditions—averaged across age groups and trial blocks—showed that participants in the static high condition were 1.26 times more likely to choose their preferred option than participants in the ecologically dynamic condition ($z = 3.43$, $p < .01$), and 1.48 times more likely to choose their preferred option than participants in the static random condition ($z = 5.86$, $p < .001$); participants in the ecologically dynamic condition were 1.18 times more likely to choose their preferred option than participants in the static random condition ($z = 2.43$, $p < .05$). Thus, participants were, on average, most likely to revisit their preferred option—and least likely to diversify—in the static high condition, followed (in descending order) by the ecologically dynamic condition and the static random condition. These findings reflect that there is a sweet spot in the ecologically dynamic condition between persistence and diversification. However, the interaction between age group and condition, $\chi^2(6) = 16.41$, $p < .05$, indicates that older children and adults adapted their persistence to the statistical structure of the environment more effectively than younger children: Children from 6 years and adults were less likely to persist with one option when high persistence was less beneficial (i.e., in the static random and ecologically dynamic conditions, respectively; see Figure 2.2). In contrast, 3- to 4-year-olds tended to persist with one option irrespective of whether or not it maximized reward.

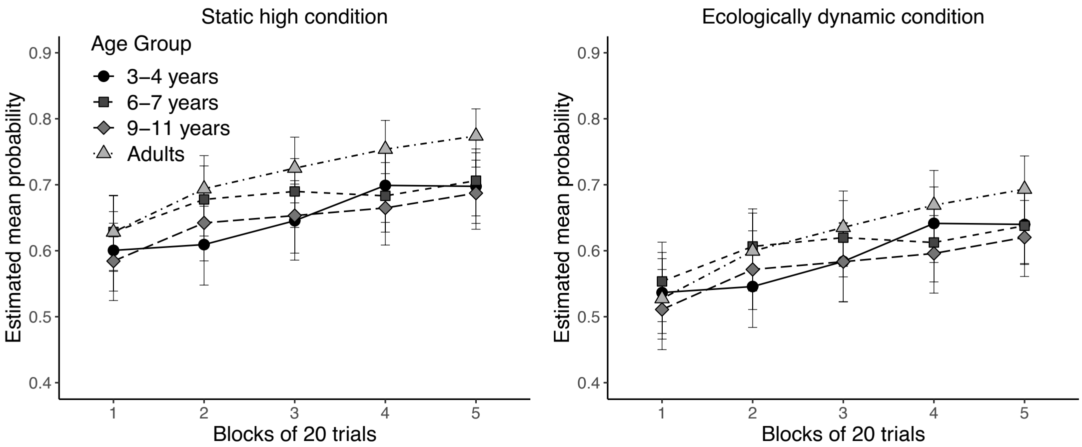
Probability Learning. However, analyzing preferred option choices does not provide full insight into the learning of underlying probabilities, nor whether people probability match or maximize. Diversification, like probability matching, yields higher average reward probabilities in the ecologically dynamic condition whereas probability maximizing is more beneficial in the static high condition. In the static random condition, it makes no difference whether a participant sticks exclusively to one option, diversifies their choices, or chooses at random: All choice behaviors lead to the same average reward probability. We therefore focused on the static high and ecologically dynamic conditions to address the research question of how much life experience is needed for adaptive choice diversification to emerge.

We estimated a mixed-effects model to predict probability learning by trial block (five blocks of 20 trials), condition (static high vs. ecologically dynamic), age group (3- to 4-year-olds, 6- to 7-year-olds, 9- to 11-year-olds, adults), and the interactions between age group and condition as well as age group and trial block. We used a logit link function to account for the binary dependent variable (choosing the high probability option or not) and implemented individually varying intercepts as a random effects structure to capture that multiple choices were made by the same individuals. Figure 2.3 shows the estimated probability of choosing the high-probability option per block of 20 trials and age group in the static high and ecologically dynamic conditions.

We found a significant main effect of condition, $\chi^2(2) = 14.76$, $p < .001$, reflecting that, averaged across trial blocks, participants in the static high condition made more choices of the high-probability option ($M = .66$) than did participants in the ecologically dynamic condition ($M = .59$). As predicted, participants, on average, learned to diversify their choices more in an ecologically plausible environment.

Figure 2.3

High-Probability Choices by Trial Block, Age Group, and Condition



Note. Estimated mean probability of choosing the high-probability option by block of 20 trials and age group in the static high (left) and ecologically dynamic (right) condition based on mixed-model analysis. Error bars represent the 95% confidence interval.

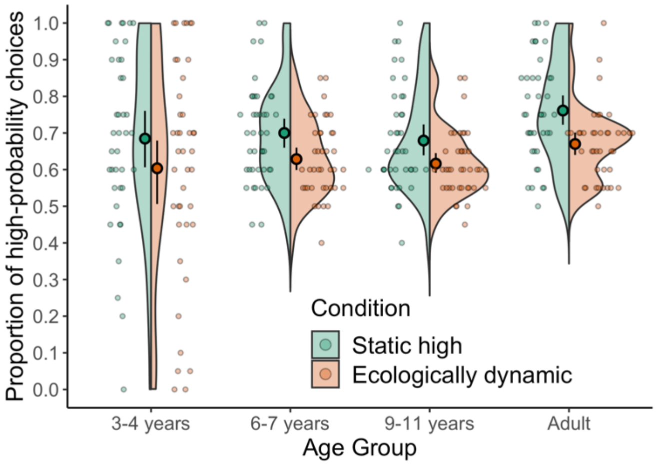
Furthermore, participants in both conditions learned to choose the high-probability option more often over time, as indicated by a main effect of trial block, $\chi^2(4) = 197.61$, $p < .001$. Additionally, we found an interaction between block and age group, $\chi^2(12) = 30.01$, $p < .05$. To determine whether children and adults differed in their propensity of choosing the high-probability option toward the end of learning, we computed two Tukey-corrected custom contrasts for the final block of 20 trials (3- to 4-year-olds + 6- to 7-year-olds + 9- to 11-year-olds vs. adults in the static high and ecologically dynamic conditions). In the static high condition, adults were 1.49 times more likely than children to choose the high-probability option by the end of the task ($z = 2.68$, $p < .05$); in the ecologically dynamic condition, children and adults did not differ significantly ($z = 1.85$, $p = .12$). In other words, whereas adults outperformed children by the end of the task in the static high condition, this difference disappeared in the more ecologically plausible statistical environment (see Figure 2.4).

Additionally, probability learning across trials seemed to proceed similarly for children and adults in the two conditions: neither age group nor the interaction between age group and condition significantly predicted learning to choose the more frequently rewarded option over the course of the experiment (all ps > .1).

In sum, we found that adults were more likely than children to choose the high-probability option by the end of the task in the static high condition, but no main effect of age group on the likelihood of choosing the high-probability option. Moreover, on an aggregate level, participants were more likely to diversify their choices in the ecologically dynamic environment, in which this behavior was adaptive. Next, we turn to the cognitive strategies used by individual children and adults in the static high and ecologically dynamic conditions.

Figure 2.4

High-Probability Choices by Age Group and Condition Toward the End of Learning



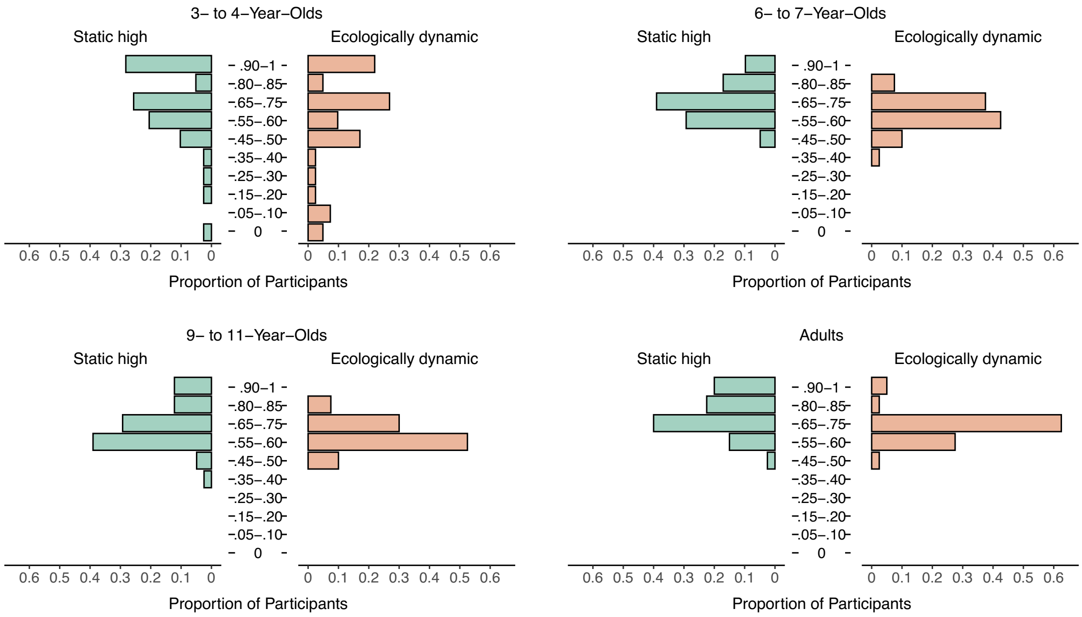
Note. Proportions of choices of the high-probability option averaged over the final block of 20 trials in the static high and ecologically dynamic condition. Error bars represent the bootstrapped 95% confidence interval of the mean.

2.3.1.2 Individual Choice Behavior: Choice Diversification and Maximizing

To investigate individual choice strategies, we calculated the proportion of choices of the high-probability option in the final block of 20 trials per participant. Figure 2.5 shows the distribution of participants' individual choice proportions by age group and condition. Most notably, 3- to 4-year-olds showed the most heterogeneous choice behavior. While about a quarter of 3- to 4-year-olds probability maximized through persistent choice, a comparable proportion used choice diversification strategies that approximated probability matching. Moreover, whereas 15% of the 3- to 4-year-olds exclusively selected the high-probability option in both the static high and the ecologically dynamic environment, 5% and 3% of them exclusively selected the low-probability option in the static high and ecologically dynamic condition, respectively. In contrast, older children and adults chose the high-probability option in at least 40% of trials in both conditions.

Figure 2.5

Distribution of the Proportion of Choices of the High-Probability Option in the Final Block of 20 Trials by Age Group and Condition



Note. In each panel, the top bar represents the participants categorized as probability maximizers and the third bar from the top represents probability matchers. Proportion of high-probability choices in the final block of trials on the y-axis; proportion of participants on x-axis.

We categorized participants as probability matchers or probability maximizers based on their individual proportions of choosing the high-probability option in the final block of trials. Definitions of probability matching and maximizing in the literature differ significantly. Here, we follow a commonly used definition in the adult literature (e.g., Schulze et al., 2015), defining probability matching as choosing the high-probability option in between 65% and 75% of trials (70% +/- 5%). To keep the boundary width of the definitions equal, we defined probability maximizing as choosing the high-probability option in at least 90% of trials. All remaining participants were classified as using other strategies. Table 2.2 shows the results of this categorization. Children of all age groups as well as adults engaged in probability matching in both the static high and the ecologically dynamic condition. However, 3- to 4-year-olds showed the least probability matching of all age groups. A Fisher's Exact Test indicated no association between choice behavior and age group in the static high condition (p = .25). In contrast, a Fisher's Exact Test showed a significant relationship between age group and choice behavior in the ecologically dynamic condition (p < .001): More 3- to 4-year-olds probability maximized and more adults probability matched than expected under independence. There were no strategy differences between conditions within each age group (all *ps* > .06). In sum, these results indicate that 3- to 4-year-olds tended to both probability match and probability maximize whereas older children mostly probability matched, irrespective of the environment. Adults adapted both probability matching and maximizing to the environment.

Table 2.2

Number of Participants Categorized as Using Probability Matching, Probability Maximizing, or Other Strategies in the Final Block of 20 Trials by Condition and Age Group

		Category			
Condition	Age group	Probability matching (%)	Probability maximizing (%)	Other (%)	*p* Fisher's Exact Test
Static high	3–4 years	10 (26)	11 (28)	18 (46)	.25
	6–7 years	16 (39)	4 (10)	21 (51)	
	9–11 years	12 (29)	5 (12)	24 (59)	
	Adults	16 (40)	8 (20)	16 (40)	
Ecologically dynamic	3–4 years	11 (27)	9 (22)	21 (51)	<.001
	6–7 years	15 (38)	0 (0)	25 (63)	
	9–11 years	12 (30)	0 (0)	28 (70)	
	Adults	25 (62)	2 (5)	13 (33)	

Note. Probability matching (maximizing) yielded higher average reward probabilities in the ecologically dynamic (static high) condition.

In the ecologically dynamic condition, diversifying choices close to probability matching can yield higher average reward rates than always choosing the initial high-probability option as it provides the opportunity to exploit sequential dependencies. When rewards were retained over trials, there was a 100% chance of obtaining a reward when selecting a reward-hold option and only a 70% or 30% chance when selecting the alternative option. The average number of trials before a reward on hold is exploited can serve as a measure of how efficiently children and adults learned to exploit the sequential dependencies. A Kruskal-Wallis test showed that age groups differed in how quickly they collected held rewards, $H(3) = 62.29$, $p < .001$. Children aged 3–4 years ($Mdn = 2.8$, $SD = 25.6$) exploited a reward on hold less quickly than children aged 6–7 years ($Mdn = 1.12$, $SD = 0.43$), children aged 9–11 years ($Mdn = 1.14$, $SD = 0.3$), or adults ($Mdn = 1.37$, $SD = 3.55$). Only two 7-year-olds pursued an optimal solution by the end of the task (i.e., always choosing the high-probability option unless an uncollected reward has been observed at the low-probability option).

2.3.1.3 Ability to Identify the High-Probability Option

To gauge how well participants understood the task, we subsequently asked those in the static high and ecologically dynamic conditions to identify the option that was more frequently rewarded. A binomial test indicated that all age groups, on average, performed above chance level in this task (range = .73–.95, $p < .05$), although it required reasoning on a more abstract level than the repeated choice task itself. We can therefore assume at least a basic understanding of the experienced frequencies and the task instructions, even in the youngest age group (for a statistical analysis of age and condition differences, see Table B2 in Appendix B).

2.3.1.4 Interim Discussion

Behavioral analyses across the three statistical conditions revealed considerable differences in general persistence and choice behavior across development. When comparing general persistence—irrespective of whether an option maximized reward or not—we found that 3- to 4-year-olds showed the strongest tendency to repeat a choice. Accordingly, more 3- to 4-year-olds probability maximized than did participants in any other age group, but a few 3- to 4-year-olds persisted with the low-probability option. In sum, the youngest age group was less sensitive to the statistical structure of the task than were older children and adults, and may have used persistent choice as an easy-to-implement strategy rather than as a deliberate strategy to maximize probability (see also Derks & Paclisanu, 1967; S. J. Jones, 1970).

But how much life experience is needed for choice diversification strategies such as probability matching to emerge? On average, children and adults chose the high-probability option less frequently, and instead diversified their choices more often, when the statistical structure of the task was ecologically plausible. Analyses of choice behavior toward the end of learning showed that adults chose the high-probability option more often than children in the static high condition, but not in the ecologically dynamic condition. This may indicate that adults have an advantage over children in statistical environments that do not reflect everyday experience and require more abstract reasoning (Schulze & Hertwig, 2021). Yet older children (6+ years) seemed to be more reactive to the environment than younger children and were better able to exploit sequential dependencies. In comparison to younger children, they seemed to have used previous outcome information more efficiently.

Our results further showed that probability matching is already prevalent in children from the age of 3 years. While about a quarter of 3- to 4-year-olds probability maximized through persistent choice, a comparable proportion of children in this age group used choice diversification strategies that approximated probability matching. Older children from 6 to 11 years, in contrast, rarely probability maximized in the static high condition (where it would have yielded maximum rewards) and never did so in the ecologically dynamic condition (where it was outperformed by diversification). Although choice diversification strategies like probability matching seem to develop early in life, our behavioral analyses suggest that children do not start using them adaptively before elementary school age.

Integrating our findings on an aggregate and individual level, it seems that younger children's choice behavior can be characterized by persistence whereas older children's behavior resembled diversification, irrespective of the environment. Both probability maximizing and probability matching can arise from different cognitive processes—some adaptive, others misguided (e.g., Gaissmaier & Schooler, 2008; Koehler & James, 2014; Otto et al., 2011; Schulze et al., 2020). Thus, it is vital to distinguish to what extent children indeed adapt to their environment rather than using a default strategy that may be a better or worse fit to the task structure. Some behavioral markers (e.g., tuning the level of persistence and exploiting sequential dependencies) suggest that older children are indeed more reactive to the environment than younger children. To further investigate this emerging adaptivity, we next describe a computational modeling approach that we used to identify the involved cognitive processes.

2.3.2 Model-Based Strategy Analysis

We implemented three computational models to gain insight into the choice mechanisms underlying probability matching, probability maximizing, and other strategies. Do similarities on a behavioral level reflect similar cognitive processes in children and adults? Or do the mechanisms underlying probability learning differ across development? And do children and adults use different diversification strategies depending on the statistical structure of the environment? We first present the strategy models considered and the estimation method used.

2.3.2.1 Strategy Models

Reinforcement learning (RL) models have proven particularly useful in characterizing developmental differences in probability and value-based learning (for a recent review, see Nussenbaum & Hartley, 2019). Depending on parameter combinations, RL models allow for flexibility in explaining various choice behaviors, including probability matching and maximizing (e.g., Rivas, 2013; Schulze et al., 2017). Win-stay lose-shift (WSLS) models have identified developmental differences in probabilistic reasoning and feedback processing (e.g., Bonawitz et al., 2014; van den Bos et al., 2009). WSLS is an easily implementable choice diversification strategy used by adults and children in similar tasks (e.g., Berman et al., 1970; Gaissmaier & Schooler, 2008; Worthy et al., 2012). We compared the RL and WSLS models with a baseline model assuming a constant probability per participant of choosing the high-probability option at any trial (for a similar approach, see Schulze et al., 2017). We fitted each model individually to participants' choice data in a nonhierarchical Bayesian framework using JAGS (Plummer, 2003) and with MATLAB as an interface (The MathWorks Inc., 2021). We used the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002) to compare model performance. The DIC describes the fit between the model prediction and the data, and incorporates a penalty for more complex models (with lower values indicating a better fit). We used the lowest DIC value per model and participant to classify strategy use. The formal implementation of the models and the details of the parameter estimation and model comparison techniques are reported in Appendix B.

Reinforcement Learning. RL models assume that the decision maker updates the values of the choice options on a trial-by-trial basis and develops a propensity toward choosing the higher-valued option (Rescorla & Wagner, 1972). Here, we analyzed a simple algorithm with two free parameters: First, the learning rate parameter scales the extent to which the computed difference between an expected and an observed value (i.e., the prediction error) is integrated into the value-updating process. Higher values of the learning rate parameter give more weight to recent outcomes when updating the value of an option; lower values give more weight to a longer window of past outcomes. To account for full feedback in our task, values of both options were updated in every trial, irrespective of the actual choice. Second, inverse temperature—often labeled choice sensitivity—captures how deterministically (higher values) or randomly (lower values) the high-valued option is chosen (for a review on how these parameters may vary across development, see Nussenbaum & Hartley 2019).

Win-Stay Lose-Shift. A WSLS heuristic is a simple strategy to achieve choice diversification (close to probability matching on an outcome level) that requires only the last outcome to be remembered. A person chooses the same option again after experiencing a win and switches to the other option after experiencing a loss (or the absence of a win). A WSLS algorithm can yield exploratory benefits in patterned or changing environments (Gaissmaier & Schooler, 2008) and has been suggested to enable children to approximate Bayesian inference in probabilistic choice tasks (Bonawitz et al., 2014). In this analysis, we used a probabilistic implementation of the WSLS heuristic that has two free parameters, estimating the probability of staying after a win—p(stay|win)—and shifting after a loss—p(shift|loss).

2.3.2.2 Strategy Classification

Figure 2.6 shows the percentage of participants by age group and condition classified as users of each strategy based on a DIC comparison. Overall, the RL model best described participants' choice behavior (47%), followed by the WSLS model (38%) and the baseline model (15%); however, there were considerable differences across conditions and age groups. In the static high condition, about 69% of participants were best described by the RL model (vs. 20% WSLS, 11% baseline). In the static random and ecologically dynamic conditions, only 36% of participants were best described by the RL model (static random: 43% WSLS, 21% baseline; ecologically dynamic: 51% WSLS, 13% baseline).

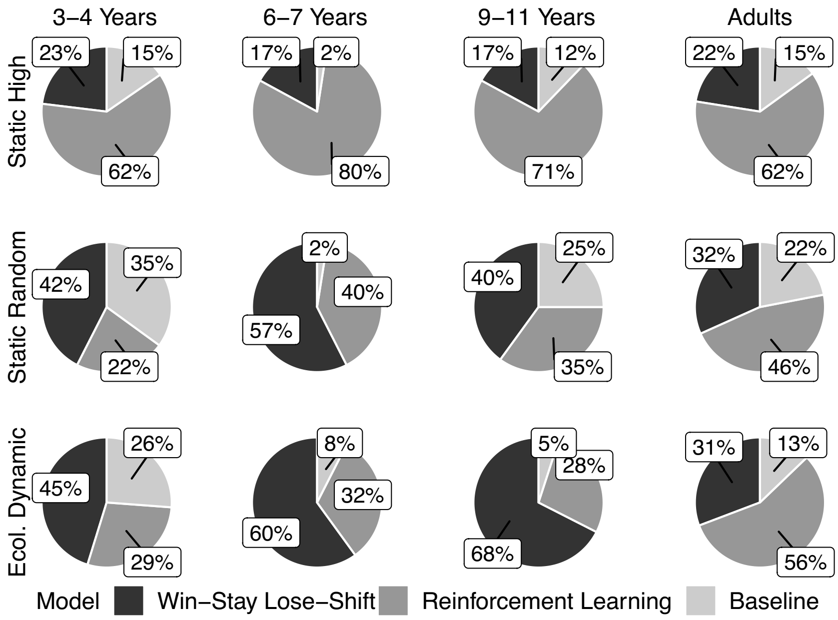
For adults, the RL model best described choice behavior across all conditions (see last column of Figure 2.6). No evidence in favor of an association between strategy use and condition emerged from either a frequentist chi-square test or a Bayesian contingency table test assuming independent multinomial sampling,[9] $\chi^2(4, N = 121) = 2.87$, $p = .58$, $BF_{10} = .02$. Children, in contrast, seemed to recruit

[9] Estimation of Bayes Factors was carried out in JASP with default settings unless otherwise stated (JASP Team, 2022). We report inclusion Bayes Factors, where $BF_{inclusion} > 1$ provides evidence in favor and $BF_{inclusion} < 1$ provides no evidence for an effect or evidence against it. The inclusion Bayes Factor quantifies the likelihood of the data under a model given the in- or exclusion of the predictor of interest. For follow-up tests, we report Bayes Factors derived from Bayesian t-tests that quantify the likelihood that the data occurred under the alternative hypothesis for $BF_{10} > 1$ or under the null hypothesis for $BF_{10} < 1$.

different strategies depending on the statistical structure of the environment. We found strong evidence for an association between strategy use and condition for 3- to 4-year-olds, $\chi^2(4, N = 120) = 16.1$, $p < .05$, $BF_{10} = 18.8$, 6- to 7-year-olds, $\chi^2(4, N = 120) = 22.8$, $p < .001$, $BF_{10} = 256.4$, and 9- to 11-year-olds, $\chi^2(4, N = 120) = 28.1$, $p < .001$, $BF_{10} = 5019.4$. While the RL model was the most common model for children in the static high condition (71% across age groups), WSLS was the most common strategy for children in the static random (47% across age groups) and ecologically dynamic (57% across age groups) conditions.

Figure 2.6

Classification of Participants to Strategies by Age Group and Condition



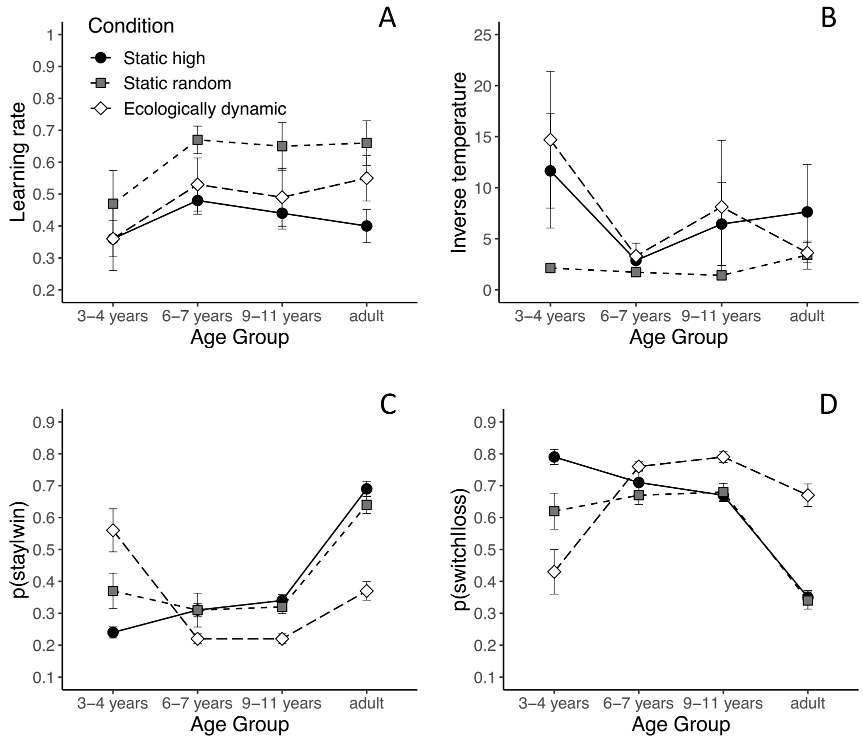
Note. Percentage of participants in each age group and condition best described by the three models, as determined by comparison of DIC values. DIC = Deviance Information Criterion.

2.3.2.3 Parameter Analysis

Did children and adults use the choice strategies in similar ways or did their usage differ? We analyzed model parameters to explore developmental and individual differences in strategy use across conditions. Model parameters were computed as the posterior medians from the samples of those participants best described by each model. Figure 2.7 shows a visual representation of mean values by age group and condition for each of the free parameters in the RL and WSLS models (see Table B3 in Appendix B for numeric values). We entered the free parameters as the dependent variable in 4 (age group) x 3 (condition) ANOVAs. In addition to conventional null-hypothesis significance tests, we report inclusion Bayes Factors ($BF_{inclusion}$) that quantify the likelihood of the data having occurred under a specific effect for ANOVAs and Bayes Factors (BF_{10}) that quantify the likelihood of the data having occurred under the alternative rather than the null hypothesis for follow-up tests (see Footnote 6). Bayes Factors for follow-up tests were derived from Bayesian *t*-tests. We additionally computed Bonferroni corrected Tukey honestly significant difference (HSD) tests. The results of these analyses are reported in detail in Tables B4 and B5 in Appendix B. In the following, we highlight the key results with respect to condition and age effects.

Figure 2.7

Differences in Model Parameters: Mean Values by Age Group and Condition



Note. Means of the posterior medians for the free parameters in the RL (panels A and B) and WSLS (panels C and D) models by age group and condition. Error bars represent +/- standard error. RL = reinforcement learning; WSLS = win-stay lose-shift.

We found strong evidence for a main effect of condition for the RL learning rate parameter, $F(2,215) = 11.22$, $p < .001$, $BF_{inclusion} = 474.47$, for the probability to stay after a win for WSLS users, $F(2,171) = 6.29$, $p < .05$, $BF_{inclusion} > 10^{10}$, and for the probability to shift after a loss for WSLS users, $F(2, 171) = 5.5$, $p < .05$, $BF_{inclusion} = 5.2 \times 10^8$. For RL users, a follow-up test indicated higher learning rates in the static random ($M = .63$) than in the ecologically dynamic ($M = .5$; $p < .05$, $BF_{10} = 2.48$) or the static high condition ($M = .43$; $p < .001$, $BF_{10} = 3926.91$; see Figure 2.7A). When updating the values of choice options, participants who used an RL strategy adaptively integrated a longer window of past outcomes in the presence of a high-probability option and were more reactive to recent outcomes in the absence of a high-probability option. For WSLS users, a follow-up test indicated that participants were, on average, less likely to choose the same option again after a win in the ecologically dynamic condition ($M = .32$) than in the static high condition ($M = .41$; $p < .05$, $BF_{10} = 1.1$; see Figure 2.7C). Furthermore, participants in the ecologically dynamic condition were less likely than participants in the static random condition to choose the same option again after a win ($M_{diff} = -.07$; $p < .05$, $BF_{10} = 1.4$) and more likely to switch after a loss ($M_{diff} = .08$; $p < .05$, $BF_{10} = 2.19$; see Figure 2.7C and 2.7D), although the Bayesian evidence remained somewhat ambiguous. Thus, across age groups, both participants using an RL strategy and participants using WSLS adapted appropriately to the different environments in our experiment.

Frequentist statistics pointed to a significant main effect of age group for the learning rate parameter of RL model users, $F(3,215) = 2.74$, $p < .05$, but Bayesian evidence was inconclusive ($BF_{inclusion} = 0.47$). Despite this mixed evidence for a main effect, follow-up tests indicated that children aged 3–4 years, on average, showed a lower learning rate ($M = .39$) than children aged 6–7 years ($M = .55$; $p < .05$, $BF_{10} = 11.04$). In other words, 3- to 4-year-olds tended to weight prediction errors less strongly than 6- to 7-year-olds. For WSLS model users, we found evidence for a main effect of age group for the probability to stay after a win, $F(3,171) = 37.00$, $p < .001$, $BF_{inclusion} > 10^{10}$, and to switch after a loss $F(3,171) = 37.00$, $p < .001$, $BF_{inclusion} = 5.2 \times 10^8$. Follow-up tests revealed that younger children and adults were more likely than older children to repeat a choice after a win (all ps $< .001$, $BFs_{10} > 114$) and were less likely to shift after a loss (all ps $< .001$, $BFs_{10} > 23.52$). Adults chose adaptively, being particularly likely to stay after a win in the static high condition ($M = .69$) and to switch after a loss in the ecologically dynamic condition ($M = .67$). Children aged 3–4 years, by contrast, were most likely to stay after a win in the ecologically dynamic condition ($M = .56$; see Figure 2.7C) and to switch after a loss in the static high condition ($M = .79$), thus making choices opposite to those that would have implied higher reward rates in these conditions. Indeed, a significant interaction between condition and age for both $p(\text{stay}|\text{win})$, $F(6,171) = 12.50$, $p < .001$, $BF_{inclusion} = 8.9 \times 10^8$, and $p(\text{switch}|\text{loss})$, $F(6, 171) = 12.75$, $p < .001$, $BF_{inclusion} = 1.9 \times 10^9$, indicates differences in adaptivity to the environment across age groups.

2.3.2.4 Interim Discussion

The aim of our computational modeling approach was to investigate the cognitive mechanisms underlying choice behavior across development. Whereas adults' strategy use did not change with the statistical structure of the task, children recruited different strategies depending on the characteristics of the environment. In the static high condition—where the best strategy is to stick with the high-probability option—most participants across age groups were best described by an RL model. In the ecologically dynamic condition—where choice diversification can lead to higher reward rates—children more frequently used a WSLS heuristic instead. The proportion of participants best described by the WSLS model in the ecologically dynamic condition was high among children aged 6–11 years, in particular. This strategy requires relatively low memory and implementation effort but allows for the concurrent exploration and exploitation of various ecologically plausible environments (e.g., with clumped or dynamically changing resources).

We further analyzed *how* children and adults used the respective strategies and found considerable differences across conditions and development. When relying on an RL mechanism, participants were, on average, sensitive to the presence or absence of a high-probability option. All age groups adaptively gave prediction errors less weight when there was a high-probability option and focused on more recent outcomes when both options were equally likely. Moreover, 3- to 4-year-olds tended to show lower learning rates than 6- to 7-year-old children. Although context-independent age differences between RL parameters are difficult to interpret (see Eckstein et al., 2022), the youngest age group, being less sensitive to the structure of the environment, may update values slower than older children. Assuming lower cognitive capacity in the youngest learners, this result is in line with findings showing that adults learn at a lower rate when under cognitive load in a dual task paradigm than in a single task condition (e.g., Otto et al., 2011).

Developmental differences in the parameters of participants best described by a WSLS strategy corroborate these conclusions. Whereas adult WSLS users seemed to fine-tune their strategy use to the demands of the environment, 3- to 4-year-old children did not. Their high probability of staying after a win and low probability of switching after a loss could be related to cognitive constraints in integrating counterfactual information about foregone outcomes (Kominsky et al., 2021). In contrast, older children and adults seemed to be able to exploit counterfactual learning opportunities more quickly.

In sum, our computational modeling approach revealed significant differences between children and adults in the strategies used and in how strategies were adapted to the statistical structure of the task. Adults relied on similar strategies across conditions but were more efficient than children in adjusting a strategy to the demands of the environment (also see Plate et al., 2018). Older children followed the ordinal pattern of adults in their strategy fine-tuning and showed signs of emerging adaptivity—but constrained by a tendency to explore.

2.4 General Discussion

Choice diversification—and probability matching, in particular—can be seen either as an adaptive mechanism learned in everyday life or as a systematic failure of the cognitive system to override intuitive but misleading responses (for reviews, see Koehler & James, 2014; Vulkan, 2000). There is increasing evidence that probability matching can be ecologically rational in real-world environments characterized by social competition or dynamic statistical structures (e.g., Ellerby & Tunney, 2019; Schulze et al., 2015, 2017; Seth, 2007). In this article, we investigated the development of adaptive probability matching and choice diversification in children aged from 3 to 11 years in an ecologically plausible statistical environment. As children grow older, they gain experience with everyday choice ecologies, and advancing brain development allows for more directed exploration (see Gopnik, 2020; Ruggeri, 2022)—two aspects that may be important for ecologically rational choice diversification. Analyzing children's choice behavior in two static and one ecologically dynamic environments, we found less sensitivity to the environmental structure in children aged 3–4 years than in any other age group and emerging adaptivity in children from 6 years onward. In line with previous research on probability learning and adaptive immaturity in childhood (e.g., Derks & Paclisanu, 1967; Gopnik et al., 2017; M. H. Jones & Liverant, 1960; Weir, 1964), our findings suggest a phase of high persistence in young children, increased diversification and exploration in older children, and the ability to overcome exploration tendencies in favor of exploitation—while still maintaining adaptivity—in adults.

The youngest age group showed a striking tendency to persevere with one option, irrespective of whether it maximized reward, and was more likely than older children or adults to maximize probability in the ecologically dynamic condition. However, this tendency to persist did not imply an increased likelihood of choosing the high-probability option. Indeed, some 3- to 4-year-olds persisted with the low-probability option, and this age group showed the largest variability in choice behavior. Taken together, these results are consistent with previous findings on young children's individual choice behavior (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960) but do not replicate earlier work showing differences in aggregate choice between younger and older children (e.g., Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980). What explains young children's tendency to persist and their low sensitivity to outcomes? A possible explanation is that young children persevere because it requires little cognitive control (S. J. Jones, 1970; Thompson-Schill et al., 2009) and can serve as a satisficing strategy (Schulze et al., 2020; Schulze & Newell, 2016). Assuming generally low sensitivity to reward also explains the counterintuitive finding that young children seemed to integrate a longer window of past outcomes in an RL model, despite having generally lower memory capacity than older children or adults (see Otto et al., 2011). Moreover, younger children's delayed response to sequential dependencies could indicate that it took them longer to grasp the somewhat abstract concept of the reward-hold manipulation in the ecologically dynamic condition. Alternatively, young children might have been limited by cognitive constraints in integrating counterfactual information about forgone outcomes into their predictions (e.g., Fischer & Ullsperger, 2013). Nonetheless, a stronger tendency to repeat responses irrespective of obtaining a reward does not necessarily reflect that the young mind is per se maladaptive (see Bjorklund & Green, 1992). Rather, reward-insensitive persistence and response repetition may in some contexts be beneficial for learning in early childhood (e.g., for training and mastering new motor responses).

Children from 6 years onward showed a strong tendency to explore across all conditions. Accordingly, they made fewer maximizing responses than adults by the end of the task in the static high condition but not in the ecologically dynamic condition. This finding could indicate that older children were able to make more adaptive choices when the statistical structure better reflected their real-world experiences. Indeed, it has previously been demonstrated that children search for information more efficiently when the statistical structure of the task is ecologically plausible (Nelson et al., 2014). Such efficient use of previous outcome information was particularly evident in the ecologically dynamic condition for children between 6 and 11 years. In this condition, consistently choosing the high-probability option and switching to the low-probability option once a reward has been observed yielded maximum rewards. Only two 7-year-olds used this optimal solution consistently in the final block of trials. Nevertheless, on average, 6- to 11-year-old children quickly exploited a reward on hold in a near-optimal way and even outperformed adults in this regard. Children's predisposition for exploration and testing a diverse set of hypotheses can help them to learn the structure of an environment better than adults (Liquin & Gopnik, 2022), but it often comes at the cost of less efficient information search (Ruggeri et al., 2016; Schulz et al., 2019) and suspends directed exploitation until later in life (Gopnik, 2020). Our modeling analyses provide further evidence for these ideas. Children who diversified their choices effectively may have benefitted from relying on a trial-by-trial decision rule like win-stay lose-shift in testing new hypotheses about the structure of the ecologically dynamic condition. In line with previous work (e.g., Schusterman, 1963), we found that older children between 6 and 11 years adapted their WSLS use to the environment in a similar ordinal pattern as adults but used the heuristic in a more exploratory manner (i.e., with a stronger tendency to shift). Yielding more profitable results in the ecologically dynamic condition, exploration through diversification was not equally beneficial across conditions. Consequently, the tendency to explore may have hindered older children from reaching adults' performance levels when less diversification was more profitable.

Lifespan developmental psychology describes cognitive development in terms of a trade-off between gains and losses (Baltes, 1987). According to this approach, children pursue new strategies with increasing cognitive capacity and age, but these new strategies occasionally provide a poor fit to the environmental structure. Using probability learning as an example (see Baltes, 1987), this view suggests that older children may develop the expectation that finding a perfect solution to the task is possible, whereas younger children may profit from not yet making such assumptions[10]. Similarly, it has been suggested that adults probability match because they search for patterns in the environment to avoid otherwise inevitable losses associated with a maximizing strategy (e.g., Gaissmaier & Schooler, 2008; Schulze et al., 2020). Our findings provide support for the notion of trade-offs between gains and losses across all age ranges in our study, while emphasizing the role of the interplay between the mind and the environment: Participants trade off probability matching and probability maximizing, diversification and persistence, and exploration and exploitation against the backdrop of the given environment structure.

A few questions remain unanswered. We need to acknowledge that young children's highly persistent choice behavior may raise the question of whether they properly understood the task. We cannot rule out the possibility that a few children had difficulties differentiating between a correct and an incorrect choice; we provided full feedback and an animal always appeared after a choice irrespective of whether it was correct or incorrect. While our results indicate that children learned to select the more profitable option more frequently in the presence of a high-probability option, it remains an interesting avenue for future research to investigate whether partial feedback helps even the youngest children to

[10] For an analysis of instructions manipulating the perceived solvability of a probability learning task, see Weir (1962).

diversify choices more, as reported for adult participants (Otto & Love, 2010; Schulze et al., 2017). Along these lines, future research could provide new insights by characterizing the statistical structures of real-world choice ecologies actually experienced by younger and older children. The sequential dependencies created in the ecologically dynamic condition are likely not representative of every real-world environment but approximate dynamic change and temporarily available outcomes that may be present in many everyday situations (e.g., Fawcett et al., 2014; Jensen & Neuringer, 2008).

A question we did not address in this study is whether learning about the underlying generating mechanism might have helped children to pick up environmental regularities even earlier (in life and in the task). Indeed, a key challenge that children face on an everyday basis is to learn about the mechanisms underlying repeated outcomes. For instance, a child might learn that the seasons of a year increase or decrease the likelihood of specific weather events. It is well-documented that causal learning plays a vital role in children's abilities to make probabilistic inferences (Bonawitz et al., 2014; Denison et al., 2013; Gopnik et al., 2015; Kushnir & Gopnik, 2007). However, knowing about causal generating mechanisms does not imply that this information is used to guide repeated choices. It has been demonstrated that children up to the age of 12 were better described by an RL model that updated values on choice outcomes alone rather than incorporating the causal structure of the task (Cohen et al., 2020). Therefore, it is crucial to understand how children develop adaptive choice behaviors to ecologically plausible statistical structures beyond incorporating causality. Many causal mechanisms in the real world may be too complex; understanding them fully might be too computationally demanding or impossible. In such situations, using frequently encountered environmental regularities to guide choices might be an adaptive response mechanism that humans learn early in life.

2.5 Conclusion

Taken together, our findings suggest that choice diversification strategies such as probability matching develop early in life, but that their adaptive use in an ecologically plausible environment seems to require either increased experience with typical choice ecologies or an explorative mind. Modeling analyses revealed that although children from all age groups adapted *which* strategy they used to the structure of the environment, adults held an advantage in *how* they fine-tuned a strategy. Our findings emphasize the importance of implementing ecologically plausible task environments in research on the development of choice behavior and cognitive development more broadly. Finally, we showed how an ecologically rational perspective can provide new insights into decades of research on the development of probability learning, and we contributed a decision-making perspective to the discussion on the adaptive functions of cognitive immaturity and increased exploration in childhood.

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3 | The Development of Probability Learning and Repeated Choice Behavior in Childhood: A Longitudinal Investigation

Abstract. Virtually all previous studies on the development of probability learning and repeated choice behavior in early childhood relied on cross-sectional designs. What is the intra-individual trajectory of probability learning in early childhood, and how does it relate to the development of executive functions? Using a longitudinal design with three measurement waves (N = 74 at T1), we investigated the development of high-probability choices, probability maximizing, and matching in relation to working memory capacity and response inhibition from 3.5 to 6.5 years. Our findings revealed different trajectories for probability learning (learning to choose the more likely option) and choice behavior. On the one hand, children became more likely to choose the high-probability option with increasing age. On the other hand, more children diversified choices close to probability matching as they became older. Across measurements, younger children in the cohort were more likely to maximize than older children. These trends may seem counterintuitive at first but are driven by decreasing inter-individual variability over time. Additional analyses revealed that as children became older, higher memory capacities predicted a reduced likelihood of high-probability choices. We discuss how young children's variability in choice behavior may affect the estimated direction of developmental change and emphasize the importance of studying cognitive development longitudinally in light of possible cohort effects.

3.1 Introduction

Early research on the development of probability learning, dating back to the 1960s, revealed the puzzling finding that younger children are more likely to maximize reward than older children (e.g., M. H. Jones & Liverant, 1960; Stevenson & Weir, 1959; Weir, 1964). Consider the following classic probability learning task (M. H. Jones & Liverant, 1960): A token delivery machine has two buttons, and pressing one button will probabilistically release a poker chip. One button delivers a poker chip on 70% of the trials (i.e., the high-probability option), and the other button on 30% of the trials (i.e., the low-probability option). Without knowing these outcome probabilities beforehand, children need to learn how likely a button press will result in getting a poker chip through feedback in a series of trials. In this task, children are explicitly instructed to make as many correct choices as possible. When probabilities are independent and identically distributed, exclusively choosing the high-probability option maximizes the probability of obtaining a reward—any deviation will lower the average reward rate. Across a variety of probability learning tasks, relatively high proportions of children below the age of 5 years have been found to show such reward-maximizing behavior (M. H. Jones & Liverant, 1960; Stevenson & Weir, 1959; Weir, 1964). Older children, in contrast, are thought to be more likely to diversify their choices by approximating probability matching (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960). When examining aggregate choice behavior—choices averaged across children—some researchers have suggested a U-shaped function between the rate of favorable high-probability choices and age. Specifically, the U-shaped function predicts that children below age 5 and adults are more likely to choose the high-probability option than older children and young adolescents (Derks & Paclisanu, 1967; Stevenson & Weir, 1959; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980).

Interest in young children's higher likelihood to make maximizing choices is not limited to research on probability learning but also served as a paradigmatic example in other domains: for instance, to demonstrate gains and losses in lifespan theory (Baltes, 1987), to inform the early development of choice sensitivity in reinforcement learning (Nussenbaum & Hartley, 2019), or to emphasize children's adaptive benefit as flexible learners (Gualtieri & Finn, 2022). However, evidence for young children's advantage in reward maximization is not as unambiguous as sometimes portrayed. For instance, our findings showed that young children persist not only on the high-probability option but occasionally also on the low-probability option (see Chapter 2). Other studies comparing the same age range sometimes reported conflicting results (Craig & Myers, 1963; Derks & Paclisanu, 1967; Lewis, 1966; Messick & Solley, 1957; Offenbach, 1964; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980), and attempts at reconciling these findings were not entirely successful (for reviews, see Fischbein, 1975; M. R. Jones, 1971).

3.1.1 Benefits of Longitudinal Research in the Development of Probability Learning

In particular, the intra-individual trajectory of probability learning and repeated choice behavior in early childhood is still poorly understood, despite high relevance for many real-world choices: For instance, children need to estimate which friend will most likely have time to play in the afternoon or predict if throwing a tantrum in the supermarket will get them their desired candy bar. Virtually all previous studies on probability learning used cross-sectional study designs. Although relying on cross-sectional data is often a viable, cost- and time-efficient substitute for studying developmental processes, intra-individual change is sometimes not adequately captured (e.g., Kraemer et al., 2000; Lindenberger et al., 2011; Louis et al., 1986). For instance, research on hippocampal and memory development in childhood showed that cross-sectional and longitudinal results suggest discrepant underlying processes (Keresztes et al., 2022). Likewise, a longitudinal analysis indicated that heightened prefrontal activation was associated with higher risk-taking in adolescents, whereas cross-sectional evidence supported the opposite effect (McCormick et al., 2017). Diverging cross-sectional and longitudinal effects may also underlie the development of probability learning, where different processes dynamically interact. Consider that a probability learning task may vary in difficulty across childhood. For instance, tracking previous outcomes and sustaining attention over numerous trials may be more difficult for younger children with fewer skills in these domains (see M. R. Jones, 1971). Older children potentially begin the task with (sometimes misleading) expectations about the underlying generating mechanism or how choices and outcomes are typically related in their everyday life (e.g., Baltes, 1987; Stevenson & Weir, 1963; Tolman & Brunswik, 1935). Accordingly, higher cognitive functions in younger children may help them to track the outcomes of the high-probability option—facilitating consistent high-probability choices. In contrast, higher cognitive functions in older children could enable more complex responses based on tracking both options—facilitating diversifying choices. Furthermore, variability in younger children's choice behavior may lead to biased estimates of change in probability learning from cross-sectional data. For instance, when some 3-year-olds persistently choose the high-probability option and other 3-year-olds the low-probability option, and they become less extreme over time, some children will inevitably experience opposite directions of change. Lastly, almost all evidence for the high prevalence of maximizing behavior in young children dates back to the 1960s (e.g., Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Weir, 1964; for a review, see Fischbein, 1975). Following considerable societal and technological changes and improvements in early education in families and formal schooling (Lynn, 2009; Shonkoff, 2010), it cannot be ruled out that differences between earlier and more recent work may arise from systematic cohort differences.

Thus, the first goal of our study is to explore intra-individual developmental trajectories in probability learning and repeated choice behavior, providing new insights into between-person and within-person change. For instance, when and how do children transition from maximizing to matching behavior? Is this transition unidirectional? And, do children learn to make more favorable choices as they grow up?

3.1.2 Probability Learning and Cognitive Development

An additional goal of our study is to explore how probability learning and repeated choice behavior are shaped by developing cognitive functions. Most theorists agree that young children's maximizing does not represent a deliberately rational behavior (e.g., M. H. Jones & Liverant, 1960; S. J. Jones, 1970; Thompson-Schill et al., 2009) and that older children's choice diversification can serve adaptive benefits (see Chapter 2; Baltes, 1987; Goldman & Denny, 1963). In Chapter 2, we showed that younger children continued to persist with one option across different statistical environments, irrespective of whether this option maximized reward. Older children, in contrast, mainly diversified their choices and were better at exploiting dynamic environmental structures. Which developing cognitive functions facilitate this behavioral transition in early childhood?

Whereas several executive functions have been suggested to fuel the development of choice behavior in early childhood (Gualtieri & Finn, 2022; S. J. Jones, 1970; Thompson-Schill et al., 2009), empirical tests of the proposed relations are yet sparse. Executive functions refer to a set of cognitive processes, such as working memory, response inhibition, and mental shifting (Miyake et al., 2000), involved in performing complex tasks (for a developmental review, see Zelazo et al., 2003). Particularly in preschool age, children rapidly improve in tasks targeting executive functions, indicating a significant change in the neural underpinnings in early childhood (for reviews, see Fiske & Holmboe, 2019; Garon et al., 2008). In the following, we will review previous work proposing that two specific executive function components—response inhibition and working memory—facilitate changes in probability learning and repeated choice behavior (e.g., M. H. Jones & Liverant, 1960; S. J. Jones, 1970; Kreitler et al., 1983; Thompson-Schill et al., 2009)

Immature response inhibition has been suggested to prevent younger children from applying diversifying choice strategies (S. J. Jones, 1970; Thompson-Schill et al., 2009). Thus, in probability learning tasks, the ability to suppress a prepotent response in favor of an alternative response may be a prerequisite for deviating from persistent choice. Moreover, response inhibition has been suggested to relate to other constructs that may be important for the development of early decision-making competencies: for instance, theory-of-mind (Carlson & Moses, 2001), search strategies (Baker et al., 2011), and counterfactual reasoning in early childhood (Beck et al., 2009).

The second executive function relevant in this context is working memory capacity. Working memory capacity has been demonstrated to facilitate children's performance, particularly in tasks that involve processing probabilistic information (van Duijvenvoorde et al., 2008; Ruggeri et al., 2018). It has been theorized that young children probability maximize because their limited working memory capacity restricts them from tracking past outcomes and making goal-directed low-probability choices (Gualtieri & Finn, 2022). In a probability learning task, children could profit from increasing working memory capacity, for instance, by increasing storage for temporary information and through more efficient information integration (Best & Miller, 2010; Garon et al., 2008). Better memory of past outcomes may help children to overcome simple response patterns (e.g., alternation) in favor of more effective diversifying strategies (Balling & Myers, 1971; Kreitler et al., 1983).

However, research with adult participants examining the connection between working memory and repeated choice behavior indicates that this relationship needs to be interpreted in the context of outcome feedback and whether working memory capacity is experimentally manipulated. For instance, higher working memory capacity may enable people to search for patterns in an outcome sequence which, in turn, leads them to choose the high-probability option less frequently (Gaissmaier et al., 2006). Yet, outcome feedback is critical for generating and testing hypotheses about possible patterns. In the absence of outcome feedback, the opposite finding has been reported: People with higher memory capacity were more likely to probability maximize (Rakow et al., 2010). When working memory capacity is experimentally taxed by requiring participants to simultaneously perform a secondary task, adults seem less sensitive to current outcomes (Otto et al., 2011; Worthy et al., 2012). Although cognitive load has been suggested to increase probability maximizing (Wolford et al., 2004), this finding has since failed to replicate (Schulze et al., 2019).

Nonetheless, it is important to acknowledge that adults and children differ in more aspects than memory capacity and that these findings need to be considered in light of the adaptive functions of children's cognition. An increasing body of evidence suggests that some cognitive characteristics and limitations inherent to childhood allow for greater flexibility in exploration and learning (for reviews, see Bjorklund & Green, 1992; Gopnik, 2020; Gualtieri & Finn, 2022). Following this account, increasing cognitive capacities in childhood may particularly facilitate their exploratory tendencies. In a standard probability learning task, children aged 5–15 years with lower general reasoning abilities have been found to make more favorable high-probability choices than children with higher scores (Goldman & Denny, 1963; Lewis, 1966). In a task where there was, indeed, a patterned outcome sequence, the opposite relationship was reported: Children with higher reasoning abilities made more favorable responses than children with lower reasoning abilities (Goldman & Denny, 1963). These findings resonate with theoretical considerations that older children may look for a perfect solution or a pattern in probability learning tasks and therefore diversify choices (Baltes, 1987; Stevenson & Weir, 1963). Exploring the associated cognitive processes driving probability learning and repeated choice behavior could provide new insights into the adaptive benefits of cognitive immaturity, specifically into what cognitive developments enable flexibility in learning and exploration.

3.1.3 The Present Study

In the current study, we use an accelerated longitudinal design to map the developmental trajectory of probability learning in early childhood from 3.5 to 6.5 years and to explore the relation to developing executive functions. At each of three measurement time points, children completed the same tasks: a standard probability learning task with static probabilities, two memory tasks, and a response inhibition task. The design and main hypotheses were preregistered, but one hypothesis needed adjustment based on the most recent findings.[11] The following section reflects our updated expectations before data analysis.

On the level of individual choice behavior, we expected that children become less likely to probability maximize with increasing age and more likely to probability match. On the level of aggregate choice behavior, there are different possibilities for how developmental trajectories may play out, dependent on the variability in young children's choice behavior. Our previous cross-sectional study (see Chapter 2) found that young children's choice behavior was highly variable and that the proportion of maximizing children was lower than reported in previous work from the 1960s. Whereas younger children were more persistent in their choices than older children, persistence was unrelated to probability learning. These results were robust across different implementations of the probabilistic task structure. Depending on the initial variability in persistent choice behavior at the first measurement time point (e.g., Chapter 2; Derks & Paclisanu, 1967; Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Offenbach, 1964; Plate et al., 2018), two trajectories seem plausible: On the one hand, average probability learning might not change over time if children, to the same extent, persist less but also make less

[11] Specifically, we initially stated that children would decrease in their likelihood to choose the high-probability option with increasing age. While this expectation was grounded in a literature review (e.g., Derks & Paclisanu, 1967; Weir, 1964; Winefield, 1980), our own results in a cross-sectional study—obtained after submitting the preregistration—render this expectation unlikely (see Chapter 2). Although deviating from a preregistered hypothesis is never ideal, this case is in particular related to the very reason why a longitudinal study on this topic is needed.

errors (i.e., fewer low-probability choices). On the other hand, if the proportion of children adopting less favorable choice behaviors is higher than for maximizing, we might expect an increase in their average likelihood of choosing the high-probability option with increasing age. Additionally, we planned to conduct exploratory analyses to shed light on the role of working memory and response inhibition in the development of probability learning and repeated choice behavior.

3.2 Method

3.2.1 Participants

The study consisted of three sessions, each one year apart in the spring of 2021 (T1), 2022 (T2), and 2023 (T3). We planned to collect a final sample size of at least 40 children who completed the probability learning task in all three measurement waves spanning the age range from 3.5 to 6.5 years. To achieve this sample size, we accounted for a total attrition rate of 30% based on reports from other cross-sectional and longitudinal studies and aimed to collect valid data from 60 children at T1[12].

We sent a total of 252 invitation e-mails to families registered in the participant database of the Max Planck Institute for Human Development who were matching the inclusion criteria: child's age between 42 and 54 months at T1, access to a tablet or laptop with touch function, and to a stable internet connection. Seventy-four children participated in the first measurement wave (M_{T1} = 47.1 months, SD_{T1} = 4 months, range = 41–54 months, 54% female)[13]. Seventy children returned to participate at T2 (M_{T2} = 59.6 months, SD_{T2} = 4 months, range = 53–67 months, 53% female). In T3, 56 children participated[14] (M_{T3} = 71.1 months, SD_{T3} = 4 months, range = 65–78 months, 52% female). All children (except for one who did not attend any institution) went to daycare centers at T1 and T2. At T3, 14% of children went to elementary school. Several children at each measurement wave were excluded from data analysis based on preregistered criteria (see Table C1 in Appendix C).

Parents provided informed written consent for their child to participate in the study upon registration; children were asked for verbal consent at the beginning of each session. Each session was recorded on video to document child consent, standardized instructions, and for data analysis of the verbal response inhibition task. After each session, parents chose the designated purpose of the recording (e.g., data analysis only or educational purposes). Families received 50.00 EUR as an expense allowance via bank transfer or as a gift voucher for a toy shop after completing all test sessions.

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[12] Longitudinal studies in other domains investigating a similar age range report an attrition rate of about 15% (Marcovitch et al., 2015; Williams & Moore, 2016). Cross-sectional probability learning studies using a similar task but slightly more trials report between one-fourth and one-third of children not completing the experiment (Plate et al., 2018; Starling et al., 2018). Based on these reports of cross-sectional and longitudinal data loss, we decided to account for an attrition rate of 30%.

[13] Nine of those children were initially recruited for a pilot study. After the pilot study, a minor change was made to the probability learning task (i.e., children in the pilot study saw a green checkmark for a correct prediction while all remaining children saw a blue circle at T1). In T2 and T3, children from the pilot study became part of the main group. Because we did not observe differences in behavior between these two groups at T1 and results for our hypothesis do not change dependent on the inclusion of the data from pilot children, we decided to aggregate the data.

[14] Due to continued repercussions of the Covid-19 pandemic, data collection in T3 was slightly delayed. At the time of the submission of this dissertation, data collection was still ongoing.

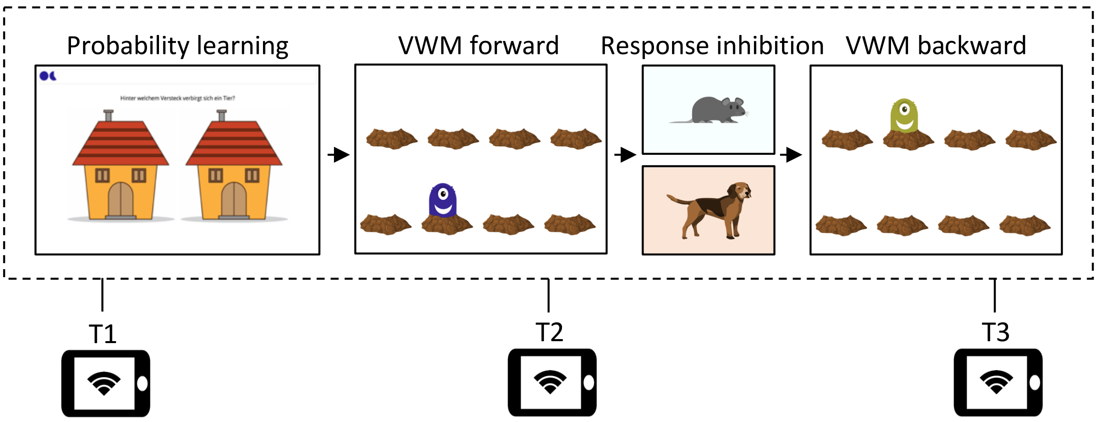
3.2.2 Design

We implemented an accelerated longitudinal design spanning the age range from 3.5 to 6.5 years in a two-year study. Design and procedure were approved by the internal review board at the Max Planck Institute for Human Development and preregistered on the Open Science Framework. The preregistration is embargoed while the study is ongoing and will be available afterward[15] or upon request.

Families received tokens and stickers prior to each test session via mail and booked an appointment with an experimenter to their convenience. The procedure was the same in every session and is schematically presented in Figure 3.1. Tasks were designed to accommodate meaningful performance differences in the age range from 3.5 to 6.5 years. Children participated under the supervision of their parents at home on a tablet or computer with a touchscreen via zoom. The experimenter shared the tasks via screen sharing and parents assisted their children with the handling of the tablet. The order of tasks was predetermined: Children played the probability learning task first and then completed the visual working memory (VWM) forward, response inhibition, and VWM backward tasks. Families were required to take a 10-minute break between the probability learning and VWM forward task, during which they turned off microphone and video.

Figure 3.1

Overview of Tasks and Procedure Across Measurement Waves T1–T3



Note. VWM = Visual working memory.

3.2.3 Tasks and Procedures

3.2.3.1 Probability Learning Task

We used a child-friendly probability learning task created for a previous cross-sectional study which required children to make 100 repeated choices between two options (see also Chapter 2). The high-probability option was rewarded on 70% of the trials, and the low-probability option was rewarded

[15] Link to the preregistration: osf.io/gxba9

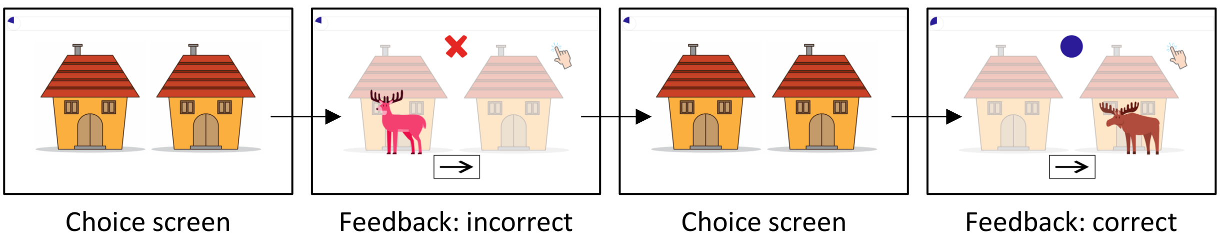
on the remaining 30% of the trials (pseudo-randomized over 100 trials). The positioning of the high- and low-probability option to the left or right side, respectively, was randomly assigned per child and wave.

Various animals were presented on the screen at the beginning of the task. The experimenter explained that the animals had escaped from a zoo and that the child needed to find them. Children completed two practice trials, guessing behind which of two simultaneously presented houses an animal would hide next (see Figure 3.2). After every choice, a feedback screen showed behind which house an animal was hiding, and the experimenter announced the kind of animal in a neutral tone. Children collected a fragment of a blue token for every correct choice, which they could exchange against stickers at the end of the task (one token was equivalent to ten correct choices). The first practice trial was programmed to be correct, and the second practice trial was always incorrect. During the practice trials, the experimenter explained the symbols appearing for feedback: A hand symbol indicated which option the child chose, a blue circle on top of the screen indicated a correct choice, and a red cross indicated an incorrect choice. Additionally, a bonus bar on top of the screen indicated progress toward collected tokens and was visible during choice and feedback.

Following the two practice trials, children completed 100 trials. After every ten correct choices, they received a physical blue token and were reminded to collect as many tokens as possible. After completing all trials, children were asked to indicate behind which house more animals were hiding throughout the task and how they decided which house to select next. Finally, children were encouraged to exchange as many tokens as they had collected in the game against animal stickers (rounded up to the next full token).

Figure 3.2

Choice and Feedback Screen in the Probability Learning Task



3.2.3.2 Visual Working Memory

As a measure of VWM, we adapted the Corsi Block Tapping Task (Corsi, 1972) as a child-friendly, computerized task. The Corsi Block Tapping Task originally requires participants to tap on wooden blocks in the same order as the experimenter demonstrated over an increasing sequence length (Corsi, 1972). The task is frequently employed across a variety of settings: in research from childhood to older age as a nonverbal measure of memory span and in clinical scenarios to detect cognitive deficits (e.g., Berch et al., 1998; Garon et al., 2008; Pagulayan et al., 2007). Children have been found to improve in their ability to recall an increasing length of tapping sequences in the age range of interest for this study (for a review, see Garon et al., 2008). In terms of Baddeley and Hitch's seminal working memory model (Baddeley & Hitch, 2000), the Corsi forward task is thought to mainly recruit the visuospatial sketchpad for shorter sequence lengths (Vandierendonck et al., 2004). Retaining longer sequences in the forward task and manipulating visuospatial information in the backward task, in contrast, additionally requires the support of the central executive (Vandierendonck et al., 2004). Task performance correlates highly with digit span recall tasks in children aged 3 to 6 years (Lehmann et al., 2014).

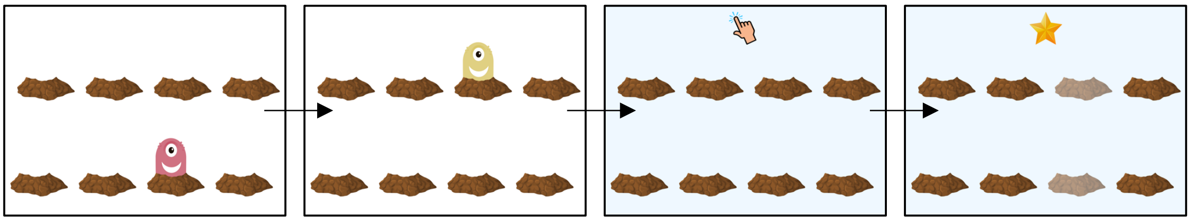
To increase young children's interest and engagement, we designed the Corsi task as a tablet-based hide-and-seek game (see Figure 3.3; for a similar implementation, see Ramani et al., 2020). The task was programmed in an internally developed JavaScript-based framework for online experiments. There were eight hills presented on the screen in two rows of four hills each (see Figure 3.3). The experimenter explained that several monsters will appear and disappear from the hills one after the other, accompanied by a short sound to increase attention. The child was asked to remember the order of hills where the monsters had appeared before and to tap on the hills in the same order (forward) or in the reverse order (backward). To demonstrate the rules, the experimenter first completed one trial by herself and commented on her choice of hills ("I saw the first monster appear here [hovering mouse over hill], that's why I tap on this hill first."). A monster could only appear once at any location, and tapping on a hill increased its transparency to indicate that it had been selected. At the top of the screen, a hand symbol appeared, and the background appeared in light blue when children could start tapping the sequence, and a star appeared after completing their response (see Figure 3.3). No outcome feedback was provided and children initiated the next trial by themselves by tapping on the star.

There were two trials of each sequence length, starting with two monsters and increasing to up to eight. Each monster appeared for 1s with 500ms between monsters. In the forward version, the task progressed to the next level if children tapped on the correct hills (but irrespective of the order) in one trial of a sequence length; in the backward version, the task progressed to the next level only if children tapped on the correct backward order in one trial of a sequence length. We implemented the more liberal stopping rule for the forward version to avoid floor effects as the task (in particular the backward version) might have been relatively difficult for young children at T1. The score in each version was the longest sequence of monsters that a child remembered in the correct order (VWM forward ordered, VWM backward) or simply at the correct locations (VWM forward unordered)[16].

[16] Technically, unordered recall would not require the *forward* prefix. However, we still label the unordered recall as a forward version as children were originally instructed to remember the order and the only difference here is that we used a less strict performance score.

Figure 3.3

Visual Working Memory Task



Note. The first two panels display sequentially appearing items. The third panel demonstrates the end of the sequence and the beginning of tapping. The last panel displays the screen when tapping was complete. Tapping on the star invoked the next trial.

3.2.3.3 Response Inhibition

As a measure of complex response inhibition, we used an adaptation of the day–night task (Gerstadt et al., 1994). The day–night task is a Stroop-like task (Stroop, 1935) building on the assumption that children have a strong association with the word "day" when presented with a bright image of a sun and to say the word "night" when presented with a dark image of a moon. The task requires children to suppress their initial tendency to say the congruent word and to say the opposite instead (i.e., "night" to the sun image and "day" to the moon image). Instead of simply suppressing an initial response as in delay-gratification-tasks (e.g., Mischel et al., 1988), the day–night task moreover requires children to keep in mind and execute a conflicting rule (for a review, see Montgomery & Koeltzow, 2010). Thus, the day–night task is thought to not only demand inhibitory control but also to require working memory components and has been reported to possess good reliability and concurrent validity when assessed online via video chat (Ahmed et al., 2022).

However, test runs with children of lab members indicated that for German-speaking children, the association between "day" and "night" and the respective images of a sun and moon may not be very strong. Instead of suppressing a prepotent response, children seemed to simply apply a newly learned rule. Indeed, the day–night task has been mostly implemented in English-speaking populations (e.g., Best & Miller, 2010; Cuevas & Bell, 2014; Eng et al., 2022; Kim et al., 2013; Petersen et al., 2021). Analogous to alternative implementations of the day–night task (e.g., grass–snow, happy–sad; for a review, see Garon et al., 2008), we presented children with images of a dog and a mouse, assuming stronger associations for well-known animals instead of relatively abstract concepts of day and night, while at the same time restraining word lengths to one syllable in German. Otherwise, we kept the procedure for the task as close to the original version as possible (Gerstadt et al., 1994).

The task was implemented on presentation slides (for a similar implementation, see Ahmed et al., 2022), with each slide showing either a picture of a dog or a mouse on a neutral background (see Figure 3.1). The experimenter explained the rules of the game (i.e., saying mouse [dog] as quickly as possible when presented with a dog [mouse]) and instructed the child in two practice trials. The practice trials counted toward the test trials when answered correctly and were repeated if not answered correctly. In sum, there were 16 trials in the same alternation order of images, as reported in Gerstadt et al. (1994). Between each image, a blank screen was displayed for 1 second. If the child did not reply to an image after several seconds, the experimenter asked, "What do you say when you see this image?" but otherwise remained silent during the test trials.

The response inhibition score was the proportion of correct (i.e., incongruent) responses in the 16 trials[17]. The video recordings of the response inhibition task were coded by three raters. Interrater reliability was examined based on a subset of eight videos and reached perfect agreement between the three raters.

3.3 Results

3.3.1 General Analysis Approach

Children had an age difference of up to one year at every measurement wave, and measurements were between 11 to 13 months apart. Thus, between-person differences in age arose from the initial age span and a small variability in the time span between measurements. We accounted for between-person and within-person variability in age by transforming the age variable in the following way (see Neuhaus & Kalbfleisch, 1998): Cross-sectional age was computed as the deviation of a child's mean age across time points from the mean age of the whole sample (i.e., a child's mean-centered age). Longitudinal age was calculated as the deviation of a child's age at each time point from its own mean age across measurement time points. We initially planned to test hypotheses based on the discrete measure of time points. However, because this information is implicitly included in the longitudinal age measure, we use the decomposed age variable as a predictor, when feasible, to provide a more detailed picture of developmental trajectories.

All analyses were conducted in R (R Core Team, 2022). We used the brms package (Bürkner, 2017) to estimate Bayesian multilevel models, which relies on Stan for parameter estimation (Carpenter et al., 2017) [18]. Unless otherwise specified, we used default priors and ran four chains with 4000 samples each, thinning out every other sample, in addition to an initial burn-in period of 1000 samples. These settings resulted in 8000 samples in total after warm-up and thinning. The $\hat{R}$-Statistic (< 1.01) indicated no convergence issues for any parameter.

[17] We also coded response time, but latency was not informative beyond the mean score.

[18] We deviate from the preregistered analysis plan where we specified a repeated measures ANOVA to investigate probability learning. The Bayesian approach allows for more flexibility in modeling choice behavior without aggregating choices and provides an estimation of the credibility of results rather than frequentist significance testing.

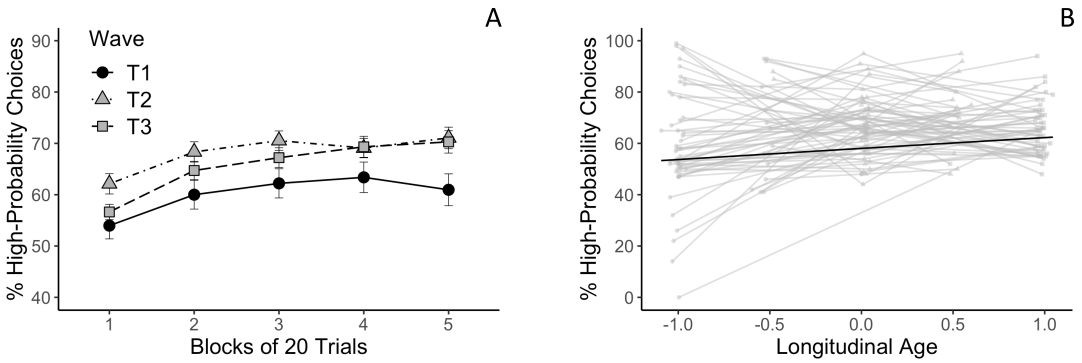
3.3.2 Probability Learning

First, we investigated the development of probability learning across time using a Bayesian mixed model approach. We expected to find either no differences across time or a higher rate of high-probability choices with increasing age. Figure 3.4A shows the observed proportion of choices children allocated to the high-probability option per trial block and measurement time point. A comparison between children's performance at T3 with children similar in age only tested once in a previous cross-sectional study revealed no performance differences (see Figure C1 in Appendix C). Any performance differences in this longitudinal study are thus unlikely to merely arise from practice or retest effects.

We investigated changes in the likelihood of high-probability choices using a logit link function to account for the binary nature of the dependent variable. We submitted the cross-sectional age variable, the longitudinal age variable, their interaction, and trial block as an ordered factor as predictors (fixed effects) and individually varying intercepts as a random effect. Results showed that children learned to choose the high-probability option more frequently over trial blocks but seemed to reach a plateau toward the end of the task, as indicated by linear ($b = .32$, 95% CI[.25,.39]) and quadratic trends ($b = -.17$, 95% CI[-.24,-.11]). High-probability choices improved with increasing longitudinal age ($b = .17$, 95% CI[.13,.21]). Although we did not find a general effect of cross-sectional age ($b = .02$, 95% CI[-.25,.29]), there was evidence for an interaction between cross-sectional and longitudinal age ($b = -.24$, 95% CI[-.35,-.13]). This indicates that the age variability between children of up to one year had less of an impact but that younger children increased in their likelihood to choose the high-probability option more than older children. Thus, the development of probability learning decelerated over time. Figure 3.4B shows the proportion of choices allocated to the high-probability option (across blocks) as a function of longitudinal age.

Figure 3.4

Changes in High-Probability Choices as a Function of Trial Blocks and Longitudinal Age



Note. (A) Observed percentage of high-probability choices per trial block and measurement time point. Error bars represent +/- standard error. (B) Observed percentage of high-probability choices, averaged across trials, by longitudinal age. Regression line derived from Bayesian mixed-effects model.

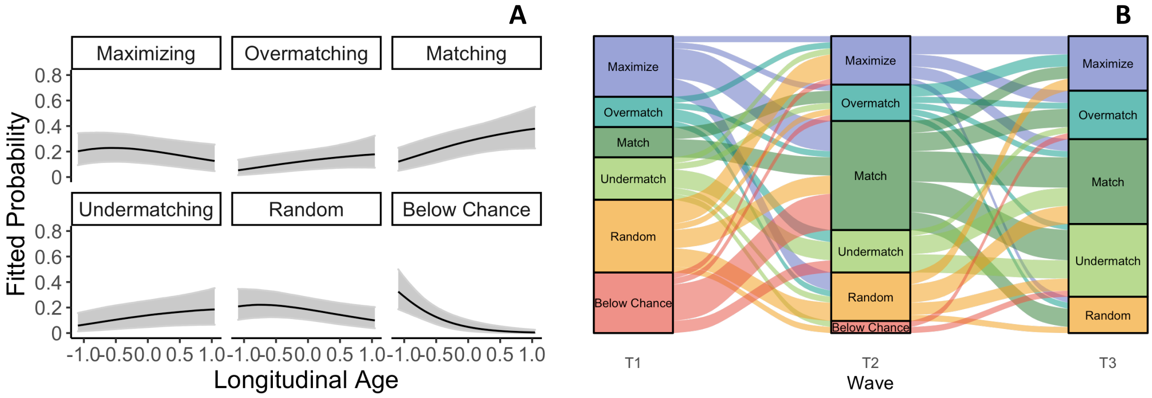
3.3.3 Individual Choice Behavior

To investigate individual choice behavior, like probability matching and maximizing, we categorized choice behavior based on the proportion of choices allocated to the high-probability option in the final block of trials. We expected that children become less likely to maximize probability over time while becoming more likely to probability match. Probability maximizing was defined as choosing the high-probability option on at least 90% of the trials; probability matching as choosing the high-probability option between 65–75% of the trials (see Chapter 2; Schulze et al., 2019). We estimated a Bayesian multinomial mixed model with a logit link function and varying individual intercepts as a random effect. Categorical choice behavior (maximizing vs. matching vs. neither) was submitted as the dependent variable. Cross-sectional and longitudinal age, and their interaction served as predictors. We found that the likelihood of maximizing behavior was negatively associated with cross-sectional age, showing that younger children in the cohort were more likely to maximize than older children ($b = -1.39$, 95% CI[-2.84,-0.16]). There was no evidence for a main effect of longitudinal age on probability maximizing, nor for an interaction between longitudinal and cross-sectional age. This does not confirm our hypothesis that probability maximizing decreases as children grow older but nonetheless indicates an effect of age, albeit between-person variability. As expected, the likelihood of probability matching behavior, in contrast, increased with longitudinal age ($b = 0.59$, 95% CI[.06,1.13]) but not as a function of cross-sectional age or their interaction. These results suggest that the likelihood of probability matching behavior by the end of the task increased as children grew older and that between-person age variability in the cohort was not related to probability matching.

To further explore more nuanced choice behavior as a function of age and how different choice behaviors transitioned over time, we additionally created categories for other behaviors (based on the proportion of high-probability choices in the final block of trials): overmatching (76–89%), undermatching (55–64%), random choice (45–54%) and below chance (0–44%). Figure 3.5A shows the predicted probabilities of category membership as a function of longitudinal age derived from a Bayesian multinomial mixed model accounting for multiple data points per participant (i.e., random participant intercepts; cross-sectional age, longitudinal age, and their interaction as predictors). Figure 3.5B shows the distribution and transition of choice behavior classification across time points. Most notably, unsystematic choices below and at chance level decreased (displayed in red and orange), while probability matching and its closely neighboring forms, undermatching and overmatching, increased in prevalence over time. By the end of the two-year study, at age 5.5 to 6.5 years, most children used some form of above-chance choice diversification (displayed in shades of green).

Figure 3.5

Classification of Choice Behavior as a Function of Longitudinal Age and Measurement Wave



Note. Classification based on the proportion of high-probability choices in the final block of 20 trials. (A) Fitted probabilities of choice behavior classification are derived from a Bayesian multinomial mixed model. The confidence band represents 95% credible interval of the posterior mean. (B) Transition between choice behavior classification over measurement time points based on individual category membership. This plot only includes data from children who completed three waves (N = 49).

3.3.4 Exploratory Analyses: Choice and Executive Functions

Table 3.1 provides an overview of children's average performance in the executive function measures across time points. As expected, children performed better in unordered recall in the forward version of the VWM task than in ordered recall in the forward and backward versions, reflecting different difficulty levels. On average, performance in the VWM tasks improved as a function of cross-sectional age (older children performed better than younger within the cohort) and longitudinal age (children perform better with increasing age; see Table C2 in Appendix C). However, children only showed minor improvements in the response inhibition task, indicating performance close to the ceiling.

Table 3.1

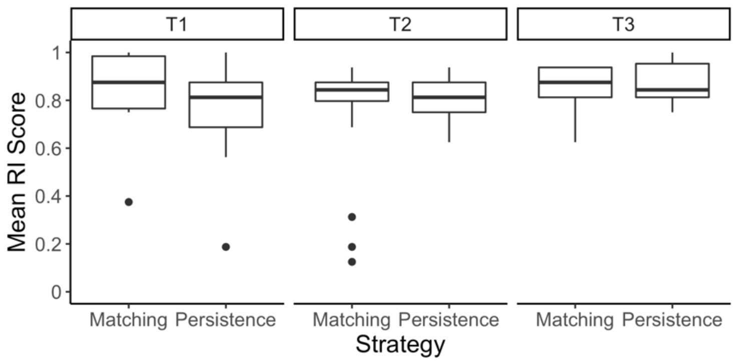
Mean (M) and Standard Deviation (SD) of Children's Executive Function Performance by Measurement Wave

			Memory					
Wave	Response Inhibition		Forward unordered		Forward ordered		Backward	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
T1	.76	.23	2.79	1.45	2.15	1.42	1.53	1.18
T2	.77	.19	3.98	1.34	2.98	1.34	2.49	1.26
T3	.87	.11	4.58	1.84	3.52	1.38	3.54	1.02

We did not specify hypotheses about the relation between executive function measures and choice behavior beforehand. Thus, the following analyses are exploratory. Immature response inhibition has been suggested to lead young children to probability maximize (e.g., Jones, 1970). If poor response inhibition does, indeed, affect highly persistent choice behavior, we might expect a difference between children who matched and children who consistently chose one option, irrespective of whether this option maximized reward. For this analysis, children were assigned to the persistence category if they exclusively chose either the high- or low-probability option on at least 90% of the trials in the final block of the probability learning task. Whereas there seemed to be a trend at T1 in the suggested direction (see Figure 3.6), there was no statistically credible evidence for a difference in the response inhibition score between matching and persistence (p = .59, BF_{10} = .47)[19]. Likewise, forward and backward memory span was unrelated to probability matching and persistence in any wave (all ps > .07, all BF_{10} < .85).

Figure 3.6

Mean Response Inhibition for Children Categorized as Probability Matching or Persistent Choice by Measurement Time Point



Note. RI = Response inhibition; probability matching and persistence were classified based on choice behavior in the final block of trials (i.e., 65–75% high-probability choices, > 90% either high- or low-probability choices).

The pattern search hypothesis (Gaissmaier et al., 2006) suggests that higher memory capacity facilitates searching and testing patterns in an outcome sequence, which requires switching between high- and low-probability options. Thus, we explored the relationship between high-probability choices and memory span. We extended the Bayesian mixed model used to investigate changes in high-probability choices by adding memory span as a predictor. Specifically, the extended model had the following specifications: high-probability choices as the dependent variable estimated via logit link; individually

[19] In Chapter 4, we argue that online testing affects young children's choice behavior over the course of a lengthy task and leads to decreases in performance. When exploring the relationship between matching, persistence, and response inhibition in the penultimate block of trials, there is weak evidence in favor of a difference in the suggested direction, $t(15.81) = 2.69$, $p < .05$, $BF_{10} = 1.93$.

varying intercepts (random effects); block as an ordered factor, cross-sectional age, longitudinal age, ordered recall forward and backward, as well as the two-way interactions between the age predictors (cross-sectional x longitudinal) and each age and memory predictors as independent variables. Table C3 in Appendix C reports the full parameter estimation results. As in the simpler model, high-probability choices increased with longitudinal age and over the course of the task, reaching a plateau towards the end. The interaction between cross-sectional and longitudinal age did not provide credible evidence as a predictor, indicating that increasing memory span might have mediated the effect. Furthermore, we found an interaction between longitudinal age and memory span. As children became older, lower backward ($b = -.21$, 95% CI [-.25,-.17]) and, to a smaller extent, forward recall span ($b = -.05$, 95% CI[-.09,-.01]) increased children's likelihood of choosing the high-probability option. The credible intervals for all other main effects and interactions included zero. Although it is possible that older children look for patterns in the environment and that higher memory capacity facilitates choice diversification (see Gaissmaier et al., 2006), this relationship needs to be confirmed in future studies for reliable evidence.

3.4 Discussion

Previous cross-sectional research showed puzzling age-related trends in probability learning tasks: Children below age 5 were found to often engage in probability maximizing (M. H. Jones & Liverant, 1960; Stevenson & Weir, 1959; Weir, 1964), whereas older children were more likely to probability match (see Chapter 2; Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960). These findings prompted some researchers to propose a U-shaped function between the rate of high-probability choices and age. (Derks & Paclisanu, 1967; Stevenson & Weir, 1959; Sullivan & Ross, 1970; Weir, 1964; Winefield, 1980). In this longitudinal study—the first one to our knowledge on probability learning—we examined children's repeated choice behavior between 3.5 and 6.5 years at three measurement time points to shed light on the underlying intra-individual trajectory and explored possible cognitive functions shaping this process.

Our analyses revealed that children, irrespective of age, learned to make more favorable choices throughout the experiment, reaching a plateau toward the end of the task. Moreover, they became more likely to choose the high-probability option with increasing age, but this process slowed down over time. These findings are consistent with other researchers reporting improvements in probability learning across early childhood (e.g., Messick & Solley, 1957; Offenbach, 1964) and emphasize that children undergo significant developments in this period that help them to improve the skills required in probability learning tasks.

As expected, we found that children, on average, became more likely to probability match as they got older. In contrast, the age difference between children of up to a year in the cohort due to the accelerated design was unrelated to probability matching. Furthermore, we observed a considerable qualitative change in diversifying choice behavior over time, reducing initial variability in choice behavior. Notably, the proportion of children choosing the high-probability option at chance or below chance level decreased continuously: By the end of the study, when children were 5.5–6.5 years old, they mostly diversified choices but retained performance above chance level. In sum, these results validate that probability matching behavior increases throughout early childhood as a function of increasing age (for cross-sectional findings, see Chapter 2; M. H. Jones & Liverant, 1960). In contrast, probability maximizing showed a different trajectory. We expected that probability maximizing decreases as a function of longitudinal age (over time points). Instead, we found a cross-sectional age effect, indicating that younger children in the cohort were more likely to maximize probability than older children. This finding is consistent with previous cross-sectional findings that did not reveal age effects for probability maximizing in a standard probability learning task (see Chapter 2) but inconsistent with earlier work indicating a decline in the propensity to maximize across age groups (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Weir, 1964). However, this inconsistency may be related to the fact that these studies found a twice or three times larger proportion of young children who maximized probability. Given the difference in the starting point, it seems plausible that we did not find evidence for a longitudinal decline in maximizing and the previously reported U-shaped function between high-probability choices and age (which would have predicted a decrease by the latest from 5 years onward; e.g., Derks & Paclisanu, 1967; Gruen & Weir, 1964).

A few differences between our study and those contributing evidence to the U-shaped function are noteworthy. For instance, several studies presented children with three choice options, of which only one was probabilistically reinforced, and the other two options never yielded a reward (e.g., Gruen & Weir, 1964; Stevenson & Hoving, 1964; Stevenson & Weir, 1959; Weir, 1964). In this version of a probability learning task, identifying the single option that occasionally delivers rewards may be easier than the paradigm used in the present study. Moreover, tasks in earlier work on probability learning development usually involved physical setups (e.g., light bulbs, token delivery machines). Yet, our study was conducted online, which may make it more difficult for younger children to sustain attention (see Chapter 4; Gijbels et al., 2021). Lastly, virtually all studies reporting that more than 50% of children below 5 years probability maximized were conducted more than half a century ago. Two newer studies that reported relatively high proportions of probability maximizing children tested either slightly older children in twice as many trials as we did (Plate et al., 2018)[20] or used a more liberal criterion to classify probability maximizing (Starling et al., 2018). In other words, the original findings were or could not be replicated in more recent years. Environmental factors that contributed to a general rise in performance in intelligence tests over the past century (i.e., the Flynn effect; Pietschnig & Voracek, 2015) may affect cohort differences with respect to earlier work on the development of probability learning.

Having discussed the trajectory of probability matching, maximizing, and probability learning in early childhood, we still need to better understand the underlying processes. The second goal of this study was to examine how working memory and response inhibition may shape these developments.

[20] Probability maximizing is known to increase with the length of a task, both in adult and child research (e.g., Derks & Paclisanu, 1967; Newell & Rakow, 2007; Plate et al., 2018; Shanks et al., 2002).

Our analyses revealed that the likelihood of choosing the high-probability option differed as a function of the interaction between memory span and longitudinal age. As children grew older, higher memory capacity was associated with a decreased likelihood of high-probability responses. In other words, we found a high-capacity advantage in diversification and a low-capacity advantage in maximization for older children. This finding is consistent with the pattern search hypothesis suggesting that adults with higher memory span have an increased propensity to search for patterns in the outcome sequence and, consequently, switch between the high- and low-probability option to test possible patterns (Gaissmaier et al., 2006). Moreover, this finding resonates with previous research on increasingly systematic exploration tendencies in childhood (e.g., Blanco & Sloutsky, 2020; Liquin & Gopnik, 2022; Schulz et al., 2019) and suggests that increasing working memory capacity may play a role in these processes. However, as our analyses were exploratory, further confirmatory research is needed.

Whereas some researchers proposed that probability maximizing in early childhood arises from protracted response inhibition development (e.g., Derks & Paclisanu, 1967; S. J. Jones, 1970), we did not find evidence in favor of this theory. On the one hand, children seemed to reach ceiling effects in the response inhibition task early on, and this was possibly strengthened by retest effects. A different response inhibition measure may confirm the expected relationship. On the other hand, the variability in persistence across time points may indicate that response inhibition only plays a small role in shaping young children's choice behavior. For instance, some children who maximized (or minimized) at T2 chose randomly before at T1 (and vice versa). Beyond failing to inhibit a prepotent response, some younger children seem to prefer strategies that do not require extensively tracking previous outcomes and are easy to implement (for a similar argument in the adult literature, see Schulze & Newell, 2016).

Nonetheless, these findings demonstrate that an increase in cognitive capacities alone does not fully explain developmental processes in probability learning. Cognitive capacities and other experiential factors, such as beliefs, expectations, or experience with statistical structures in the real world, seem to influence the development of probability learning and choice behavior (also see Chapter 2; Baltes, 1987; Plate et al., 2018). For instance, school-aged children may differ in why they (do not) probability maximize. Whereas some children aged 5–6 years in the present study maximized, children aged 6–7 years did not maximize probability in a previous cross-sectional study where outcomes were sequentially dependent. This may indicate that school-aged children persistently choose the high-probability option as a veritable reward maximization strategy[21] that they only abandon when a diversification strategy provides adaptive benefits. Tracking children's choice behavior longitudinally in an ecologically plausible probability learning task may provide new insights into such considerations. Moreover, an extended longitudinal investigation into adolescence may reveal how and when the transition from heightened exploration to adult-like exploitation occurs.

[21] An initial cue may be that children who maximized at T3 explained their choices by stating that they selected the option where more animals were hiding while children who maximized at T1 said they guessed or knew where the animals were hiding.

Despite the unique benefits of longitudinal research, we acknowledge that retest and practice effects are possible limitations (e.g., Rabbitt et al., 2004). While retest effects may underestimate change in studies investigating cognitive decline in older age (Lövdén et al., 2004), they may lead to overestimation of effects in research on cognitive development in childhood. We believe that retest or practice effects influence the measures used in this study to a different extent. First, the response inhibition task was possibly most affected by practice effects as children could have remembered the rule of the game. Second, in the probability learning task, the high-probability option was randomly assigned at every time point: children did not benefit from remembering which side was more favorable over measurement waves—even if they could do so over a year-long break. A comparison with previous cross-sectional results showed that children's performance at T3 was equal to children of a similar age who played the game only once. Third, studies reporting training effects in working memory tasks for preschoolers typically require more practice sessions in a much shorter period to observe improvements than we used in the present study (e.g., ten sessions within a few weeks vs. three sessions in two years; Ramani et al., 2020; Thorell et al., 2009). Thus, we believe practice effects may have only had a minor impact on our main findings. Overall, our results show the feasibility and benefit of longitudinal research in developmental processes in early childhood.

3.5 Conclusion

In line with previous findings, we provided credible evidence that choice diversification, like probability matching, increases longitudinally from early to middle childhood. Probability maximizing, in contrast, did not decrease over time but was related to age variability in the cohort. Our results emphasize the variability of choice behavior in early childhood and show that, on average, children improve their performance in standard probability learning tasks. Furthermore, exploratory analyses revealed that increasing cognitive capacities may facilitate choice diversification rather than maximization and contribute to developmental research on exploration tendencies. Lastly, our study outlines the interplay between the developing mind and children's experience with real-world statistical structures as a fruitful avenue for future research on probability learning.

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4 | Young Children Recruit Different Choice Strategies When Tested Online

Abstract. Using remote technologies in research on cognitive development is becoming increasingly prevalent, but evidence for the generalizability of results across online and offline conducted studies is mixed. Here, we investigated behavioral and strategy differences in a probability learning paradigm in 3- and 4-year-old children instructed online via video chat (n = 39) or offline in person (n = 69). We found an interaction between testing modality and trial block: Children in the online sample chose the more frequently rewarded option less often toward the end of the experiment. Moreover, computational modeling analyses revealed considerable differences in strategy use across the entire task, not only toward the end. Children in the online sample were more likely to rely on a win-stay lose-shift heuristic, whereas a reinforcement learning model best described children in the offline sample. Our results emphasize that the testing modality is a key factor in shaping cognitive processes underlying young children's choice behavior and needs careful consideration in designing online studies for developmental research.

4.1 Introduction

The internet is increasingly shaping how people communicate and work, and there is little doubt that the Covid-19 pandemic has accelerated this process (Zhu & Benwell, 2021). With the need to find creative solutions to the problems that social distancing posed, remote technologies have seeped into areas where they have been rarely used before. While online data collection was a widely used method in research with adult participants already prior to the Covid-19 pandemic (e.g., Peer et al., 2022), this method has become increasingly popular among developmental scientists over recent years (e.g., Scott & Schulz, 2017; Sheskin et al., 2020a; Sheskin & Keil, 2018; Zaadnoordijk & Cusack, 2022). Remote testing kept research projects running while labs, schools, and other public testing sites were locked down. In addition to these pragmatic concerns, online data collection offers a chance to reach a demographically more representative sample and to increase sample size while reducing the time needed to collect data (e.g., Sheskin et al., 2020a). But are in-person and online data collection indeed interchangeable in a developmental context?

While the question of data quality in online studies is not limited to developmental research (e.g., Newman et al., 2021; Peer et al., 2022; Webb & Tangney, 2022), moving developmental studies online is particularly challenging. For instance, task setups previously relying on physical objects (e.g., toy blocks, cards, or other stimuli) and dependent measures requiring a child to move toward or touch an object had to be transformed into their digital counterpart; instead of asking children or families in a public testing site if they want to participate, new online recruitment strategies needed to be developed; and as children typically give verbal, not written consent, alternative methods to document children's voluntary participation had to be created for unmoderated online studies. The publication of several papers on best practices for developmental online data collection within a short period illustrates the urgency to solve these issues (e.g., Gijbels et al., 2021; Kominsky et al., 2021; Segal & Moulson, 2021; Shields et al., 2021). These guidelines typically differentiate between synchronous and asynchronous studies: Synchronous studies are moderated by an experimenter, for example, via video chat; asynchronous studies do not require the presence of an experimenter, but participants can complete the study on an online platform at any time. Although asynchronous studies offer the opportunity to collect large sample sizes cost-efficiently, they provide little control over parental interference or verification of a child's presence. Synchronous studies, in contrast, resembles in-person testing more closely because an experimenter interacts directly with the child and caregiver. However, this method is fairly unique to developmental research. Direct interaction has been suggested to be an important factor for children to sustain attention (Gijbels et al., 2021) and to complete longer online tasks (Sheskin et al., 2020). To minimize methodological differences between online and offline testing, we focus on synchronous online testing in the present study.

Previous comparisons between synchronous online and offline studies with young children (i.e., < 5 years) showed promising results but, at the same time, raised several questions. Although a general developmental pattern can often be reproduced in online studies, considerable behavioral differences can arise from different testing methods. For instance, several online studies using violation-of-expectation or false-belief paradigms reported comparable results across testing methods; however, children tended to perform more poorly in online studies (Chuey et al., 2021; Schidelko et al., 2021; Scott et al., 2017; Sheskin & Keil, 2018; Smith-Flores et al., 2021). Similarly, a study on second-order inferences showed that 3-year-olds in the online sample performed at chance level and yet did not behave significantly differently from children in an offline sample (Lapidow et al., 2021).

Moreover, a yet unpublished meta-analysis showed a trend for smaller effect sizes in online samples (Chuey et al., 2022). While this effect was not statistically significant, the meta-analysis allowed online replications to use a different dependent measure than offline studies (e.g., preferential looking time instead of touch) and did not address the different domains or abilities that these studies investigated (Chuey et al., 2022). However, depending on the research questions, tasks, and examined abilities, not all studies may be equally suited for online testing with young children. Explicitly addressing these different domains in evaluating online testing methods could provide helpful new insights on cognitive development beyond mere validation of the data collection method. Until now, only a smaller number of domains is represented in online validation studies: for instance, word learning, memory, number knowledge, shape discrimination, or theory-of-mind (e.g., Bánki et al., 2022; Bochynska & Dillon, 2021; Escudero et al., 2021; Morini & Blair, 2021; Nelson et al., 2021; Schidelko et al., 2021; Sheskin & Keil, 2018; Silver et al., 2021). The decision-making domain in younger children has not yet been addressed (for an asynchronous study with older children, see Nussenbaum et al., 2020). Studying children's decision-making abilities with remote technologies becomes more important as their digital media and internet use increases from early childhood to adolescence, for instance, for education, communication, and entertainment purposes (e.g., Feierabend et al., 2020; Kieninger et al., 2020; Rideout & Robb, 2020). This research may provide new insights into how instruction via a digital device affects their decision-making competencies compared to in-person settings (e.g., remote vs. classroom instruction).

The present study investigates children's repeated choices in online and offline probability learning paradigms. In classic probability learning paradigms, children make repeated choices between two or more options and receive reinforcement when making a correct choice (e.g., a token, candy, or just the information of having made a correct choice; e.g., Derks & Paclisanu, 1967; Plate et al., 2018; Weir, 1964). Outcome probabilities are not known at the beginning of the task but need to be learned from trial-wise feedback. The development of probability learning has been studied for several decades, showing that children as young as 3 years old are able to learn about the underlying probabilistic schedule by increasingly choosing the option associated with the highest probability of holding a reward (i.e., the high-probability option; Derks & Paclisanu, 1967; Lewis, 1966; Siegel & Andrews, 1962).

Because the strength of evidence for previous online replications of in-person findings in child development is somewhat mixed, it is important to investigate *why* children perform slightly worse in online tasks and sometimes even at chance level, in addition to the general comparability across testing modalities. There are two possibilities for why young children's choice behavior in probability learning tasks might differ across testing modalities. Online testing characteristics could elicit qualitatively different strategies when performing a task or make it more challenging to implement a specific choice strategy. While a maladjusted strategy will likely result in decreased performance, a shift in strategy use to a simpler process does not necessarily allow such a prediction. Some strategies may be less adaptive, but others could result in similar performance levels. For instance, the fast-and-frugal heuristics program has demonstrated that even when ignoring some of the available information, simple decision rules can enable people to make accurate choices (e.g., Gigerenzer & Gaissmaier, 2011). Seminal work on adaptive strategy selection suggests that people consider time and effort when selecting a strategy, trading off between accuracy and costs (Payne et al., 1988). Suppose online testing increases the difficulty of attending to all information (e.g., due to environmental distractions, difficulties imposed by handling the device, internet lag, etc.). In that case, we might expect children to switch to a simpler strategy that requires less effort or attention.

However, if children across testing modalities rely on the same strategies, but strategy adjustment is more difficult online, we may observe a decline in performance because children make more errors and choose the high-probability option less frequently (for a similar argument for adults, see Olschewski et al., 2018). In associative or reinforcement learning models, the extent to which participants consistently choose a higher-valued over a lower-valued option is governed by a sensitivity parameter. This parameter is viewed as an indicator of random exploration in children but also as decision noise or error-proneness in the choice process (e.g., Eckstein et al., 2022; Giron et al., 2022; Schulz et al., 2019; van den Bos et al., 2011). If children tested online show a decline in performance compared to children tested offline (i.e., choosing the high-probability option less often), this might be reflected in lower values of a sensitivity parameter.

In the current study, we will investigate behavioral and strategy differences in probability learning between 3- and 4-year-old children tested offline in-person or online via video chat. To this end, we use two compatible datasets previously collected for other research projects (see Chapters 2 and 3). We will analyze performance based on high-probability choices and switching behavior and further use a computational modeling approach to explore children's underlying cognitive processes. For this purpose, we will fit several models to children's choices that have previously been used to describe how task characteristics (e.g., Newell et al., 2013; Otto & Love, 2010; Rakow & Miler, 2009; Schulze et al., 2015, 2017) and cognitive factors shape strategy use in adults (e.g., a win-stay lose-shift heuristic or reinforcement learning mechanisms, Otto et al., 2011; Worthy et al., 2012).

Based on the trend for worse performance in online settings and assuming that online instruction and testing add complexity to the task, we expect children in the online sample to choose the high-probability option less often than children in the offline sample. Given that much of the previous work on online- and offline comparisons required only a few trials per child, a detrimental effect of online testing may particularly emerge in later trials. That is, if children in the online sample fail to sustain attention to the task over time, we might expect them to increasingly choose the low-probability over the high-probability option. On a behavioral level, this could result in more reward-insensitive switching behavior. On a strategy level, this could lead to a decrease in choice sensitivity and an increase in random exploration (Olschewski et al., 2018). Examining behavioral and strategy differences in an online and offline conducted probability learning task will provide new insights into the generalizability of findings across testing modalities and inform our understanding of how methodological considerations may shape young children's choice process.

4.2 Method

4.2.1 Participants

Thirty-nine children completed the offline study (*M* = 4.12 years, *SD* = 0.57 years, 44% female), and sixty-eight the online study (*M* = 3.94 years, *SD* = 0.33 years, 53% female)[22]. Ten additional children participated but were excluded from data analysis: five children in the offline study and two children in the online study because they did not complete all choice trials; three children in the online study because of parental interference (affecting children's choices, e.g., "You do not always have to choose the left option."); and one child in the online study due to internet connectivity issues. Data exclusion criteria for the online sample were preregistered.

[22] The target sample size for both datasets was predetermined based on their original research questions with N = 40. The offline sample fell short by one child due to testing restrictions arising from the Covid-19 pandemic. Online data was collected in the context of the first measurement wave of a longitudinal study and accounts for possible dropouts during later waves.

Offline data collection took place from December 2019 to March 2020 in a local museum in Berlin, Germany. Children for the online sample were recruited via the participant database at the Max Planck Institute for Human Development and instructed online via video chat; recruitment and data collection took place from January to March 2021. Parents or children's legal guardians provided written consent for the child to participate and for their data to be used for secondary analyses. Children were additionally asked for verbal consent at the beginning of the task. To document consent and standardized instructions, each session was video recorded.

4.2.2 Design and Procedure

We kept the procedure across both testing modalities as similar as possible—including the same two experimenters collecting the data in both samples. All children played the same, child-friendly probability learning task on a tablet. Children repeatedly predicted behind which of two houses an escaped zoo animal would hide next. Children in the offline sample completed the task on a Lenovo Tab (1280 x 800 px); children in the online sample used either a tablet or a laptop with touchscreen. The images' and buttons' relative size and positioning were held constant across devices. Additional technical prerequisites for the online study were that the videoconference app *Zoom* was installed on the device and that families had access to a stable internet connection. In contrast to children in the museum who participated on site, parents of children in the online sample made an appointment at their convenience. A test session took approximately 20 minutes in both testing modalities.

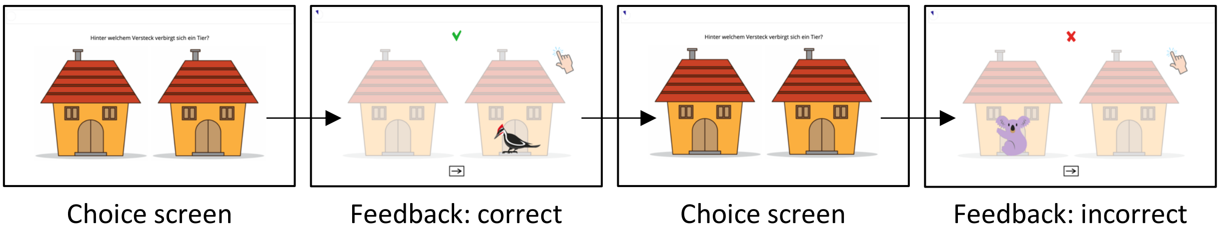
The instructions were the same for children tested online and offline. Children in the offline sample were instructed by an experimenter sitting next to them, assisting with handling the tablet; children in the online study were instructed via video chat. The experimenter shared the task via screen sharing and granted remote access to the participating family. Parents in the online sample helped children with the handling of the tablet but were asked to allow their child to make choices independently and to refrain from commenting on their child's behavior or giving feedback.

Figure 4.1 displays the probability learning task. To introduce the task, the experimenter explained that all animals escaped from the zoo. Children were then presented with a selection of escaped animals to give them an idea that there were, in fact, many animals. Afterwards, they completed two practice trials: the first was programmed to be correct, and the second was incorrect. To make a choice, the child touched the house behind which they believed an animal was hiding. On the following feedback screen, a previously hidden animal appeared, a hand symbol indicated which option was last chosen, and a green checkmark (online: blue circle) or red cross above the houses indicated whether a choice was correct. Except for eight children, participants in the online sample saw a blue circle instead of a green checkmark (see Figure 3.2 in the previous Chapter). However, we did not observe behavioral differences between these two groups in the online sample and hence, aggregated the data. Correct and incorrect choices were further accompanied by a high- or low-pitched sound, respectively. Children were instructed to collect fractions of blue tokens when making a correct prediction that they could later exchange against animal stickers from a box (offline) or an envelope (online). A bonus bar at the top of the screen, consisting of blue circles, informed children about their progress. Throughout the experiment, children received a physical token representing a blue circle for every ten correct choices. Children in the online sample received the material via mail before the test session.

The probability of animals hiding behind either house remained constant over trials: the high-probability option concealed an animal in 70% of the trials, and the low-probability option in 30% of the trials. Probabilities were pseudo-randomized, and only one animal appeared in any trial. Probabilities were not stated explicitly, but children had to learn about the likelihood of animals hiding behind the houses from feedback. After completing all 100 trials, children were asked to indicate the house behind which they believed more animals were hiding throughout the task, to estimate how many animals were hiding behind the houses using a response slider, and to explain how they decided which house to select. Lastly, correct choices were rounded up to the next blue token, and children were allowed to select as many stickers as they had collected tokens.

Figure 4.1

Example Screens in the Offline Probability Learning Task: Choice and Feedback



4.3 Results

4.3.1 Behavioral Results

The primary goal of this study was to examine performance differences between children tested online and offline. To this end, we investigated whether children tested online or offline differed in their likelihood of choosing the high-probability option and switching responses over the experiment. All analyses were conducted in R (R Core Team, 2023). We used the brms package with default priors (Bürkner, 2017) with the statistical modeling software Stan (Carpenter et al., 2017) to estimate Bayesian mixed models, and the BayesFactor package to compute Bayes Factors for *t*-tests and contingency tables (Morey & Rouder, 2022). Bayesian generalized linear mixed models had the following specifications: We used a logit link function to predict the dependent variable (model 1: choosing the high-probability option or not; model 2: switching or repeating choice) and included random participant intercepts to account for repeated choices per child. We entered testing modality (offline vs. online), trial block, and their interaction as fixed effects. Trial block was submitted as an ordered factor allowing to test for linear and quadratic trends. For each model, we ran four chains with 5000 samples each after discarding the first 1000 samples as warm-up, and thinning every other sample. This yielded 8.000 samples post warm-up and thinning. The $\widehat{R}$-statistic ($\leq$1.01) indicated no convergence issues for any of the predictors.

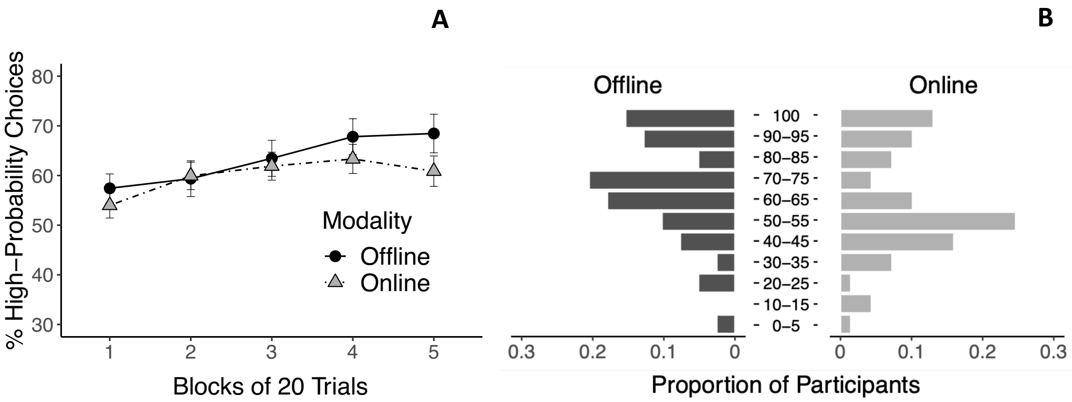
4.3.1.1 High-Probability Choices

We expected young children tested online to make fewer high-probability choices than children tested offline. If performance differences are related to sustained attention, this effect would particularly emerge over the course of the task. Figure 4.2A shows the percentage of choices allocated to the high-probability option per trial block and testing modality. Results from a Bayesian generalized linear mixed model showed that, when averaging across modalities, children learned to choose the high-probability option more often throughout the task, as indicated by a positive linear trend over trial blocks ($b = .49$, $CI_{95\%}$[.33, .65]). Aggregating over trial blocks, we did not find evidence that children performed worse when tested online than offline ($b = -.13$, $CI_{95\%}$[-.57, .32]). However, there was evidence for an interaction between the linear ($b = -.22$, $CI_{95\%}$[-.42, -.02]) and quadratic polynomials ($b = -.21$, $CI_{95\%}$[-.41, -.01]) of trial block and online testing modality. In other words, toward the end of the task, children in the online sample chose the high-probability option less often than children in the offline sample.

Figure 4.2B displays how children allocated choices to the high-probability option in the final block of trials. We find bimodal distributions in both testing modalities. In both modalities, one peak approximates persistently choosing the high-probability option. The second peak, however, centers on approximate probability matching for children tested offline (between 70–75% high-probability choices) but on random choice for children tested online (50–55% high-probability choices).

Figure 4.2

Percentage of Aggregate and Individual High-Probability Choices Across Testing Modalities



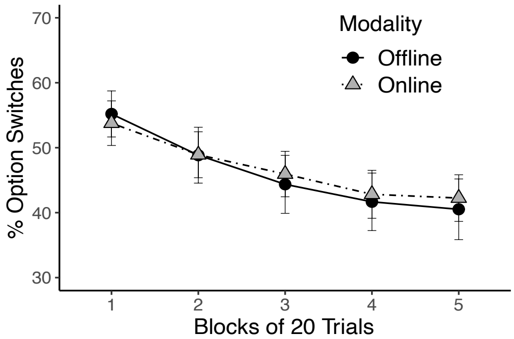
Note. (A) Percentage of high-probability choices per trial block and testing modality. Error bars indicate +/- 1 standard error. (B) Distribution of individual participants' allocations to the high-probability option in the final block of trials per testing modality. Values on the y-axis in percent (e.g., the top bar represents children exclusively choosing the high-probability option in the final 20 trials).

4.3.1.2 Switching

To investigate whether the online testing modality increased reward-insensitive switching behavior between the high- and low-probability option, we analyzed children's tendency to switch or repeat a choice using a Bayesian generalized linear mixed model. The likelihood of switching responses instead of repeating a response decreased over trial blocks irrespective of testing modality, as indicated by a linear trend (b = -.58, $CI_{95\%}$[-.74, -.42]). However, the decrease slowed over trial blocks, indicated by a quadratic trend (b = .16, $CI_{95\%}$[.01, .33]; see Figure 4.3). The estimated credible intervals of the remaining predictors included zero, indicating no effect of testing modality nor an interaction between linear or quadratic polynomials of trial block and testing modality.

Figure 4.3

Percentage of Option Switches by Trial Block and Testing Modality



Note. Error bars indicate +/- standard error.

4.3.1.3 Ability to Identify the High-Probability Option

To explore whether children learned that one option had a higher outcome probability than the other, we asked them to identify the high-probability option at the end of the task. A binomial test revealed that children in the online (M = .77) and offline group (M = .66) were able to correctly indicate the high-probability option above chance level (all ps < .05, all BFs_{10} > 16). A Bayesian contingency test assuming independent multinomial sampling with their total fixed and a chi-square test showed that children in both samples were similarly likely to identify the high-probability option correctly, $\chi^2(1)$ = 1.1, p = .34, BF_{10} = 0.43. That is, although children in the online sample seemingly had more difficulties identifying the high-probability option correctly, statistical analyses did not provide credible evidence for an effect of testing modality.

4.3.1.4 Interim Summary

In sum, behavioral results extend previous offline findings (see Chapter 2) and demonstrate that young children between 3 and 4 years can successfully learn about the probabilistic structure of a probability learning task when instructed online via video chat. However, our analyses also show that children's choices in the online sample were not equivalent to those in the offline sample. In particular, with an increasing number of trials, differences in performance emerged. To further investigate whether children tested online and offline relied on qualitatively different strategies when making decisions or only changed the fine-tuning of a given strategy, we next model children's choices with a set of different strategies that have proven useful to study children's and adults' repeated choice behavior (see Chapter 2; Otto et al., 2011; Schulze et al., 2017; Worthy et al., 2012).

4.3.2 Model-Based Strategy Analysis

We used a computational modeling approach to investigate possible differences in strategy use between children in the online and offline samples. Do performance differences toward the end of the task mean that children generally rely on different strategies? Or, if children rely on the same strategies, are there differences in how they tune a strategy to the task?

Instruction via video chat may tax children's cognitive resources more in a probability learning task than when instructed in person. Adult participants have been found to recruit reinforcement learning (RL) and win-stay lose-shift (WSLS) strategies differently when their cognitive resources are taxed under dual-task conditions compared to a single task condition (Worthy et al., 2012) and to show less sensitivity to the higher-valued option (Olschewski et al., 2018). Both WSLS and RL have been shown to underlie children's choice behavior in related tasks (Bonawitz et al., 2014; for a review on RL modeling across development, see Nussenbaum & Hartley, 2019) and, thus, may be helpful to characterize possible differences across testing modalities. We also estimated a baseline model that assumes children choose the high-probability option with a constant probability throughout the task. The free parameter from the baseline model equals the mean high-probability choice per participant (see Schulze et al., 2017). Models were implemented in the Bayesian framework JAGS (Plummer, 2003) and fit to each participant's choice data separately using MATLAB as an interface (The MathWorks Inc., 2021). We selected the model best describing each participant's choice behavior based on a comparison of the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002). As a measure of model fit penalizing complexity, we selected the model with the lowest DIC value per participant. The following section provides an overview of the implemented models, but see Appendix B for more details on model implementation and parameter estimation techniques.

4.3.2.1 Reinforcement Learning

The central assumption of RL models is that a decision-maker gradually updates the values of alternative choice options over trials and makes choices based on these values (Rescorla & Wagner, 1972; Sutton & Barto, 2018). In simple RL models, two parameters characterize people's choice process. The *learning rate* captures the weight of recent outcomes in the value-updating process. To this end, a prediction error is computed on every trial and describes the difference between the expected and an observed outcome. As a scaling parameter, the learning rate determines if recent outcomes are weighted more strongly (higher learning rates) or if a longer window of outcomes is considered in the value-updating process (lower learning rates). The second parameter, choice sensitivity or inverse temperature, describes how deterministically people choose the higher-valued option. Higher parameter values suggest that a person chooses the high-valued option more deterministically; lower values indicate that a person more randomly explores the low-valued option. RL models have been used successfully to describe older children's and adolescents' choice behavior, learning, and exploration (e.g., Ciranka & van den Bos, 2021; Decker et al., 2016; Nussenbaum et al., 2020; Smid et al., 2022; van den Bos et al., 2011).

4.3.2.2 Win-Stay Lose-Shift

In contrast to RL models that capture value learning processes over several trials, WSLS describes a heuristic that is only based on the single last outcome. Using a WSLS rule, a person repeats a choice if a reward was obtained and switches to the alternative option if no reward was obtained (Berman et al., 1970). WSLS is a common strategy used by children, adults, and other species in various tasks (e.g., Bonawitz et al., 2014; Ellerby & Tunney, 2017; Gaissmaier & Schooler, 2008; Maboudi et al., 2020; Scheibehenne et al., 2011). Despite requiring little memory, a WSLS heuristic can serve to explore alternative choice options beyond reward-insensitive switching in numerous environments, for instance, including more ecologically plausible statistical structures (Scheibehenne et al., 2011) or social competition (Nowak & Sigmundt, 1993). To explore whether children in the online and offline sample treat a win and a loss (i.e., absence of a win) differently when using a WSLS heuristic, we used a probabilistic implementation with two parameters that allowed to estimate separate probabilities for staying after a win and switching after a loss (e.g., Worthy et al., 2012).

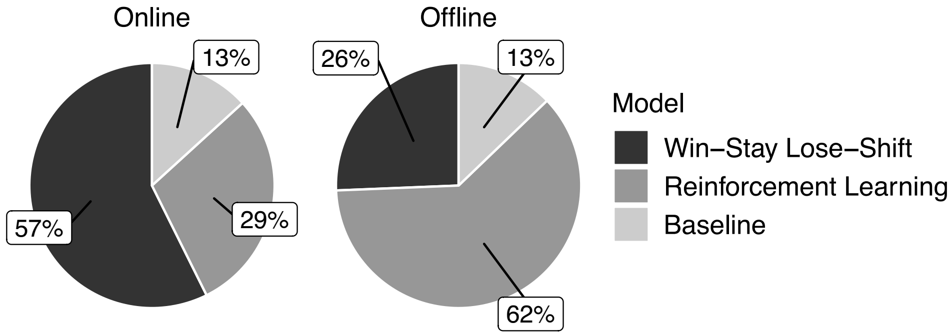
4.3.2.3 Strategy Classification

Figure 4.4 shows the proportion of children per testing modality classified as using one of the three strategies. Strategy classification differed significantly across testing modalities, $\chi^2(2) = 11.67, p < .01$, $BF_{10} = 24.87$. As confirmed by inspection of the residuals, more children in the offline sample relied on an RL mechanism, and more children in the online sample used a WSLS heuristic than expected under independence between strategy classification and testing modality[23]. A similar proportion of children in both samples was best described by the baseline model. Apart from differences in *what* strategy children used, does the testing modality also affect *how* children use a strategy?

[23] Behavioral analyses suggest that performance in the online sample declines only in the second half of the experiment. To explore whether this indicates a shift in strategy use, we also fit the models to children's choice data only from trial blocks 3–5 (see Figure D1 in Appendix D). While the proportion of children best described by the baseline model increased in this analysis, the overall pattern and statistical results remain the same as when fitting the models to all data: the majority of children in the online sample were best described by the WSLS model and the majority of children in the offline sample were best described by the RL model. The increase in baseline users suggests that some children stopped learning toward the middle of the task and choose the high-probability option with a constant probability. Indeed, about half of the baseline users (47%) were maximizers or minimizers. We decided to report the full-data analysis here due to some convergence issues for the inverse temperature parameter when using a subset of data.

Figure 4.4

Strategy Classification by Testing Modality



4.3.2.4 Parameter Analysis

To answer this question, we explored differences in the models' parameter estimates for those children best described by the respective models per testing modality. A Welch's t-test revealed that children tested online (M = .44) had a higher probability to repeat the same choice after a win than children tested offline (M = .25), but Bayesian evidence was anecdotal $t(46.35) = -3.4$, $p = .001$, $BF_{10} = 1.37$. There was no evidence for an effect of testing modality on the probability to shift after a loss, $t(26.73) = 1.96$, $p = .06$, $BF_{10} = 0.7$. In sum, evidence for a distinct use of a WSLS heuristic remains ambiguous.

Analyses of the RL parameter estimates revealed similar learning rates ($M_{online} = .22$, $M_{offline} = .36$), $t(41.96) = 1.76$, $p = .09$, BF = .98, and sensitivity, ($M_{online} = 11.45$, $M_{offline} = 11.69$), $t(30.79) = 0.04$, $p = .97$, BF = .30, for those children best described by the RL model in both samples. In sum, our results suggest that children tested online and offline differed in the kind of strategy they relied on rather than in how they used a given strategy.

4.4 Discussion

In the present study, we investigated 3- and 4-year-olds' performance in a probability learning task when instructed offline in person or online via video chat. Previous research on cognitive development reported similar developmental patterns across online and offline studies. However, children tended to perform slightly poorer in online than offline conducted tasks (e.g., Schidelko et al., 2021; Scott et al., 2017; Sheskin & Keil, 2018; Smith-Flores et al., 2021). Consequently, effect sizes in online studies seemed slightly smaller than in offline studies (Chuey et al., 2022). Our behavioral results and computational modeling analyses substantiate evidence that online and offline testing methods for young children are, in fact, not interchangeable. We found that 3- and 4-year-old children performed better toward the end of a probability learning task when instructed offline in person and that children recruited different strategies depending on the testing modality across the entire task.

Our behavioral analyses revealed that children instructed offline were more likely to choose the high-probability option than children in the online sample toward the end of the probability learning task. This indicated that although there was no main effect of testing modality on performance, differences may emerge over the course of a lengthy experiment. Yet, this was unrelated to children's likelihood of switching between options or repeating the same choice. Instead, frequent switching seemed to be a typical choice behavior for most children at the beginning of the task, with a slowing decrease over trial blocks (see also Rabinowitz & Cantor, 1967). Nevertheless, whereas approximately two-thirds of children tested online were able to identify the more frequently rewarded option after the task correctly, approximately three-fourths of children in the offline sample were able to do so. However, there was no evidence for a credible effect of testing modality on the ability to identify the high-probability option. Although some children might have had difficulties with the task, our results suggest that performance differences toward the end of the task cannot be solely attributed to misunderstanding task instructions.

When looking at individual choice proportions in the last block of trials, we found bimodal distributions of choice behavior in both testing modalities: One group of children persisted on the high-probability option irrespective of testing modality. In contrast, another group of children diversified choices differently across modalities—the peak of this second group of children was at a higher rate of high-probability choices in the offline than in the online sample. Indeed, the modal individual choice behavior in the online sample by the end of the task was random choice.

Moreover, our computational modeling approach showed considerable differences in strategy use. Whereas an RL mechanism best described most children in the offline sample, most children in the online sample were better described by a probabilistic WSLS model. Parameter analyses suggested that children best described by the respective models were using the strategy in a similar way. Our modeling approach relied on all choices to provide enough data to discriminate between choice models. However, the general pattern of results remained the same when using only the second half of choice data to fit the models. In sum, the modeling analyses suggest that children tested offline relied on a more associative learning strategy, whereas children tested online tended to use a simple rule-based strategy. Both models can accommodate variability in high-probability choices. However, whereas RL requires updating options' values over repeated trials, a WSLS heuristic only requires memory of the single last outcome. From the perspective of heuristic and adaptive strategy selection (Gigerenzer & Gaissmaier, 2011; Payne et al., 1988), the shift in strategy use between offline and online testing might suggest that a simpler WSLS heuristic wins the effort–accuracy tradeoff when the implementation of an RL mechanism becomes more difficult.

However, what specific aspects of the online testing environment affected strategies and performance? One mechanism pointed out in the literature is decreasing sustained attention in online settings due to distractions in the home environment (Shields et al., 2021). However, more distractions in a home environment are unlikely to account for our findings: Children in the offline sample were tested at a local museum where people were passing by at a relatively close distance. Difficulties with sustained attention could rather be related to aspects inherent to the online testing situation instead of the physical location. For instance, features of the physical presence of an experimenter, like facial expressions and gestures, are difficult to convey in an online environment or may be altered by time lag or low frame rates. In our study, the experimenter was only visible in a small window, as the screen-shared experiment took up most of the screen on the tablet. Moreover, a slow internet connection or lower processing speed of the tablet could have introduced a small time lag between the choice through physical touch and the appearance of the feedback screen. It has been suggested that increased inter-trial intervals may lead to more response variability of children's choices, even in a physical probability learning task (Weir & Gruen, 1965). One possibility to directly test for an effect of attention in future studies would be to combine a probability learning task with smartphone- or webcam-based eye-tracking methods to measure how children attend to outcomes across testing modalities (e.g., Erel et al., 2022; Werchan et al., 2022).

4.5 Conclusion

To conclude, we demonstrated that performance differences in a probability learning task might arise with increasing task length between young children tested online via video chat or offline in person. Moreover, computational modeling analyses revealed considerable strategy differences. Children in the online sample primarily relied on a simple WSLS heuristic, whereas a reinforcement learning mechanism better described children in the offline sample. Our findings show that online testing can shape children's cognitive processes underlying repeated choices and that such methodological aspects need to be appropriately addressed when generalizing across testing modalities. Focusing on validation studies with the goal of proving the equivalence of online and offline testing in research with young children may miss out on the opportunity to uncover which and how factors in online testing affect children's cognitive processes. However, this research could have important implications for creating effective study designs in developmental research. Since remote technologies seem to have come to stay in life and science (Sheskin et al., 2020), it is essential to better understand how they affect children's cognition and behavior.

4.6 References

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5 | Do Children Match Described Probabilities? The Sampling Hypothesis and Risky Choice

Abstract. We investigated how repeated choices develop in early childhood when outcome probabilities are learned from description. Integrating previous findings from children's causal learning and adults' repeated choice behavior, we expected young children to probability match in a repeated risky choice paradigm and predicted that the perceived dependency between choices shapes the underlying sampling process. Two hundred one children between 3 and 7 years and 100 adults participated in a child-friendly guessing game with described outcome probabilities. We were unable to replicate findings reported by the studies that inspired this research but found that children broadly diversified choices and that switching between options dominated older children's choice behavior. These findings are consistent with an amplification of developmental differences reported in experiential repeated choice tasks and hold implications for studying a description–experience gap in repeated risky choice across development.

5.1 Introduction

Learning about the probability of a desired outcome and applying this knowledge when making repeated decisions—a process typically referred to as probability learning (Estes, 1964)—is an important skill to develop while growing up. How likely will a child's feet get wet when repeatedly jumping in a puddle while wearing boots? Who will be more likely to play with a child, their older or younger sibling?

Decades of research have shown that adults often behave suboptimally in standard probability learning tasks and tend to choose an option with the same frequency as the option results in a desired outcome (i.e., they probability match; see Vulkan, 2000). In classic behavioral experiments, where outcome probabilities remain stationary, probability matching is a mistake because it yields lower average reward rates than exclusively selecting the option with the highest outcome probability (i.e., probability maximizing). But why do adults probability match? Several explanations have been suggested, differing in their optimism about human rationality. Traditionally, probability matching is attributed to cognitive limitations and the failure to identify the superiority of a maximizing strategy (e.g., Koehler & James, 2010; Vulkan, 2000). Yet, there is growing evidence that probability matching may instead be a cognitive mechanism adapted to complex real-world environments that allows people to exploit, for instance, autocorrelated or clumped resources (e.g., Ellerby & Tunney, 2019; Gaissmaier & Schooler, 2008; Green et al., 2010; Schulze et al., 2017, 2020). Indeed, people who probability match in the absence of patterns are often better able to detect existing patterns in an outcome sequence (Gaissmaier & Schooler, 2008; Schulze et al., 2020). This pattern detection ability significantly improves in probability learning tasks during childhood (Goldman & Denny, 1963).

When does probability matching enter the stage of available choice strategies? In previous longitudinal and cross-sectional studies (see Chapters 2–3), we demonstrated that although the prevalence of probability matching considerably increases from early to middle childhood, only school-aged children used probability matching adaptively. Younger children between 3 and 5 years are more variable in their choice behavior but also more likely than older children to persist on one option, often resulting in probability maximizing (Goldman & Denny, 1963; Jones & Liverant, 1960; Sullivan & Ross, 1970; Weir, 1964). Changes in probability learning and repeated choice behavior across development may arise from an interaction between the developing mind and the environment but still need to be better understood.

The importance of understanding the inference and choice processes shaping young children's probability matching and maximizing behavior is not limited to standard probability learning tasks but extends to research addressing other reasoning domains such as causal or inductive inference (Denison et al., 2013; Schulz, 2012; Sobel et al., 2004). For example, Denison et al. (2013) suggested that children probability match on an aggregate level in a causal learning task. Specifically, they suggested that 4- and 5-year-old children draw independent samples from an internal distribution when selecting a hypothesis from a set of possibilities. If children make probabilistic inferences by drawing repeated, independent samples, their behavior should also reflect individual-level probability matching over repeated trials by the same child. This contrasts with younger children maximizing in classic probability learning tasks (e.g., Weir, 1964). One methodological aspect that may contribute to these contradictory findings relates to the different learning modes used in probability learning and causal or probabilistic inference studies. While Denison et al. (2013) used a task in which probabilities—represented by differently colored blocks—were known to children before making an inference, standard probability learning paradigms typically require children to learn outcome probabilities from trial-by-trial feedback. There is convincing evidence that the learning format strongly impacts probabilistic inferences by both children and adults (see Schulze & Hertwig, 2021, 2022). Indeed, the effect of descriptive versus experiential task formats on people's risky decisions is well-known as the description–experience gap (Hertwig & Erev, 2009) and has been demonstrated for adults' and older children's choice processes alike (Rakow & Rahim, 2010).

The format of explicit probabilistic information needs to be adapted to children's abilities. For example, probabilistic information adapted for children is often presented in a graphical format based on natural frequencies. Such visual representations have improved children's inferences from 7 years onward in other domains, such as in an Iowa Gambling Task (van Duijvenvoorde et al., 2012) and Bayesian reasoning problems (Gigerenzer et al., 2021). Little is known, however, about how children make repeated choices in purely descriptive analogs of probability learning paradigms. Can explicit outcome probabilities elicit rational sampling behavior and increase probability matching even in younger children between 3 and 4 years? Providing descriptive probabilistic information could potentially alleviate memory demands (van Duijvenvoorde et al., 2012) and help children apply more flexible strategies. Many adults continue to probability match even when knowing the outcome probabilities beforehand (e.g., James & Koehler, 2011; Newell & Rakow, 2007). For instance, James and Koehler (2011) showed in a descriptive repeated choice task that generating sequence-wide expectations shapes choice diversification. They found that when adults made decisions in a series of *different* gambles, their predominant choice strategy was probability maximizing; when they made a series of decisions in the *same* gamble, adults probability matched more often. James and Koehler (2011) argue that when thinking about a sequence as a whole, people erroneously expect the outcomes to reflect the underlying probabilities. However, when playing different gambles, this expectation is disrupted. An alternative interpretation of their findings is that repeatedly playing the same gamble leads people to perceive outcomes as more dependent than outcomes generated by separate independent gambles. Outside of artificial laboratory environments, perceiving outcomes as dependent might serve as a valid cue to look for a pattern or regularity in the outcome sequence that can be exploited using a probability matching strategy. Similarly, it has been demonstrated that people's responses are closer to probability matching when they perceive a generating process as less random (either by control over the chance device, see Peterson & Ulehla, 1965, or by direct instruction, see Beach & Swensson, 1967) and closer to probability maximizing when they perceive the process as more random (Beach & Swensson, 1967; Peterson & Ulehla, 1965).

The hypothesis that the perceived dependency between outcomes affects choice behavior is also central to Denison et al.'s (2013) sampling hypothesis. In their low-dependency manipulation, children made three guesses while waiting one week between each guess; in their high-dependency condition, children made three consecutive guesses without a prolonged waiting time between trials. Denison et al. (2013) argued that children draw less independent samples from a set of possible hypotheses when they perceive guesses to be dependent and, as a result, make systematically patterned responses (e.g., alternating). Despite coming from different research streams and using different methodologies, the behavioral results in the studies by Denison and colleagues (2013) and James and Koehler (2011) show an interesting consistency: the modal response of participants in their low-dependency conditions was maximizing, whereas participants in the high-dependency conditions either probability matched or showed a strong tendency to alternate. Suppose young children can already benefit from using perceived dependency between outcomes as a cue to guide choices. Will they probability match more when the perceived dependency is high, and probability maximize more when the perceived dependency is low between sequential outcomes?

In the current study, we aim to bridge research on classic probability learning and development of causal inference, which has remained largely disconnected—despite investigating related research questions and cognitive processes. We will use a descriptive repeated choice paradigm inspired by the tasks used by James and Koehler (2011) to test whether the sampling hypothesis proposed by Denison et al. (2013) extends to a domain other than causal reasoning but that also requires drawing samples from a frequency distribution. To match age samples previously reported to differ in choice behavior in the probability learning literature, we will recruit children between 3 and 7 years. Consistent with the sampling hypothesis, we expect to find response patterns in children that reflect the outcomes' underlying probability distribution. Thus, contrary to developmental work using probability learning paradigms, we expect young children to probability match. With increasing age and cognitive capacity, we predict older children's distribution of choice behaviors to more narrowly match the expected distribution. Furthermore, we aim to reproduce the effect of perceived dependency between outcomes resulting in more maximizing behavior under low dependency and more matching under high dependency. Finally, we expect to replicate the results reported by James and Koehler (2011) in a different adult sample using a child-friendly task.

5.2 Method

5.2.1 Participants

We recruited 207 children (105 children aged 3–4 years and 102 children aged 6–7 years) and 111 adults via the participant database at the Max Planck Institute for Human Development. Five children aged 3–4 years and one 7-year-old did not complete the experiment and were excluded from data analyses. Six adults, who were part of a pilot study[24], and five adults who indicated that they tracked objects on the screen as a strategy to make predictions were also excluded from data analyses. The final sample consisted of 100 children aged 3–4 years (*M* = 3.96 years, *SD* = 0.56 years, 54% female), 101 children aged 6–7 years (*M* = 6.99 years, *SD* = 0.55 years, 49% female), and 100 adults between 18 and 41 years (*M* = 27.92 years, *SD* = 5.68 years, 52% female).

The sample size was determined before data collection by submitting the proportions of strategy users reported in James and Koehler (2011) to a power analysis in G*Power (Faul et al., 2007). To detect an effect with power .80 and a significance criterion of $\alpha = .05$, the average required sample size per condition was n = 44. To account for potentially noisier choice behavior of children compared to adult participants, we increased the required sample size by approximately 15% to n = 50 per age group and condition. One additional 6-year-old participated in the study due to a higher number of registrations than expected.

The experimental procedure received ethical approval from the institutional review board at the Max Planck Institute for Human Development. Adult participants and parents of minor participants gave digital consent to participate in the study. Children were asked for verbal consent at the beginning of the test session. Parents of minor participants agreed to the session being video recorded, documenting child consent and standardized instructions. Participants (for children, their legal guardian) received a fixed payment of 3.00 EUR and could earn a performance-based bonus of 0.50 EUR for every correct prediction.

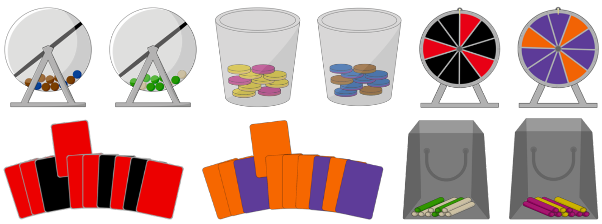
[24] After piloting, we filtered out participants who reportedly tracked objects on the screen despite being instructed not to do so.

5.2.2 Design and Material

We developed child-friendly versions of the tasks and procedures used in Experiment 1 by James and Koehler (2011). Based on their reported material, we created ten guessing games in which we asked participants to predict the color of a randomly drawn object (e.g., balls in a bingo cage, a wheel of fortune, etc.; see Figure 5.1). Each type of game was implemented with two sets of colors resulting in ten unique color-game combinations (henceforth "games"). Objects were displayed in one of two different colors representing the probabilistic structure of the task: seven objects had one color (e.g., red), and three objects were of a second color (e.g., blue). We selected colors based on good discriminability in case of possible color vision deficiencies.

Figure 5.1

Overview of Guessing Games



As in Experiment 1 by James and Koehler (2011), we tested two conditions as a between-subjects factor. In the low-dependency condition, participants played ten different games; in the high-dependency condition, participants played ten trials of the same game. Participants were randomly assigned to a condition upon registration for the study. In the low-dependency condition, the order of games was randomized under the constraint that no two games with the same type (e.g., bingo) or color set (e.g., red–black) could follow in consecutive trials. In the high-dependency condition, we randomly selected one game per participant. The majority-color—i.e., the more common color—was counterbalanced across participants.

The guessing games were implemented as a web-based experiment. We used an internally developed JavaScript framework for online experiments and implemented shuffling animations (e.g., spinning the wheel of fortune) to visualize the random generating mechanism in each game.

5.2.3 Procedure

Adults completed the task asynchronously in an unmoderated online experiment, whereas an experimenter instructed children via video chat. Before the testing session, parents of participating children received tokens and stickers via mail. The task was the same for children and adults except for the delivery method of the instructions (written vs. oral). Due to the simplicity of the task, we refrained from implementing comprehension checks for adults.

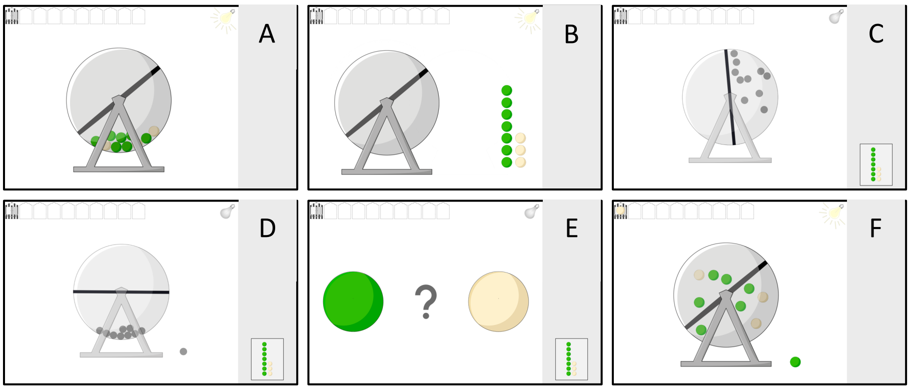
Before the experiment, we inquired about basic demographic information. For the choice experiment, participants were asked to imagine playing multiple guessing games at a fun fair. Participants in the high-dependency condition were told that they would play the same games ten times in a row; participants in the low-dependency condition were told that they would play ten different games. Afterwards, participants were familiarized with the mechanics of the guessing game in a practice trial consisting of a similar type of guessing game as the ones included in the test trials. All trials—including the practice trial—followed the same general procedure (see Figure 5.2). First, the specific game was introduced (see Figure 5.2A), and for children, the experimenter counted out loud how many objects of each color there were (see Figure 5.2B). Except for the practice trial with five objects of each color, the distribution for the test trials was seven objects of one color and three objects of a second color, respectively. During test trials, the experimenter also asked children which color they believed was more frequent. If children did not answer this comprehension check correctly, the experimenter counted the colored objects again and highlighted which color was more frequent. Afterwards, the experimenter explained that the colors in the game were only visible while a light—presented as an icon in the top right corner of the screen (see Figure 5.2)—was switched on. During the following animation visualizing the randomization process of the game, the light was switched off, and all colors appeared gray-scaled in the same hue (see Figure 5.2C). After that, one out of 10 objects was randomly drawn (e.g., a ball fell out of the bingo cage; see Figure 5.2D), and participants were prompted to guess the color of the randomly drawn object by choosing from a set of two colors (see Figure 5.2E). Adults and older children used the mouse to indicate their response; younger children pointed to the color, and their parents executed their choice by clicking on the colored icon. Except for the practice trial, we did not provide immediate feedback about the correct outcome but only at the end of the experiment. Children received a token after every choice as a motivation to collect more tokens as the experiment progressed.

After completing all trials, participants answered control questions about strategy use, previous visits to fun fairs, and their favorite color out of all ten occurring colors. Participants in the high-dependency condition—who experienced the same two colors across all trials—were additionally asked which of the two colors they preferred. Finally, participants received feedback about their choices, actual outcomes for every trial (Figure 5.2F), and the monetary bonus they achieved. Children were then encouraged to select as many stickers as they made correct guesses. A session with a child participant took approximately 20 minutes, while adults completed the practice and 10 test trials, on average, in 6 minutes (without welcoming instructions and additional questions).[25]

[25] Children's moderated test sessions took longer than unmoderated sessions for adults. To test for an effect of sustained attention, we analyzed choices for the first and second half of the experiment separately in a repeated measures ANOVA. Majority-color choices in the first and second half of the experiment differed at an anecdotal level, $\chi^2(1,197) = 3.58$, $p = .06$. The marginal trend pointed toward more majority-color choices in the second half of the experiment and did not support the assumption of more random behavior due to attentional deficiencies.

Figure 5.2

Overview of the Trial Procedure



Note. (A) Introduction of the type of game. (B) Display and counting of the frequency of each colored object. (C) Animated randomization process with switched-off light. (D) Sampling of one object. (E) Choice screen. (F) Feedback screen after completing all trials.

5.3 Results

We first analyzed majority-color choices across age groups. Then we investigated the prediction for probability matching on an aggregate level on the first trial and across trials based on the sampling hypothesis (see Denison et al., 2013). Afterwards, we analyzed individual-level probability matching (see Koehler & James, 2011). All analyses were conducted in R version 4.2.3 (R Core Team, 2023). For mixed-models, we used the afex package (Singmann et al., 2022) and the package emmeans (Lenth, 2022) for follow-up analyses.

5.3.1 Majority-Color Choices Across Age Groups

When learning from graphic frequency distributions, are there differences across development in choosing the more likely option? To answer this question, we performed a mixed-effects regression with per-participant intercepts as a random effect. We included age group (3–4 years, 6–7 years, adults), condition (repeated, unique), their interaction, and whether the majority-color was a participant's favorite color as fixed effects. We used a logit link function to model the dependent variable's binary nature (choosing the majority-color or not). We found a significant main effect for age group, $\chi^2(2) = 122.68$, $p < .001$, but for none of the remaining fixed effects (all *ps* $> .28$). To further investigate the difference between age groups, we computed pairwise contrasts and used the Benjamini-Hochberg method to correct *p*-values for multiple testing (see Benjamini & Hochberg, 1995). Results showed that adults were eight times more likely than 3- and 4-year-old children ($z = 10.72$, $p < .001$) and 5.7 times more likely than 6- and 7-year-old children ($z = 9.08$, $p < .001$) to choose the majority-color. Moreover, 6- and 7-year-olds were 1.4 times more likely than 3- and 4-year-olds to choose the majority-color ($z = 2$, p

< .05). In sum, adults outperformed children with respect to choosing the option with the higher frequency, but we also observed improvements between 4 and 6 years of age.

5.3.2 Aggregate Probability Matching

5.3.2.1 Probability Matching on the First Trial

First, we tested whether participants' first choices differed across conditions. Chi-square tests revealed no differences concerning the proportion of children choosing the majority-color on the first trial in the high- and low-dependency conditions, respectively (all ps > .37). For adults, a Fisher's Exact Test[26] indicated no association between condition and number of majority-color predictions on the first trial (p = .11). We, therefore, aggregated data across conditions to investigate aggregate probability matching on the first trial. Binomial tests revealed that 3- and 4-year-olds performed at chance level (M = .56, p = .27) while 6- and 7-year-olds (M = .6) and adults (M = .93) chose the majority-color significantly above chance (all ps < .05). The proportion of children and adults predicting the majority-color on the first trial, differed significantly from the underlying distribution of p = .7 (all ps < .05). In contrast to the sampling hypothesis, we did not find evidence for aggregate probability matching on the first trial for any age group.

5.3.2.2 Probability Matching Across Trials

Next, we analyzed aggregate probability matching across trials to determine whether participants' choices reflected independent sampling from the frequency distribution (see Denison et al., 2013). For ten trials, there are 1024 different possible response patterns. We summed up expected probabilities for those patterns that included the same number of majority-color choices (see Figure 5.3A). For example, strict probability matching based on choosing the majority-color precisely 7 out of 10 times has a posterior probability of $p = .7^7 \times .3^3 = .002$ (i.e., multiplying the outcome probability for every trial: .7 x .7 x … x .3). Multiplied by 120 response patterns, that contain precisely seven majority-color and three minority-color choices, the expected proportion of probability matching participants would be p = .27.

Chi-square-goodness-of-fit tests revealed that the observed proportions of participants differed significantly from the expected proportions derived from the sampling hypothesis (all ps < .001; see Table 5.1). Moreover, there was no difference between conditions for any age group (all ps > .09). Hence, our results neither support aggregate probability matching across trials nor an effect of the experimental manipulation.

[26] We used a Fisher's Exact Test instead of a chi-square test because few adults predicted the minority-color on the first trial.

Table 5.1

Fit of Observed and Expected Majority-Color Choice Proportions: Results From Chi-Square Tests

	Condition			
	Low-dependency		High-dependency	
Age group	χ^2	df	χ^2	df
3–4 years	55280*	10, N=100	122237*	10, N=100
6–7 years	54162*	10, N=101	54579*	10, N=100
Adults	1804382*	10, N=100	2118372*	10, N=100

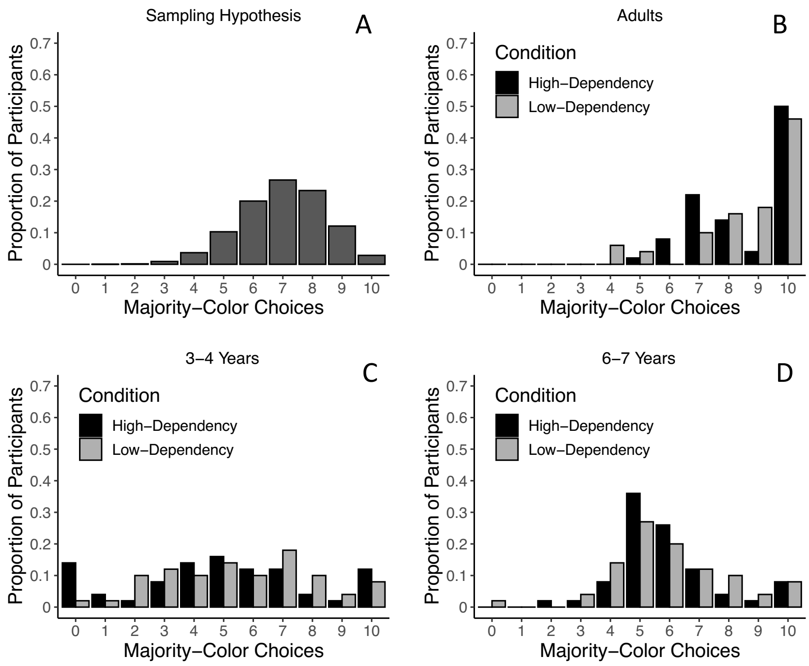
Note. $p < .001$*

5.3.3 Individual-Level Probability Matching

To investigate the effect of perceived dependency on individual-level probability matching and maximizing across development, as typically reported in the probability learning literature, we replicated the analysis reported in Koehler and James (2011) but corrected for multiple testing. Consistently with their original method, we classified participants as probability matchers, if they chose the majority-color in seven out of 10 trials and as probability maximizers, if they chose the majority-color in 10 out of 10 trials. Figure 5.3 shows the proportion of participants per age group and condition across summed majority-color choices.

Figure 5.3

Choice Proportions by Sum of Majority-Color Choices



Note. (A) Expected proportion of majority-color choices predicted by the sampling hypothesis. (B–D) Observed proportion of participants by age group and condition, allocating between 0 and 10 choices to the majority-color.

Unlike in the original study (James & Koehler, 2011), we did not exclude participants if they chose the low-probability option on more than half of the trials, as this is a regularly observed behavior in children. Results from chi-square tests indicated no association between probability matching or maximizing and condition (see Table 5.2)[27]: Within each age group, participants were equally likely in the high-dependency and low-dependency condition to probability match and maximize, respectively. However, probability matching was the modal response for 3- and 4-year-olds in the low-dependency condition. Recall that James and Koehler (2011) found more maximizing under low-dependency and more matching under high-dependency. Thus, we did not replicate these results in a different adult sample, nor did we extend their findings to a developmental context.

Table 5.2

Strategy Classification by Age Group and Condition: Chi-Square Test Statistics

		Condition				
Strategy classification	Age group	LD	HD	df	χ^2	*p*
Probability matching	3–4 years	9	6	1,100	.71	.50
	6–7 years	6	6	1,101	< .01	.98
	Adults	5	11	1,100	2.68	.20
Probability maximizing	3–4 years	4	6	1,100	.44	.50
	6–7 years	4	4	1,101	< .01	.98
	Adults	23	25	1,100	0.16	.69

Note. LD = low-dependency; HD = high-dependency; *p*-values were corrected for multiple comparisons based on the Benjamini-Hochberg method; n per condition = 50 except for 6- and 7-year-olds in low-dependency with n = 51.

5.3.4 Exploratory Analysis: Switching Behavior

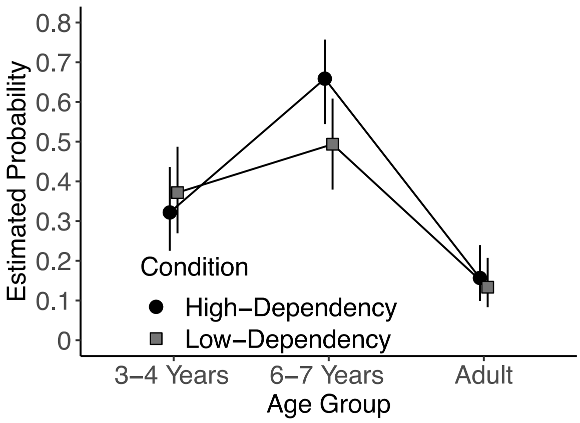
To further investigate the reasons for the unsuccessful replication of results reported in the literature, we conducted an additional exploratory analysis. Based on the high proportion of children showing switching behavior in the high-dependency condition reported by Denison and colleagues (2013), we examined the likelihood of children and adults switching between responses without outcome feedback. To this end, we computed switching as a binary variable indicating whether a participant revisited the same option or changed options in the subsequent trial (from majority- to minority-color or vice versa). We submitted switching as a dependent variable to a mixed-effects logistic regression and used age group, condition, and their interaction as predictors (fixed effects). We accounted for multiple responses

[27] Using a more liberal criterion for probability matching (7 +/- 1 majority-color choices) and maximizing (9 or 10 majority-color choices) to account for possibly noisier behavior across development did not change any of the conclusions reported in the main text.

per participant by implementing random intercepts (random effect). Figure 5.4 shows the model-derived estimated probability per age group and condition to switch responses. Likelihood ratio tests indicated a significant main effect of age group, $\chi^2(2) = 65.85$, $p < .001$, but not of condition, $\chi^2(1) = 1.11$, $p = .29$, nor their interaction, $\chi^2(2) = 3.46$, $p = .18$. Pairwise contrasts between the levels of age groups revealed that 6- and 7-year-olds (M = .58) were 8.1 times more likely than adults ($M = .15$, $z = 8.04$, $p < .001$), and 2.6 times more likely than 3- and 4-year-olds to switch responses ($M = .35$, $z = 3.9$, $p < .001$). In addition, children aged 3–4 years were 3.1 times more likely to switch responses than adults ($z = 4.4$, $p < .001$)[28].

Figure 5.4

Estimated Probability of Switching Responses by Age Group and Condition



Note. Estimated probability of switching to the alternative choice option derived from mixed-model analysis. Error bars indicate the lower and upper bound of a 95% confidence interval.

5.4 Discussion

We investigated the development of repeated choice in a descriptive paradigm by connecting findings from two lines of research that have previously operated in parallel: probability learning and causal inference. We expected young children to probability match and predicted that the perceived dependency between sequential outcomes would influence their choices. Analyzing repeated choices from 201 children and 100 adults, we did not replicate central findings previously reported in the literature: We were unable to find evidence for children and adults drawing independent samples from a probability distribution when making either one or repeated choices (cf. Denison et al., 2013), and for choice behavior differing as a function of the high- and low-dependency manipulation (cf. Denison et al., 2013; Koehler & James, 2011).

[28] *p*-values were corrected for multiple testing using the Benjamini-Hochberg method.

Regarding our initial prediction that young children would probability match in repeated choice from description, we observed that probability matching was the modal response for 3- and 4-year-olds in the low-dependency but not in the high-dependency condition. Indeed, most 3- and 4-year-olds diversified choices widely. Consistently with our results, other research investigating young children's probabilistic inferences from description, found that children under 5 years of age showed little consideration of stated proportions (Girotto et al., 2016). Moreover, fewer young children probability maximized than typically reported in experiential probability learning studies with children (e.g., Weir, 1964), and some 3- and 4-year-olds persisted with the minority-color. In light of previous findings from experiential repeated choice, persistence seems to decrease in description but does not disappear. Finally, we found that switching responses dominated 6- and 7-year-olds' choice behavior. This finding is in line with Denison et al. (2013) but contradicts other research based on non-symbolic probability judgments showing that children in this age group either chose based on the absolute number of objects (Falk et al., 2012) or, with increasing age, based on ratios (O'Grady & Xu, 2020)—however, this was not the case in our study as children repeatedly switched between options. In the present task, where outcome probabilities were known beforehand, and no trial-by-trial outcome feedback was provided (two features uncharacteristic of standard probability learning tasks), switching or alternation is a mistake. In many real-world situations, switching—including reward-sensitive strategies like win-stay lose-shift—may entail exploratory benefits and is commonly used by children in experiential paradigms (Berman et al., 1970; Bogartz, 1965; Bonawitz et al., 2014; Rabinowitz & Cantor, 1967). In fact, childhood has been suggested to be a developmental period during which the mind is particularly well prepared for wide exploration (Gopnik, 2020). Yet without feedback, explorative strategies are difficult to implement. It seems that knowing outcome probabilities beforehand helped children to diversify choices. Not receiving additional feedback, however, might have been counterproductive (e.g., see Rakow & Newell, 2010). An interesting avenue for future research is to disentangle the effect of trial-by-trial feedback and descriptive probabilistic information on the development of repeated choice behavior.

A central question that arises from the discrepancies between our results and previous studies is if the differences between methodologies were too large to replicate results. In contrast to Denison et al. (2013), children in our task were not prompted to think about a causal relationship between the randomly drawn object and another event. Instead, the task was framed as a guessing game. Thinking about causal relationships might help young children to make better (i.e., less random) predictions based on probabilistic information. There is evidence that causal explanations can impact probabilistic inferences in adults (e.g., Hayes et al., 2014, 2018). For children, however, it still needs to be determined whether thinking about a causal relationship or the requirement to explain a choice directly impacts probabilistic inferences. In any case, considering causal relationships alone cannot sufficiently explain the present results: Other studies investigating proportional reasoning that did not implement causal relationships in their task reported higher performance for children at a similar age (e.g., Falk et al., 2012; Ruggeri et al., 2018).

Furthermore, unlike Denison et al. (2013) and James and Koehler (2011), we offered monetary incentivization and rewarded children with stickers. The magnitude of a reward has been shown to improve performance in probability learning tasks in children and adults (Shanks et al., 2002; Stevenson & Hoving, 1964; Weir & Gruen, 1965). The monetary incentive in our study might have contributed to more adults maximizing than typically found in experiential probability learning tasks (Chapter 2; for a review, see Vulkan, 2002). The graphical representation of the frequency distribution as a mnemonic aid may have further strengthened this effect by acting as an additional individuating feature and prompting adults to make single "best guesses" rather than to think about the sequence as a whole. In this case, the question remains why this effect did not impact (older) children's choice behavior similarly. One possibility might be that children's smaller cognitive capacity and their tendency for wider exploration compared to adults prevented them from pursuing a more economically rational solution to the task (see Rakow et al., 2010). Likewise, deliberation has been found to increase adults' maximizing behavior in a similar task (Koehler & James, 2010). Indeed, when asked about their strategy, only three children between 6 and 7 years stated that they always chose the majority-color—adults more frequently reported a maximizing strategy.

Another methodological difference was that we used a computerized task instructed via video chat—unlike Denison and colleagues (2013), who used a face-to-face setting. While previous research has shown that online and offline testing methods in developmental research reproduce comparable developmental patterns, there seems to be a trend for children to perform slightly worse in online tasks (e.g., Chuey et al., 2021; Schidelko et al., 2021; Scott et al., 2017; Smith-Flores et al., 2021). A comparison between online and offline testing methodologies in an experiential probability learning task revealed that 3- to 4-year-olds perform worse in an online study toward the end of a lengthy task and use qualitatively different strategies (Chapter 4). Moreover, it has been demonstrated that preschoolers made more accurate predictions when learning from a physical compared to a computerized deck of cards (Nikiforidou, 2019). However, more research is needed on how specific features of an online instruction format may impact children's performance in inference tasks.

Although the online format might have made the task more difficult than offline testing, our task posed fewer demands than Denison et al. (2013) regarding numerosity, including only ten objects. In our task, the experimenter counted out loud the number of differently colored objects (seven to three). Yet, children could also only use the graphic representation of frequencies to make a prediction. Infants in their first year of life can already discriminate between quantities at smaller ratios than those used in the present study (see Cantlon et al., 2009). There are several reasons to believe that children in the present study understood the frequencies and general instructions. First, children answered most of the comprehension checks correctly about which color was more frequent. Second, participants did not choose their favorite color more often than other colors—an artifact suggested to impact young children's probability learning and choices (e.g., Goldberg, 1966). Third, children did not show negative effects of attention (i.e., decreased majority-color choices in later trials). Despite demonstrating a general understanding of the instructions, the task was possibly more difficult for children than adults. This may have enhanced developmental differences observed in previous experiential repeated choice tasks (see Chapters 2–4): highly variable choice behavior in younger children, more goal-directed diversification in older children, and the ability to overcome diversification to achieve maximum rewards in adults.

5.5 Conclusion

We created synergies across different research streams in cognitive development and adult decision-making to examine how children use probabilistic information when making repeated choices. Whereas we did not find evidence for the sampling hypothesis in children's repeated choices from description, our findings indicate the importance of considering the learning format in a developmental context. Compared to previous findings from experiential probability learning, description may have amplified developmental differences: Young children were highly variable in their choice behavior, whereas older children largely diversified choices. Diversification did not yield higher reward rates than persistently choosing the majority-color reward in this task but may serve the exploration of choice options in other task structures inspired by real-world characteristics. In sum, our findings contribute to increasing evidence of childhood as a phase for heightened exploration and integrate into a series of studies showing that children's probabilistic inferences are highly context-dependent and often difficult to reproduce.

5.6 References

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6 | General Discussion

This dissertation examined the development of probability learning and repeated choice behavior in childhood, proposing that an interaction between the developing mind and the environment shapes this process. In the following sections, I will briefly summarize key findings and discuss implications, limitations, and possible future work in light of the previous literature.

6.1 Summary of Key Findings

Chapter 2 investigated how children adapt to an ecologically plausible statistical structure in probability learning and, more specifically, if children rely on probability matching as an ecologically rational strategy. Results showed increasing choice diversification, like probability matching, and emerging adaptivity from school-age onwards. In the ecologically plausible condition, characterized by choice–outcome dependencies, older children resembled adults more in their choice behavior than younger children. Computational modeling revealed that children were more likely to rely on a win-stay lose-shift heuristic that is reactive to environmental changes but showed poorer strategy fine-tuning to the environment. Indeed, there was evidence that older children seemed to be constrained by their tendency to explore and, thus, failed to diversify less when this would have yielded higher reward rates. In contrast, on an aggregate level, younger children from 3–4 years were more likely to persist with one option, irrespective of whether this option maximized reward. Regarding individual choice behavior, younger children showed the greatest between-person variability in choice behavior, including maximizing, matching, random choice, and minimizing. Integrating results in the age group from 3–4 years, findings suggest that younger children maximize as a satisficing strategy that requires low implementation effort. In sum, Chapter 2 points to a phase of high persistence but also high inter-individual variability in younger children, increased diversification and environmental sensitivity in older children, and the ability to adaptively balance diversification and exploitation in adults.

But how valid are cross-sectional findings as a proxy for intra-individual development, and what is the role of executive functions? These questions were examined in Chapter 3 in a longitudinal study spanning the age range from 3.5 to 6.5 years. Results showed that probability matching and, more broadly, choice diversification considerably increased longitudinally (validating results from Chapter 2). Moreover, higher working memory capacity in older children was related choice diversification. In other words, there was a high-capacity advantage for diversification and a low-capacity advantage for making high-probability choices. This somewhat counterintuitive finding may indicate that other processes (e.g., expectations, beliefs, or pattern search) shape the development of probability learning in concert with cognitive development. Probability maximizing, in contrast, proved to be more affected by age differences between children in the cohort than by increasing longitudinal age: Younger children were more likely to maximize than older children across measurement waves. Moreover, there was greater variability in the choice behavior of younger than older children (also see Chapters 2 and 5). As a result of decreasing between-person variability, children became more likely to make favorable high-probability choices over the two-year study. Taken together, Chapter 3 disentangled intra- and inter-individual change in probability learning from early to middle childhood and emphasizes the importance of longitudinal designs in developmental research.

Although Chapters 2 and 3 replicate similar performance levels and choice behavior for school-aged children when tested offline in-person and online via video chat, this was not the case for younger children. Inspired by a recent increase in online data collection methods in developmental research, Chapter 4 examined how the testing modality may impact young children's performance and strategy use in a probability learning task between 3–4 years. Findings suggest that younger children tested online via video chat decrease in their performance over longer experimental procedures. Moreover, computational modeling analyses revealed that children in the online sample relied on a heuristic strategy, whereas an associative learning strategy better described children in the offline sample. These findings hold implications for research on both probability learning and, more broadly, cognitive development: First, the complexity associated with a probability learning task may elicit differences in strategy use in early childhood. Second, the testing modality needs to be explicitly addressed when generalizing studies in early childhood conducted online and offline.

Whereas the first three chapters approached the development of repeated choices using a learning-from-experience format, Chapter 5 investigated how children between 3 and 7 years compared to adults make repeated choices when probabilistic information is learned from description before making a choice. This study aimed to connect two research streams that had mainly operated in parallel before: probabilistic inference in childhood and repeated risky choice. Results showed that the youngest children performed at chance level and, again, showed the greatest variability in choice behavior. Children aged 6–7 years performed above chance level but showed a high degree of switching behavior. Adults, in contrast, were mainly maximizing probability, although some continued to probability match under description. Taken together, these findings indicate that high inter-individual variability and exploratory tendencies are characteristic of younger and older children's choices, respectively, and emphasize the importance of considering contextual factors in investigating the development of repeated choice, such as the learning format and trial-wise feedback.

6.2 Implications, Limitations, and Future Directions

In the following sections, I will discuss how the results comprised in this dissertation advance the understanding of developmental processes in probability learning and repeated choice, which limitations need to be considered, and what potential directions for future work arise.

6.2.1 The Development of Ecological Rationality in Probability Learning and Repeated Choices

In real-world environments, desired outcomes are only rarely generated by a mechanism that fulfills the assumptions of independent and identically distributed random variables (e.g., weather systems build up slowly, resources decay, etc.). Under these conditions, persistently choosing the option with the initially highest probability does not yield maximum rewards. Previous research with adult participants demonstrated that choice diversification, like probability matching, can reflect an adaptive mechanism in dynamic or patterned environments and suggested that people sometimes misapply strategies learned from everyday life (e.g., Gaissmaier & Schooler, 2008; Green et al., 2010; Schulze et al., 2017). But how much life experience is needed to adaptively probability match? The empirical work in this dissertation addressed this gap in the literature. Chapters 2 and 3 demonstrate that probability matching, among other choice behaviors, is already present early in life. However, despite 3- to 4-year-olds showed some sensitivity to the environmental structure (e.g., recruiting qualitatively different strategies in different environments), they did not attain older children's abilities in adapting to sequential dependencies (Chapter 2). From school age onward, children mostly diversified their choices in an adaptive manner close to probability matching (Chapter 2). Moreover, longitudinal results emphasize that probability matching and choice diversification become particularly prevalent in middle childhood and may be related to increasing working memory capacity (Chapter 3). Thus, adaptive probability matching rests on both developing cognitive functions and increasing experience with real-world environments in middle childhood. These findings suggest that children capitalize on the structure of the environment by diversifying choices, which may hold adaptive benefits across numerous dynamically changing environments. In sum, this dissertation contributes to the increasing body of work arguing for an adaptive view on probability matching (e.g., Gaissmaier & Schooler, 2008; Green et al., 2010; Schulze et al., 2017). Nonetheless, the evidence presented in this dissertation also suggests that older children may be particularly prone to misapply probability matching to laboratory environments where it does not yield maximum rewards.

The question of how children become ecologically rational decision-makers is highly complex. As children grow older, they improve cognitive capacities and gain increasing experience in everyday life, for instance, with statistical structures or causal mechanisms (see Figure 1.1). Experience is a cornerstone of plasticity and influences the development of the brain and cognition (e.g., Frankenhuis & Walasek, 2020; Greenough et al., 1987; Oakes, 2017). This dissertation carves out three intertwined questions to better understand the development of ecological rationality in the future: First, what are (statistical) characteristics prevalent in everyday life, across the lifespan, or specific to different age groups? Second, what cognitive developments facilitate the development of learning and choice strategies adapted to these characteristics? Third, how does experience with these characteristics shape children's knowledge, beliefs, and expectations contributing to adaptive choice behaviors and strategies?

There are several approaches to how researchers could address the first question: for instance, analyzing time-series datasets across a variety of domains that may capture statistical commonalities experienced across the lifespan irrespective of age (for examples of ecological analyses, see Lejarraga & Lejarraga, 2023; Pleskac & Hertwig, 2014), or coding events from video recordings of children in their natural settings for age-specific data (e.g., helmet cameras; Barbaro, 2022; Smith et al., 2018). Recording and coding real-life situations could provide detailed information, for instance, whether choices are made alone or in social situations (for social feedback in developmental probability learning, see Lewis et al., 1963; Stevenson & Odom, 1964), or if children can learn from causal mechanisms that underlie outcomes. Such ecological analyses may inform myriad investigations across different fields of research. Indeed, the role of natural environments in shaping cognition and learning across the lifespan has been recently emphasized by several scholars also outside of the domain of ecologically rational judgment and decision-making (e.g., Adolph, 2019; Hartley, 2022; Ruggeri, 2022).

Turning to the second question, asking which cognitive developments facilitate adaptivity to environmental characteristics, it is vital to acknowledge that multiple processes interact with each other: from improvements in (selective) attention (e.g., Betsch & Lang, 2013; Mata et al., 2011; Plebanek & Sloutsky, 2019) to general processing speed (e.g., Fry & Hale, 2000; Kail, 2016). Findings from the longitudinal investigation in Chapter 3 provide preliminary evidence for the contribution of increasing working memory capacity (which may be related to general processing speed in children, Fry & Hale, 2000). Under the assumption that choice diversification is beneficial in many real-world environments, marked by autocorrelation or sequential dependencies, increasing working memory capacity may enable children to store and manipulate more information about past outcomes. As children became older in the longitudinal study, higher working memory capacity was associated with a decreased likelihood of choosing the high-probability option (i.e., which implies diversification). This finding is consistent with the hypothesis that adults and children with higher memory capacity or general reasoning abilities make less maximizing responses because they search for patterns in the outcome sequence (Gaissmaier et al., 2006; Goldman & Denny, 1963). Likewise, adolescents have been reported to detect patterns in an outcome sequence more quickly than children (Crandall et al., 1961). For adults, it has been suggested that trial-wise outcome feedback determines the direction of the relationship between memory and maximizing: Without outcome feedback, adults with higher memory capacity make more maximizing responses (Rakow et al., 2010). Although it seems plausible to assume, based on the current evidence, that memory capacity or general reasoning abilities influence the relationship between outcome feedback and pattern search, such investigations still need to be conducted for children. In any case, such analyses need to consider that cognitive development changes how children learn from feedback; for instance, how they process positive or negative feedback (e.g., Nussenbaum et al., 2022; van den Bos et al., 2009) or if they learn equally well from experienced or counterfactual information (e.g., Kominsky et al., 2021; Palminteri et al., 2017).

Concerning the third question—following the proposition that even young children generate, sometimes misleading, expectations about probabilistic structures in laboratory tasks (Tolman & Brunswik, 1935)—ecological analyses could provide new insights into what (ecologically plausible) beliefs underlie and shape children's choice behavior. For instance, older children are thought to enter an experimental task assuming that a perfect solution exists (Baltes, 1987; Stevenson & Weir, 1963; Weir, 1962). Similarly, children may generate expectations about statistical structures or causal mechanisms. Some expectations may even persist when all probabilistic information is provided before making a choice (see Chapter 5). However, it has not yet been investigated in repeated choice tasks if knowledge of causal mechanisms or causal explanations help children to make adaptive choices and to exploit environmental characteristics already earlier in life. Young children's striking probabilistic reasoning abilities in causal learning tasks may support this assumption (Gopnik et al., 2015; Kushnir & Gopnik, 2007; Tenenbaum et al., 2011), whereas the protracted development of model-based reinforcement learning may not speak in favor of a positive effect (Bolenz et al., 2017; Cohen et al., 2020).

6.2.2 Adaptive Benefits of Cognitive Immaturity

The results comprised in this dissertation contribute to a growing body of research highlighting evolved adaptive benefits of childhood and the cognitive constraints under which children operate (e.g., Bjorklund & Green, 1992; Gopnik, 2020; Gopnik et al., 2017; Gualtieri & Finn, 2022; Liquin & Gopnik, 2022; Ruggeri, 2022). From this perspective, plasticity in childhood serves the goal of wide exploration and learning, whereas adult-like cognition favors exploitation (Gopnik, 2020). Cross-sectional (Chapters 2 and 5) and longitudinal evidence (Chapter 3) illustrate 6- to 11-year-olds' propensity to diversify choices, which may be viewed as an indicator of exploration. When persistence yields maximum rewards, this tendency seems to prevent children from reaching adult-like performance levels.

Even when a probability learning task provides full feedback, switching between options is crucial to test hypotheses about how choices may influence sequential outcomes or if a pattern exists. Children are thought to have more lenient stopping rules than adults when collecting evidence for a hypothesis (Ruggeri et al., 2016) and to explore more than beneficial for reward maximization (Meder et al., 2021). This tendency may come at the cost of lower efficiency in information search but may facilitate detecting regularities in environmental structures (Liquin & Gopnik, 2022). In the present research (Chapter 2), only two 7-year-olds adopted the optimal strategy to exploit sequential dependencies in an ecologically plausible environment. School-aged children, in general, collected retained rewards more quickly than adults or younger children. These findings highlight the role of ecologically plausible task structures in research on the development of adaptive exploration in childhood (also see Nelson et al., 2014). Children may not necessarily explore more than beneficial for reward maximization in all environments, but only when diversification and exploitation oppose each other (for instance, as in standard probability learning tasks). Disentangling children's exploration and exploitation in a probability learning task could illuminate these processes in future research (e.g., in observe-or-bet-tasks; Rakow et al., 2010; Tversky & Edwards, 1966).

Having discussed diversification as an adaptive tendency in childhood, there may also be an adaptive side to persistence in younger children. Response repetition may positively strengthen synaptic connections and facilitate learning of fundamental skills in early childhood (for a similar argument on unrealistic over-optimism in early childhood, see Bjorklund & Green, 1992). For instance, throwing a ball over and over again may improve motor skills, whereas repeating the same word many times may promote word learning and speech production. The protracted development of response inhibition in childhood may facilitate such processes (for a review on response inhibition in preschoolers, see Garon et al., 2008). Analyses in Chapter 3 did not find evidence for a relationship between persistent choice and a child-friendly response inhibition task. On the one hand, a more extensive test battery may be better suited to detect an effect. On the other hand, results from Chapter 2 demonstrated that persistence with one option increased over the length of the task, which cannot be explained by poorer response inhibition alone and points to an interaction with other processes.

Lastly, although young children's persistence may benefit some domains of development, the present research provides credible evidence that it does not represent a superior ability in using probabilistic information (Chapters 2–5). However, this claim has been made in the past to illustrate cases where young children are more proficient in using probabilistic information than older children or adults (Gualtieri & Finn, 2022). The results comprised in this dissertation emphasize the viewpoint that not all maximizing, or matching for that matter, reliably reflect a superior ability and that contextual factors must be appropriately considered.

6.2.3 Probability Maximizing and the U-Shaped Function of Probability Learning in Childhood

Recall that previous work on the development of probability learning in childhood painted a somewhat inconclusive picture of underlying developmental trajectories. The empirical research in this dissertation sheds light on some of these inconsistencies.

On the level of individual choice behavior, several researchers suggested that children younger than 5 years are more likely to probability maximize than older children and reported that more than half of the children in their sample demonstrated this behavior (Derks & Paclisanu, 1967; Goldman & Denny, 1963; M. H. Jones & Liverant, 1960; Weir, 1964). Older children, in contrast, have been reported to be more likely to probability match (Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960). Based on these findings, some researchers suggested a U-shaped relationship between high-probability choices and age: Younger children and young adults are thought to be more likely to make high-probability choices. Evidence for this U-shaped function was contested in several other studies (Goldman & Denny, 1963; Lewis, 1966; Messick & Solley, 1957; Offenbach, 1964), but the proposition that younger children outperform older children in probability learning tasks continues to attract interest across research disciplines (e.g., Gualtieri & Finn, 2022; Nussenbaum & Hartley, 2019; Thompson-Schill et al., 2009).

Notably, findings central to this argument have not been replicated since the first wave of probability learning research in the 1960s.

What does the present research contribute to this matter? A large consistency between the present research and earlier work is that children increasingly diversify choices as they get older (see Chapters 2–3). Moreover, the present research strengthens the view that young children do not pursue probability maximizing as a deliberate reward maximizing strategy (e.g., M. H. Jones & Liverant, 1960; S. J. Jones, 1970). Chapter 2 demonstrates that some 3- to 4-year-olds persistently chose one probability option irrespective of whether this option maximizes reward, and the longitudinal analysis (Chapter 3) revealed little stability in reward maximizing behavior. Lastly, Chapter 5 showed that children rarely maximized probability in a risky choice task even though no memory demands were associated with pursuing this behavior. Instead, Chapter 5 emphasizes that between-person variability and persistence characterize young children's choice behavior and suggests that experiential learning formats may help them to direct their persistence to the high-probability option. Taken together, these findings support previous work with adults showing that probability maximizing can serve as a satisficing strategy, requiring only little implementation effort (Saldana et al., 2022; Schulze et al., 2020; Schulze & Newell, 2016).

Remarkably, the proportions of maximizing children reported in earlier work are at least two times larger than the proportion of maximizing children in the current experiments. In Chapters 2 and 3, which implemented a probability learning task with two options and static probabilities (70% vs. 30%), only 21–23% of 3- to 4-year-old children probability maximized, and yet fewer older children or adults. This difference in the starting point would have made it very difficult to recover a U-shaped function between high-probability choices and age. Several aspects need to be considered when directly comparing these results to previous research. For instance, in some earlier studies, children seemingly had already participated in similar experiments using the same paradigm (Weir, 1964), and explanations of how children who did not (want to) complete the task were handled are largely missing (see Derks & Paclisanu, 1967; M. H. Jones & Liverant, 1960; Weir, 1964). However, based on more recent evidence (see Chapters 2–5; Plate et al., 2018; Starling et al., 2018), it seems unlikely that there was, indeed, not a single child who quit the task prematurely. Thus, it is possible that previous research obtained somewhat biased samples. Moreover, to my knowledge, all developmental probability learning studies conducted in the 20th century relied on physical task setups (e.g., token machines, light bulbs, deck of cards, containers concealing items), whereas the more recent work used digital games on a computer (Plate et al., 2018) or tablet (see Chapters 2–4; Starling et al., 2018). Performance decline and strategy differences demonstrated by young children tested online (see Chapter 4) indicate that such methodological differences should not be taken lightly.

Furthermore, the time difference between the early stages of probability learning research and the current work may reflect a blink of an eye regarding evolutionary history but deserves consideration concerning cohort differences. Evidence from the longitudinal study (Chapter 3) suggests that cohort differences might play a role in discrepant proportions of probability maximizing children. Children did not decrease their likelihood to maximize probability as they grew older over repeated measurements. Instead, younger children in the sample were more likely to maximize than older children, highlighting that differences arise from between-person and not within-person age variability. However, did young children in the 1960s possess the same cognitive capacities as children today? Research on changes in general reasoning abilities of children and adults over the past century suggests that this may not be the case (i.e., the Flynn effect; Lynn, 2009; Pietschnig & Voracek, 2015). Several environmental factors, like improved pre- and post-natal nutrition or education in families and the schooling system (e.g., Bratsberg & Rogeberg, 2018; Lynn, 2009; Pietschnig & Voracek, 2015), may contribute to cohort differences in young children's probabilistic reasoning abilities and choice behavior.

In sum, it can be said with some confidence that in digital probability learning tasks, the proportion of young children maximizing probability falls short of the proportion reported from tasks involving physical objects conducted in the 1960s. However, only an exact replication could verify sampling biases, an effect of physical or digital tasks, and underlying cohort differences. Until such analyses are conducted, the evidence gathered in this dissertation suggests that a unifying interpretation of the previous and more recent literature is that younger children show a higher degree of persistence, whereas older children show a higher degree of diversification, transitioning in the preschool period.

6.2.4 Risky Choice and Probabilistic Inference in Childhood

Probability matching and maximizing have not only been studied in experiential probability learning tasks but also in probabilistic causal learning paradigms with children (Denison et al., 2013) and descriptive risky choice paradigms with adults (e.g., James & Koehler, 2011; Koehler & James, 2010; Newell & Rakow, 2007; Schulze & Newell, 2016; West & Stanovich, 2003). Chapter 5 connected these lines of research to investigate how repeated risky choice develops in early childhood when probabilistic information is known before making a choice. Whereas more adults probability maximized than in previous experiential tasks (see Chapter 2), this was not the case for children. Surprisingly, although a mnemonic aid was provided at the time of the choice, children continued to diversify their choices widely. Compared to experiential probability learning tasks (see Chapter 2), it seems that the descriptive version enhanced developmental differences: Across learning formats, young children's choices are best characterized by high persistence but also high inter-individual variability (Chapters 2–5). School-aged children are best described by a high degree of choice diversification across tasks (Chapters 2, 3, and 5). However, without outcome feedback in description, children rarely matched probabilities (on an individual or aggregate level; Chapter 5). Adults differed from children with respect to overcoming diversifying tendencies in favor of maximization across tasks, which was most evident in description (although adults also continued to probability match in description; Chapters 2 and 5; see also Koehler & James, 2010; Newell & Rakow, 2007). Taken together, these results suggest that experiential probability learning tasks help children to make the best out of their underlying task-irrespective repeated choice tendencies. The descriptive risky choice task, in contrast, seemed to have been more difficult for children, resulting in poorer choices.

The descriptive risky choice (Chapter 5) and experiential probability learning tasks (Chapters 2–4) differ in two important aspects that may contribute to these differences: the learning format (description vs. experience) and whether outcome feedback was provided after every choice. Both of these aspects are known to impact adults' repeated choice behavior (Newell et al., 2013; Newell & Rakow, 2007; Rakow et al., 2010), but systematic investigations for children are rare (but see, Rakow & Rahim, 2010; Rolison et al., 2022). Disentangling these two features in future research will improve our understanding of the description–experience gap of risky choices in early childhood (see also Schulze & Hertwig, 2021). For instance, does additional feedback improve children's repeated choices in description (see also Schulze & Hertwig, 2022)? How do children balance exploration and exploitation when these processes are separated (see also Rakow et al., 2010; Tversky & Edwards, 1966)?

In any case, the current findings not only hold implications for research on decision making but also for research on the development of probabilistic inferences in early childhood. Unexpectedly, Chapter 5 was unable to capture previously reported striking abilities of young children to make probabilistic inferences based on proportions (for reviews, see Denison & Xu, 2019; Schulze & Hertwig, 2021). Nonetheless, this was not the first study that failed to demonstrate substantial probabilistic reasoning skills for 3- and 4-year-old children (e.g., Girotto et al., 2016). Schulze and Hertwig (2021, 2022) argue that the degree of experience in learning probabilistic information might contribute to discrepant findings. Moreover, younger children seem to learn better the more tangible task and instructions are: for instance, using physical objects instead of digital ones (see also the video deficit in learning; Kirkorian, 2023; Strouse & Samson, 2021) or instructing in person as compared to online (see Chapter 4). These contextual factors may shape and direct children's attention toward specific aspects of the task. Thus, a possible way forward in reconciling differences between studies on probabilistic intuitions in early childhood and repeated choice may be to combine eye-tracking, measuring attention, and behavioral choice data to investigate how young children attend to information. Research with adult participants has demonstrated that attention affects probability weighting and preference formation in risky choice (Zilker & Pachur, 2022). Studies examining probabilistic intuitions in early childhood often only collect data from a few trials per child (see Denison & Xu, 2019). Under these conditions, computational modeling techniques, otherwise applicable to gain insight into underlying cognitive processes, are often not feasible. Adding eye-tracking[29] to repeated risky choice or probability learning paradigms in childhood that include many trials could, thus, provide new insights into how task features influence cognitive processes and may further illuminate random and directed exploration (see Fan et al., 2023; Kozunova

[29] Looking times are commonly used as a dependent variable in infant research on probabilistic intuitions (for a review, see Denison & Xu, 2019). However, using computational modeling approaches, eye-tracking may provide information about underlying cognitive processes beyond indicating surprise about the occurrence of an unlikely event.

et al., 2022). The computational modeling approach implemented in this dissertation provides some general insights into the feasibility of such techniques in studying early childhood decision-making.

6.2.5 Merits and Pitfalls of Modeling Children's Choices

Computational modeling analyses can illuminate the underlying mechanism of children's choices. However, such analysis approaches have only been used more recently with preschool children (e.g., Blanco & Sloutsky, 2020; Meder et al., 2021). Strategy classification based on model comparison in Chapter 2 revealed that children from 3 to 11 years show a similar ordinal pattern in strategy use, contingent on the structure of the environment. In the presence of sequential dependencies, children often relied on a probabilistic win-stay lose-shift heuristic, capitalizing on environmental changes. However, whereas children adopted qualitatively different strategies in different environments, adults had an advantage in fine-tuning strategies. Older children seemed to be constrained by their tendency to explore. These findings draw parallels to previous research on the development of search and decision making strategies. For instance, computational modeling analyses revealed that children explore less randomly and more systematically with increasing age (Blanco & Sloutsky, 2020; Meder et al., 2021). Likewise, children's efficiency in searching and integrating probabilistic information only slowly improves with age (Betsch et al., 2016, 2021; Lindow & Betsch, 2019; Mata et al., 2011). In sum, these findings are consistent with the proposition that developmental processes "cool off" in favor of more adaptive behavior with increasing age (Giron et al., 2022; Gopnik et al., 2017).

Generally, the empirical work in this dissertation demonstrated the feasibility of computational modeling approaches with preschool children. Nevertheless, it also became evident that the variability in young children's choice behavior can be a risk to modeling techniques and potentially yield parameter estimates outside of a meaningfully interpretable space. Because some models may not adequately capture the underlying choice process, parameter analyses in the present work were conducted only for those participants and respective models that provided the best fit. This has the advantage that parameters may capture less noise (e.g., parameters may otherwise absorb processes that are not explicitly specified in the model) but comes at the cost of introducing possible bias due to error or uncertainty in the model comparison process. A different approach that may be promising is latent-mixture modeling which allows inferring category membership (strategy use) while providing an estimate of how accurately a person follows a strategy (e.g., Bröder & Schiffer, 2003; Steingroever et al., 2019).

Future research will need to address such considerations, particularly when investigating model-specific developmental trajectories. For instance, the longitudinal study (Chapter 2) may provide a suitable dataset to study intra-individual trajectories of reinforcement learning processes in preschool children. Such analyses mark a clear gap in the current developmental reinforcement learning literature. Many questions remain unanswered about how value-guided learning processes develop in early childhood (see Nussenbaum & Hartley, 2019).

6.2.6 Methodological and Policy Implications

The empirical work in this dissertation highlights several methodological and policy implications. First, children's ability to capitalize on the structure of the environment seems to hinge on the ecological plausibility of the study design (see also Dhami et al., 2004). Like the description–experience differentiation, ecological plausibility is not black or white. It may be better described as a continuum and is contingent on age-related changes in choice ecologies. Increasing the degree of ecological plausibility can happen in various ways: for instance, by implementing ecologically valid statistical structures (Chapter 2; Green et al., 2010; Pleskac & Hertwig, 2014; Schulze et al., 2017), using ecological stimuli (Young et al., 2022), or choosing a learning format that is representative of typical age-related choice ecologies (for younger children, this will typically include some form of experience; see also Schulze & Hertwig, 2021). Such considerations may prove beneficial from a policy perspective in designing effective education targeting children's more formal acquisition of probabilities or in communicating risks to young citizens (e.g., traffic, unhealthy nutrition).

Second, offline and online data collection with young children are not equivalent (see Chapter 4), and generalizations across testing modalities need to be made cautiously. Not all research questions and study designs may be equally suitable to be implemented as an online experiment when children aged 4 years and below are the target sample. Potentially detrimental effects of online testing decrease from early to middle childhood. However, knowing that online and offline studies may potentially lead to discrepant results should not be viewed as a threat to online developmental research but as a chance to improve study designs and methodologies. This may not only provide new insights into cognitive development but also help to address replicability issues in developmental psychology (see Davis-Kean & Ellis, 2019; Youyou et al., 2023).

Third, children are a particularly vulnerable group in risky choice scenarios in the real world that may hold perilous outcomes. For instance, in the world of online or smartphone gaming, so-called loot boxes have become increasingly prevalent even in games marked as age appropriate for children (Zendle et al., 2020). Loot boxes probabilistically contain desired game items (e.g., highly desirable items occur with a low probability) and can be bought with real money or time played (Zendle et al., 2020). Children's exploratory tendencies and still developing abstract probabilistic reasoning skills may make them particularly susceptible to such implementations (effectively representing a gamble). This danger has been recognized by policymakers, for instance, in the European Parliament (see Cerulli-Harms et al., 2020). However, the present research shows that the policy proposition to explicitly inform about the underlying probabilities in order to reduce the harm of entering repeated gambles may be rather ineffective for children (Cerulli-Harms et al., 2020).

6.3 Conclusion

Learning to make sound choices becomes more and more important as children grow up and gain increasing independence. How do children become adaptive decision makers, capable of navigating myriad uncertain real-world environments? In this dissertation, I examined the inter- and intra-individual development of probability learning and repeated choice behavior in childhood, considering ecological, cognitive, and methodological aspects. Evidence from three cross-sectional and one longitudinal empirical investigation suggests that the interaction between developing cognitive capacities, growing first-hand experience with real-world environments, and characteristics of the task environment shape adaptive choice behavior in childhood. The current work proposes that probability learning and repeated choice behavior progress from high persistence but also high inter-individual variability in early childhood to emerging adaptivity characterized by diversification and exploration in middle and late childhood. In conclusion, this dissertation highlights the benefit of taking an ecological rationality perspective in studying the development of decision making abilities and emphasizes the importance of ecologically plausible study designs in revealing the young mind's ability to capitalize on the structure of the environment.

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Appendices

A | Supplemental Material for Chapter 1

General Introduction

Table A1

Overview of Experience-Based Probability Learning Studies (With Sequential Feedback) Reporting Proportions of Individual-Level Probability Matchers: Adults

Reference	N sample	*p*-levels	Chance device	Last n trials (total)	Task characteristics	Criterion probability matching	% PM
Derks, 1962	10	$p_1 = .75$ $p_2 = .25$	Light bulbs	100 (250)	Standard task, no incentive	p_1 +/- computed deviation	40%
"	"	"	"	"	15 sec outcome delay	"	50%
"	"	"	"	"	15 sec inter-trial interval	"	50%
"	"	"	"	"	limited response latency: ~0.2 sec; excluded if required > 0.5 sec on 25% of trials	"	90%
"	"	"	"	"	win .05 USD if correct	"	30%
"	"	"	"	"	win .05 USD if correct, loss of 0.05 USD if wrong	"	30%
"	"	"	"	"	partial feedback	"	50%
"	"	"	"	"	partial feedback + win .05 USD if correct, loss of .05 USD if wrong	"	10%
"	"	"	"	100 (1000)	Standard task, no incentive	"	30%
Gaissmaier et al., 2016	92	$p_1 = .67$ $p_2 = .33$	Slot machine (virtual)	96 (288)	habitual gamblers; 0.10 USD if correct + 4 random participants received actual cash payout	p_1 +/- 5%	31.9%
"	72	"	"	"	0.10 USD if correct + 4 random participants received actual cash payout	"	15.7%
Saldana et al., 2022	20	$p_1 = .70$ $p_2 = .30$	Digital task (shapes)	60 (240)	correct: 0.02 USD; incorrect: 0 USD	p_1 +/- binomial 95% CI [0.568, 0.812]	20-30%
"	39	"	"	60 (480)	"	"	31-33%
"	19	"	"	60 (240)	always 0.01 USD (if correct right away, if incorrect: feedback + correction)	"	21-32%
Schulze, et al. 2015	25	"	Light bulbs (virtual)	50 (500)	.04 AUD if correct; outcome information remained available for 10 trials;	p_1 +/- 5%	8%
"	"	"	"	"	.04 AUD if correct; outcome information remained available for 10 trials; competing against opponent	"	20%
Schulze et al., 2016a	"	"	Digital task (shapes)	100 (500)	2 cents if correct; varied color-key mapping + WM load	"	28%

Note. p-levels = outcome probabilities of options; last n trials = trials based on which probability matching was computed; CI = confidence interval; PM = probability matching.

Table A2

Overview of Descriptive Repeated Choice Studies Reporting Proportions of Individual-Level Probability Matchers: Adults

Reference	N sample	*p*-levels	Chance device	N trials	Feedback	Task characteristics	Criterion probability matching	% PM
James & Koehler, 2010	84	$p_1 = .70$ $p_2 = .30$	10-sided-die	10	No	1 CAD if correct; 10 bets on same device	matching exact frequency of p_1	26%
James & Koehler, 2011	66	"	Fun fair games (described)	"	"	low dependency: unique games (bingo, wheel of fortune, etc.); hypothetical 1$ if correct	"	3%
"	61	"	"	"	"	high dependency: repeated games (e.g., bingo, wheel of fortune, etc.); hypothetical 1$ if correct	"	38%
"	38	"	10-sided-die (described)	"	"	low dependency: unique die in every game	"	3%
"	89	"	"	"	"	high dependency: same die across games	"	18%
"	41	"	"	"	"	global-focus: "In 10 rolls of the die, how many times would you expect each outcome?" prior to game; 1$ per correct guess	"	61%
"	42	"	"	"	"	local-focus: "On any individual roll of the die, which color is more likely to be rolled?" prior to game; 1$ per correct guess	"	38%
Koehler & James, 2009	102	$p_1 = .75$ $p_2 = .25$	marbles (virtual)	20	"	proportion reported across 4 conditions (learning: sequential x aggregate; test: sequential x. aggregate); $0.50 if correct	matching subjective p_1 probability	45%
"	121	"	"	"	"	replication across the same four conditions: complete information hypothetical $0.50 if correct	"	38%
"	30	"	"	"	"	aggregate-aggregate condition, i.e., described proportions and all choices at once	"	80%
Schulze & Newell, 2016b	60	$p_1 = .70$ $p_2 = .30$	10-sided die (virtual)	50	Yes	0.2 EUR per correct choice, sequential choice	p_1 +/- 5%	10%
"	"	"	"	"	No	0.10 AUD per correct choice; allocating all choices at once	"	35%
West & Stanovich, 2003	397	"	deck of cards (described)	10	"	hypothetical $100 if correct	matching exact frequency of p_1	66%

Note. p-levels = outcome probabilities of options; last n trials = trials based on which probability matching was computed; CI = confidence interval; PM = probability matching.

Table A3

Overview of Experience-Based Studies Reporting Individual-Level Matching and Maximizing: Children

Reference	Age groups (in years)	N	Paradigm	*p-levels*	N trials	Reward	Criteria for matching + maximizing	% Match	% Max
Derks & Paclisanu, 1967	3–4	29	Hand with toy	$p_1 = .75$ $p_2 = .25$	200	M&M candy if correct	Probability matching: 66% to 84% high-option choices per 100 trials	Trial 0–100: 38% Trial 101–20: 10%	-
“	5–6	29	Light bulbs	“	“	“	“	Trial 0–100: 10% Trial 101–20: 10%	-
“	6–7	20	“	“	“	“	“	Trial 0–100: 35% Trial 101–20: 25%	-
“	7–8	“	“	“	“	“	“	Trial 0–100: 35% Trial 101–20: 40%	-
“	8–10	“	“	“	“	“	“	Trial 0–100: 40% Trial 101–20: 50%	-
“	10–12	“	“	“	“	“	“	Trial 0–100: 60% Trial 101–20: 65%	-
“	12–13	“	“	“	“	“	“	Trial 0–100: 55% Trial 101–20: 65%	-
“	18–25	“	“	“	“	“	“	Trial 0–100: 45% Trial 101–20: 65%	-
Goldman & Denny, 1963	5–6	26	“	“	150	Toy; 2 USD for best performer	Fixating: choosing either high-option or low-option on 96% of last 50 trials	-	50%
“	7–8	34	“	“	“	“	“	-	15%
“	9–10	17	“	“	“	“	“	-	12%
“	11-12	25	“	“	“	“	“	-	4%
“	14-15	20	“	“	“	1 penny for 5 correct; 2 USD for best performer	“	-	5%

Reference	Age groups (in years)	N	Paradigm	*p-levels*	N trials	Reward	Criteria for matching + maximizing	% Match	% Max
Jones & Liverant, 1960	4–6	"	Token delivery machine	$p_1 = .70$ $p_2 = .30$	100	Candy	Maximizing: 9–10 high-option choices (last 10 trials); matching: 6–8 high-option choices (last 10 trials)	20%	65%
"	9–11	"	"	"	"	1 penny for every 5 correct	"	70%	25%
"	4–6	"	"	$p_1 = .90$ $p_2 = .10$	"	Candy	"	20%	70%
"	9–11	"	"	"	"	1 penny for every 5 to-kens	"	50%	45%
Plate et al., 2018	M = 7.7 SD = 1.99	31	Computer game: 8 rocks hiding coins	$p_1 = .70$ $p_2 = .10$ $p_3 = .10$ $p_4 = .05$ $p_5 = .05$ $p_6 = .00$ $p_7 = .00$ $p_8 = .00$	200	Prize + 20 dollars	Model comparison: pure probability match-ing or model that transitions from matching to maximizing	26%	74%
"	M = 20.5, SD = 1.7	32	"	"	"	20 dollars or course credit	"	19%	81%
"	M = 7.9 SD = 1.9	32	"	"	"	Prize + 20 dollars	"	69%	31%
"	M = 20.6, SD = 1.9	33	"	"	"	20 dollars or course credit	"	45%	55%
Stevenson & Weir, 1959	3	10	Token delivery machine	$p_1 = 1.0$ $p_2 = .00$ $p_3 = .00$	80	Two toys	Maximizing: exclusively choosing the high-option on last 20 trials	-	100%
"	5	"	"	"	"	"	"	-	80%
"	7	"	"	"	"	"	"	-	80%

Reference	Age groups (in years)	N	Paradigm	*p-levels*	N trials	Reward	Criteria for matching + maximizing	% Match	% Max
Stevenson & Weir, 1959	8–10	10	Token delivery machine	$p_1 = 1.0$ $p_2 = .00$ $p_3 = .00$	80	Two toys	Maximizing: exclusively choosing the high-option on last 20 trials	-	80%
Sullivan & Ross, 1970	5	15	"	$p_1 = .80$ $p_2 = .20$	"	toy prize	Maximizing: high-option 18 out of 20 trials in last block	-	46%
Sullivan & Ross, 1970	17	15	"	"	"	2 people received 3 or 2 USD, respectively	"	-	33%
Weir, 1964	3	10	"	$p_1 = .66$ $p_2 = .00$ $p_3 = .00$	"	Prize	"	-	70%
"	5	35	"	"	"	"	"	-	66%
"	7	20	"	"	"	"	"	-	25%
"	9	15	"	"	"	"	"	-	20%
"	13	10	"	"	"	None	"	-	20%
"	18	"	"	"	"	"	"	-	50%
"	3	"	"	$p_1 = .33$ $p_2 = .00$ $p_3 = .00$	"	Prize	"	-	50%
"	5	27	"	"	"	"	"	-	33%
"	7	31	"	"	"	"	"	-	0%
"	9	15	"	"	"	"	"	-	0%
"	10	26	"	"	"	None	"	-	0%
"	14	26	"	"	"	"	"	-	4%
"	18	35	"	"	"	"	"	-	17%

Note. M = mean; SD = standard deviation; match = probability matching; max = probability maximizing.

B | Supplemental Material for Chapter 2

Emerging Adaptivity in Probability Learning: How Young Minds and the Environment Interact

Table B1

Sample Size, Age in Years, and Gender Distribution by Age Group and Experimental Condition

	3–4 years			6–7 years			9–11 years			Adults		
	SR	SH	ED	SR	SH	ED	SR	SH	ED	SR	SH	ED
N	40	39	41	40	41	40	40	41	40	41	40	40
Age *M*	4.12	4.12	3.99	6.86	6.85	7.04	10.16	10.18	10.09	25.68	27.38	25.64
(SD)	(0.53)	(0.57)	(0.58)	(0.56)	(0.59)	(0.53)	(0.77)	(0.77)	(0.82)	(6.23)	(6.41)	(5.26)
% Female	42	44	59	62	59	52	55	49	60	49	58	50

Note. SR = static random; SH = static high; ED = ecologically dynamic; SD = standard deviation

Table B2

Ability to Correctly Identify the High-Probability Option by Condition and Age Group: Results of an Analysis of Variance

	M	*SD*	*F*	df	η_p^2
Condition			4.59*	1,314	.01
Static high	.88	.33			
Ecologically dynamic	.79	.41			
Age group			6.01**	3,314	.05
3–4 years	.73	.45			
6–7 years	.78	.42			
9–11 years	.88	.33			
Adults	.95	.22			
Condition × age group			0.61	3,314	> .01

Note. $p < .001$**, $p < .05$*.

Computational Modeling Approach to Chapters 2 and 4

We used a computational modeling approach similar to that implemented in Schulze et al. (2017), but generated estimates in a Bayesian framework using JAGS (Plummer, 2003) and with MATLAB as an interface (The MathWorks Inc., 2021).

Model Specifications

Baseline

The baseline model makes no assumptions about the choice process. It has just one free parameter that captures a constant probability of choosing the high-probability option, *p(H), p(L)* = 1 – *p(H)*.

Reinforcement Learning (RL)

We implemented a simple RL model assuming that a person gradually updates the values of the two choice options. The current value $q_t(i)$ of an option *i* at trial *t* is described by

$$q_t(i) = q_{t-1}(i) + \alpha \times [r_t(i) - q_{t-1}(i)] \quad \text{(B1)}$$

where $r_t(i)$ determines whether the current choice resulted in a reward, $r_t(i) = 1$, or not, $\mathrm{r_t(i)} = 0$. The experienced reward is compared with the expected value of the option in the previous trial, resulting in a prediction error (here in brackets). The learning rate parameter α scales the extent to which the prediction error affects the value-updating process, with higher (lower) values indicating that recent prediction errors are weighted more (less) heavily.

Following a softmax choice rule (Sutton & Barto, 2018), the higher-valued option is then selected more or less deterministically depending on the inverse temperature parameter θ:

$$p_{t+1}(i) = \frac{e^{\theta \times q_t(i)}}{e^{\theta \times q_t(j)} + e^{\theta \times q_t(i)}} \quad \text{(B2)}$$

Win-Stay Lose-Shift (WSLS)

We used a probabilistic version of the WSLS heuristic (e.g., Worthy et al., 2012) that has two free parameters: the probability of repeating the same choice after experiencing a win in the previous trial, denoted as $p_{t+1}(stay|win_t)$, and the probability of shifting after a loss, denoted as $p_{t+1}(shift|loss_t)$.

Parameter Estimation and Strategy Classification

To estimate parameters, we modeled each participant's choices across all 100 trials. Posterior distributions of model parameters were sampled via the Gibbs sampling method implemented in JAGS (Plummer, 2003). We assigned uninformed beta prior distributions to the constant probability in the baseline model, to the win-stay and lose-shift parameters in the WSLS model, and to the learning rate in the RL model, $Beta(1,1)$. For the inverse temperature in the RL model, we used a gamma prior distribution, $Gamma(1.1051, 1.1051)$.

In the RL model, the choice options were assumed to have an initial expected value of 0, and the propensity toward the high-valued option was initialized with p = .5. In the WSLS model, a decision maker was assumed to randomly choose one option in the first trial.

For each model, we ran 20 chains with 50,000 samples each and an initial burn-in period of 2,000 samples. For the model fitting in Chapter 2, the $\hat{R}$ statistic indicated no convergence issues (< 1.01), except for the learning rate for one 3-year-old and the inverse temperature parameter for one adult who chose the high-probability option below chance and seemed to switch their behavior for every block of trials ($\hat{R}$ < 1.2). However, excluding these participants from analysis did not change the results.

We used the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002) to evaluate which strategy model provided the best fit to each participant's choice data. The DIC penalizes model complexity. Lower DIC values indicate a better fit between model predictions and the data. For each participant, we selected the model with the lowest DIC value as best describing their strategy.

Table B3

Mean (Standard Deviation) of Model Parameters by Age Group and Condition for Those Participants Best Described by Each Model

		Models and parameters							
		Win-stay lose-shift			Reinforcement learning			Baseline	
Condition	Age group	N	p(stay|win)	p(shift|lose)	N	α	θ	N	p(const)
Static high	3–4 years	9	.24 (.05)	.79 (.07)	24	.36 (.28)	11.65 (27.43)	6	.45 (.32)
	6–7 years	7	.31 (.14)	.71 (.10)	33	.48 (.25)	2.88 (1.75)	1	.58
	9–11 years	7	.34 (.05)	.67 (.05)	29	.44 (.27)	6.44 (21.86)	5	.60 (.13)
	Adults	9	.69 (.07)	.35 (.06)	25	.40 (.26)	7.63 (23.21)	6	.77 (.17)
Static random	3–4 years	17	.37 (.23)	.62 (.23)	9	.47 (.31)	2.13 (1.45)	14	.41 (.42)
	6–7 years	23	.31 (.10)	.67 (.14)	16	.67 (.17)	1.72 (0.65)	1	.52
	9–11 years	16	.32 (.08)	.68 (.11)	14	.65 (.28)	0.34 (0.10)	10	.52 (.10)
	Adults	13	.64 (.10)	.34 (.10)	19	.66 (.30)	3.40 (6.01)	9	.51 (.18)
Ecologically dynamic	3–4 years	19	.56 (.29)	.43 (.31)	11	.36 (.33)	14.69 (22.17)	11	.65 (.35)
	6–7 years	24	.22 (.08)	.76 (.08)	13	.53 (.30)	3.31 (4.53)	3	.78 (.10)
	9–11 years	27	.22 (.08)	.79 (.09)	11	.49 (.30)	8.12 (21.65)	2	.57 (.14)
	Adults	12	.37 (.10)	.67 (.12)	23	.55 (.34)	3.63 (4.72)	5	.72 (.14)

Note. α = learning rate; θ = inverse temperature. The constant probability of choosing the high-probability option estimated in the baseline model equals the average probability of choosing the more likely option in the static high and ecologically dynamic condition and a randomly drawn option in the static random condition and is therefore not considered here (see Behavioral Results section Chapter 2). Where no standard deviation is reported, N = 1.

Table B4

Model Parameters in the Reinforcement Learning and Win-Stay Lose-Shift Models: Results of an Analysis of Variance

Model and parameter	Variable	F	df	η_p^2	$BF_{inclusion}$
RL					
Learning rate	Condition	10.22 **	2,215	.09	207.89
	Age group	2.74 *	3,215	.04	0.47
	Condition × age group	0.34	6,215	< .01	0.05
Inverse temperature	Condition	1.67	2,215	.02	0.19
	Age group	1.95	3,215	.03	0.14
	Condition × age group	0.48	6,215	.01	0.01
WSLS					
p(stay|win)	Condition	6.28 *	2,171	.07	2.1×10^{8}
	Age group	37.00 **	3, 171	.39	$> 10^{10}$
	Condition × age group	12.5 **	6, 171	.30	8.8×10^{8}
p(shift|loss)	Condition	5.51 *	2,171	.06	$> 10^{10}$
	Age group	28.39 **	3,171	.33	5.2×10^{8}
	Condition × age group	12.76 **	6,171	.31	1.9×10^{9}

Note. $p < .001$**, $p < .05$*; RL = reinforcement learning; WSLS = win-stay lose-shift.

Table B5

Post-hoc Analysis for Group-Level Differences in Model Parameters Based on Tukey HSD and Bayesian t-test Derived Bayes Factor

Model and parameter	Variable and levels	Difference	95% CI	BF_{10}
RL				
Learning rate	Condition			
	SR − SH	.21 **	[.10,31]	3926.91
	ED − SH	.07	[−.03,.18]	0.56
	ED −SR	−.13 *	[−.26,−.01]	2.48
	Age group			
	6–7y − 3–4y	.15 *	[.01,.3]	11.04
	9–11y − 3–4y	.12	[−.03,.26]	1.47
	Adult − 3–4y	.12	[−.02,.26]	2.48
	9–11y − 6–7y	−.04	[−.17,.1]	0.25
	Adult − 6–7y	−.03	[−.16,.09]	0.2
	Adult − 9–11y	0	[−.13,14]	0.21
Inverse temperature	Condition			
	SR − SH	−4.52	[−10.62,1.58]	0.64
	ED − SH	−0.27	[−6.37,5.83]	0.16
	ED − SR	4.24	[−2.74,11.24]	1.76
	Age group			
	6–7y − 3–4y	-7.56^{+}	[−15.71,0.58]	4.32
	9–11y -3–4y	−4.75	[−13.14,3.64]	0.4
	Adult − 3–4y	−5.02	[−13.04,3]	0.56
	9–11y − 6–7y	2.81	[−4.87,10.5]	0.37
	Adult − 6–7y	2.54	[−4.74,9.82]	0.39
	Adult − 9–11y	−0.27	[−7.83,7.28]	0.2
WSLS				
p(stay|win)	Condition			
	SR − SH	−.01	[−.09,.6]	0.24
	ED − SH	−.08 *	[−.15,−.01]	1.12
	ED − SR	−.07 *	[−.12,−.01]	1.41
	Age group			
	6–7y − 3–-4y	−.15 **	[−.23,−.08]	138.7
	9–11y − 3–4y	−.15 **	[−.22,−.07]	114.26
	Adult − 3–4y	.13 **	[.04,.21]	3.85
	9–11y − 6–7y	.01	[−.07,.08]	0.21
	Adult − 6–7y	.28 **	[.20,.36]	6.1×10^{12}
	Adult − 9–11y	.27 **	[.19,.36]	5.6×10^{12}
p(shift|loss)	Condition			
	SR − SH	−.02	[−.10,.05]	0.25
	ED − SH	.06	[−.02,.13]	0.47
	ED − SR	.08 *	[.02,.14]	2.19
	Age group			
	6–7y − 3–4y	.14 **	[.06,.22]	23.36
	9–11y − 3–4y	.15 **	[.07,.23]	79.71
	Adult − 3–4y	−.11 **	[−.20,−.02]	1.57
	9–11y − 6–7y	.01	[−.06,.09]	0.31
	Adult − 6–7y	−.25 **	[−.34,−.16]	7.1×10^{8}
	Adult − 9–11y	−.26 **	[−.35,−.18]	1.1×10^{10}

Note. $p < .001$**, $p < .05$*, $p < .1^{+}$; SR = static random, SH = static high, ED = ecologically dynamic; CI = confidence interval.

C | Supplemental Material for Chapter 3

The Development of Probability Learning and Repeated Choice Behavior in Childhood: A Longitudinal Investigation

Table C1

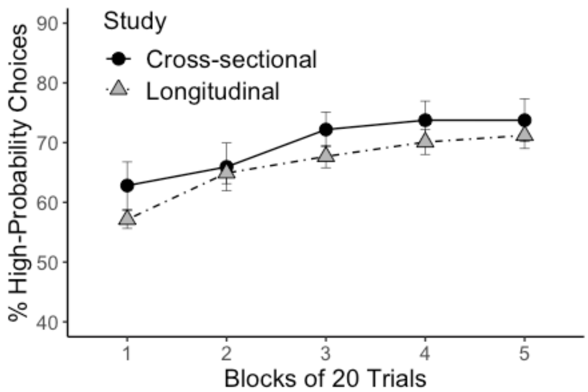
Number and Reasons for Exclusion From Data Analysis by Task and Wave

Exclusion criterion	PL		RI		VWMB		VWMF	
	T1	T2	T1	T3	T1	T2	T1	T2
Technical issues	1	0	1	1	1	0	1	1
Intervention parent	3	0	0	0	0	0	0	0
Stopped prematurely	2	4	3	0	0	1	0	0

Note. PL = probability learning; RI = response inhibition; VWMB = visual working memory backward ; VWMF = visual working memory forward.

Figure C1

Comparison of Probability Learning Across Trial Blocks Between Children Aged 5–6 Years in the Longitudinal (T3) and Cross-Sectional Study



Note. Data for the cross-sectional study obtained in study from Chapter 2. Longitudinal and cross-sectional studies used the same probability learning paradigm.

Table C2

Age Effects on Executive Function Measures Derived From Bayesian Mixed-Model With Individually Varying Intercepts

Parameter	Response inhibition			Memory backward			Memory forward ordered			Memory forward unordered		
	β	Error	95% CI	β	Error	95% CI	β	Error	95% CI	β	Error	95% CI
Random effect												
ID (Intercept)	.11	.02	[.07,.15]	0.44	0.15	[0.09,0.69]	0.06	0.05	[0,0.18]	0.33	0.19	[0.02,0.71]
Fixed effects												
Intercept	.79	.02	[.76,.83]	2.41	.10	[2.22,2.59]	1.00	.05	[0.91,1.09]	3.69	.12	[3.46,3.93]
$\text{Age}_{\text{cross-sectional}}$	.12	.04	[.03,.20]	1.14	.23	[0.68,1.61]	0.24	.11	[0.02,0.47]	0.83	.28	[0.28,1.39]
$\text{Age}_{\text{longitudinal}}$	.04	.02	[.01,.07]	0.98	.10	[0.77,1.18]	0.28	.06	[0.16,.39]	0.98	.14	[0.70,1.27]
$\text{Age}_{\text{cross-sectional}}$ x $\text{age}_{\text{longitudinal}}$	-.03	.04	[-.12,.05]	0.08	.27	[-0.46,.61]	-0.21	.16	[-0.52,.10]	-0.55	.38	[-1.31,.21]

Note. CI = Credible interval; total of 8000 post-warmup samples per model; $\hat{R}$ = 1.00 for all parameter estimates

Table C3

Age and Memory Effects on High-Probability Choices Derived From Bayesian Mixed-Model With Individually Varying Intercepts

Parameter	β	Error	95% CI
Random effect			
ID (Intercept)	.50	.05	[.41,.60]
Fixed effects			
Intercept	.58	.09	[.41,.76]
Block (linear)	.32	.04	[.25,.39]
Block (quadratic)	-.18	.04	[-.24,-.11]
$\text{Age}_{\text{cross-sectional}}$	-.10	.20	[-.50,.29]
$\text{Age}_{\text{longitudinal}}$	.77	.07	[.63,.90]
$\text{Age}_{\text{cross-sectional}}$ x $\text{age}_{\text{longitudinal}}$	-.05	.09	[-.22,.12]
VWM forward	.05	.02	[0,.08]
VWM forward x $\text{Age}_{\text{cross-sectional}}$	.02	.04	[-.05,.10]
VWM forward x $\text{Age}_{\text{longitudinal}}$	-.05	.02	[-.09,-.01]
VWM backward	.03	.02	[0,.07]
VWM backward x $\text{Age}_{\text{cross-sectional}}$	.01	.05	[-.08,.11]
VWM backward x $\text{Age}_{\text{longitudinal}}$	-.21	.02	[.-25,-.17]

Note. CI = Credible interval; total of 8000 post-warmup samples per model; $\hat{R}$ = 1.00 for all parameter estimates

D | Supplemental Material for Chapter 4

Young Children Recruit Different Choice Strategies When Tested Online

Computational Modeling Approach in Chapter 4

The modeling approach implemented in this Chapter is equivalent with the one described in Appendix B (please refer to that section for a detailed description). When modeling the full choice dataset in Chapter 4, the $\hat{R}$-statistic indicated no convergence issues, except for the inverse temperature parameter for one child in online sample ($\hat{R}$ = 1.1). However, this child was better described by a different model than RL, and thus, does not affect the analyses results.

The deline in performance toward the end of the task in the online sample may suggest that children start using a different strategy with increasing length of the experiment. To examine this possibility, we separately modeled children's choices for trial blocks 3–5. Figure D1 shows the strategy classification based on this approach. However, the $\hat{R}$-statistic ($\hat{R}$ > 1.01). indicated convergence issues, in particular, for the inverse temperature parameter in the RL model for eight children offline and 16 children online. Moreover, inspection of the choice data reveals that some children stopped "learning" after two trial blocks and were choosing the high-probability option at constantly very high or low rate, explaining some of the increase in baseline users compared to modeling the full dataset.

Figure D1

Strategy Classification by Testing Modality: Trial Blocks 3–5