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Who You Know Is What You Know: Modeling Boundedly Rational Social Sampling

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The social environment provides a sampling space for making informed inferences about features of the world at large, such as the distribution of preferences, risks, behaviors, or other events. How do people search this sampling space and make inferences based on the instances sampled? Inspired by existing models of bounded rationality and in accord with research on the structure of social memory, we develop and test the *social-circle model*, a parameterized, probabilistic process account of how people make inferences about relative event frequencies. The model extends to social sampling the idea that cognitive search is both structured and limited; moreover, it captures individual differences in the order in which sections of the sampling space are probed, in difference thresholds, and in response error. Using a hierarchical Bayesian latent-mixture approach, we submit the model to a rigorous model comparison. In Study 1, a reanalysis of published data, the social-circle model outperformed both a model assuming exhaustive search and a simple heuristic assuming no individual differences in search or difference thresholds. Study 2 establishes the robustness of these findings in a different domain and across age groups (adults and children). We find that children also consult their social memories for inferential purposes and rely on sequential and limited search. Finally, model and parameter recovery analyses (Study 3) demonstrate the ability of the social-circle model to recover the characteristics of the cognitive processes assumed to underlie social sampling. Our analyses establish that social sampling in both children and adults follows key principles of bounded rationality.

Keywords: availability, Bayesian cognitive modeling, child development, individual differences, probabilistic inference

In the popular TV show *Family Feud*, contestants compete to guess the responses most frequently given by 100 people surveyed about everyday topics and phenomena. For more than 40 years, this favorite of American daytime TV, with numerous local spin-offs airing around the globe, has probed people's knowledge of what other people think about questions such as "Which risk do most people take at least once in their lives?" or "What is an illness that children catch from each other?" Why did this long-running TV fixture prove so successful? Perhaps because it taps into a key ecological property: the frequency distributions of people's behaviors, preferences, and beliefs in diverse domains of life. This ecological property can inform important actions and decisions. For instance, the prevalence of hazardous events may guide precautionary actions (Lichtenstein, Slovic, Fischhoff, Layman, & Combs, 1978); the number of people who have acquired particular products may indicate differences in product quality that influence consumer choice (Salganik, Dodds, & Watts, 2006); the popularity of different political opinions may impact people's willingness to express their own political views (Noelle-Neumann, 1974); and the relative frequency of others' behaviors hints at descriptive social norms that should be followed (Cialdini, 2007).

In everyday life, people generally do not have access to summary tables of *social statistics* that indicate the objective frequencies of behaviors, preferences, or beliefs in a population. Instead, they need to infer them. One way of inferring population-wide social statistics is to sample, from memory, relevant instances of events experienced by the members of one's social network. For instance, according to Tversky and Kahneman's (1973, 1974) availability heuristic, people "may assess the risk of heart attack among middle-aged people by recalling such occurrences among one's acquaintances" (Tversky & Kahneman, 1974, p. 1127). In fact, there is considerable evidence that people make many types of judgments and decisions by recruiting knowledge about the people they know, including themselves (e.g., Galesic, Olsson, &

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Rieskamp, 2012, 2018; Hertwig, Pachur, & Kurzenhäuser, 2005; Pachur, Hertwig, & Steinmann, 2012; Ross, Greene, & House, 1977; Tversky & Kahneman, 1973; Wood, Brown, & Maltby, 2012). We will refer to this process as *social sampling* (see also Galesic et al., 2012, 2018).

But how do people search the social sampling space in memory? That is, what are the cognitive mechanisms that underlie social sampling? Three important properties of cognitive processes have been identified in other domains of decision making, such as multi-attribute, risky, and intertemporal choice. First, cognitive search is both structured, tending to follow a systematic order, and limited, that is, terminated before all the available information has been consulted (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; see also Klein & O'Brien, 2018). This assumption of structured and limited search is key to Herbert Simon's influential notion of *bounded rationality* (Simon, 1955, 1956). Second, there are individual differences in the cognitive processes underlying decision making—as a function of age, gender, expertise, or working memory span, for instance (e.g., Davidson, 1991; Garcia-Retamero & Dhami, 2009; Mata & Nunes, 2010; Pachur & Marinello, 2013; Rakow, Newell, & Zougkou, 2010; Slovic, 1966). Third, judgment and decision making is probabilistic in nature—the same person may make different choices at different times, even when presented with the same evidence—and seminal models of judgment and decision making incorporate this notion (e.g., Luce, 1959; Thurstone, 1927; Tversky, 1972).

Previous research has, however, not integrated these insights into models of social sampling. In this article, we propose a cognitive process model of social sampling, the *social-circle model*, which draws on these key assumptions from cognitive psychology in conceptualizing the kind of judgments that are typically considered in social psychology. First, we propose that people might exploit regularities of the external social environment to structure and terminate the internal search in memory (see also Hills, Todd, & Goldstone, 2008). Second, the social-circle model is parameterized, which allows us to map out individual differences between decision makers in (a) the order in which sampling spaces in social memory are considered; (b) sensitivity to differences in the evidence recalled for each alternative, which in turn determines when search is terminated; and (c) response noise. Third, the model takes the probabilistic nature of judgment and decision making into account. In accommodating these aspects in a computational model of social sampling, we build on and extend previous attempts to formalize probabilistic aspects of structured and limited search in multi-attribute and risky choice (see Bergert & Nosofsky, 2007; Rieskamp, 2008).

In the following, we first review existing models of social sampling and outline their assumptions about the internal search spaces consulted, heterogeneity among decision makers during social sampling, and variability within individuals in terms of probabilistic responding. Second, we describe the social-circle model and the hierarchical Bayesian latent-mixture approach that we use to test the model against alternative accounts. Third, we submit the social-circle model to a rigorous model comparison, pitting it against strategies that assume exhaustive search or no individual differences. In Study 1, we use published data on judgments of the relative popularity of participative sports (Pachur, Hertwig, & Rieskamp, 2013). In Study 2, we test the generalizability of Study 1's conclusions by drawing on new data from a different domain (popularity of holiday destinations). In addition, we illustrate how the model can be used to study individual differences in and group differences between adults and children. Finally, Study 3 presents a model and parameter recovery analysis. Using computer simulations, we demonstrate the ability of the modeling framework to recover the characteristics of the cognitive processes assumed to underlie social sampling in terms of search order, difference threshold, and response noise.

Should I Stop or Should I Go? Structured and Limited Search in Social Memory

The decision about when to terminate sampling determines the amount of information on which an inference is based. Most previously proposed models of social sampling implicitly assume that people aim to retrieve all relevant instances stored in memory and that all instances can, in principle, be traded off against one another (e.g., Galesic et al., 2012, 2018; Hertwig et al., 2005; Pachur et al., 2012; Tversky & Kahneman, 1973). Some models of social sampling have proposed constraints on the retrieval space (e.g., limiting it to the people one knows personally) or constraints on the retrieval process (e.g., similarity-based activation of instances) but nevertheless assume exhaustive search within those limits (Galesic et al., 2018; Hertwig et al., 2005; Pachur et al., 2012). This assumption of exhaustive search is in line with common implementations of search in computational models of memory (e.g., Raaijmakers & Shiffrin, 1981; Shiffrin & Steyvers, 1997) as well as in exemplar models of frequency judgments (such as MINERVA-DM; Dougherty, Gettys, & Ogden, 1999) or categorization (e.g., Nosofsky, 1986).

Yet in several other domains of judgment and decision making, it has been found that decision makers do not always engage in exhaustive information search. For instance, there is evidence from computational modeling and process tracing approaches that people inspect only part of the available information in multiple-cue judgment (e.g., Pachur & Marinello, 2013), multi-attribute choice (Bröder & Schiffer, 2003; Payne et al., 1993; Russo & Dosher, 1983), risky choice (Brandstätter, Gigerenzer, & Hertwig, 2006; Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013; Payne & Braunstein, 1978; Su et al., 2013), intertemporal choice (e.g., Dai, Pleskac, & Pachur, 2018), and estimation (Juslin & Persson, 2002). Moreover, for categorization, in which—as in social sampling—decisions are informed by exemplars stored in memory, it has been shown that models that assume consideration of a limited set of stored exemplars are better able to account for decisions than are unbounded models that require extensive similarity computations across all stored exemplars (De Schryver, Vandist, & Rosseel, 2009). This limited information search often also appears to be structured: Attributes are not consulted randomly but processed hierarchically based on importance, validity, or usefulness (e.g., Newell, Rakow, Weston, & Shanks, 2004).

Given the evidence for structured and limited search in several domains of judgment and decision-making research, the question arises as to whether these same principles of boundedly rational information processing also hold, to at least some extent, in social sampling—another manifestation of cognitive search. Research has shown that social memory is strongly structured and may even be organized hierarchically. Hills and Pachur (2012), for instance, showed that participants asked to spontaneously recall the members of their social networks often retrieved clusters of names from the same social category—such as family, friends, or acquaintances (see also Bond, Jones, & Weintraub, 1985; Fiske, 1995). Thus, social category might serve as an important retrieval cue in social memory. Moreover, Hills and Pachur (2012) found that the social categories seemed to be hierarchically organized: on average, partners and family members were retrieved earlier than friends, who were in turn recalled before acquaintances.

If recall from social memory commonly follows such a "patchwise" search process, it stands to reason that social sampling may follow a similar structure. In a first attempt to conceptualize the structured and possibly limited nature of sampling from one's social network, Pachur, Hertwig, and Rieskamp (2013) proposed the *social-circle heuristic*. This heuristic assumes that people judging the relative frequency of two events search their social memory for relevant instances by sequentially probing their social circles and terminating search as soon as one circle distinguishes between the options (i.e., there are more instances of one option than the other in a circle). The circles (or "patches") that the social-circle heuristic uses to guide, and potentially terminate, the search for relevant instances in memory reflect the natural segmentation of social memory into distinct social subgroups, such as family, friends, and acquaintances (e.g., Bond et al., 1985; Fiske, 1995; Hills & Pachur, 2012). In line with the finding that people are disproportionately influenced by their own behavior when inferring its prevalence in the population (false-consensus effect; Ross et al., 1977), the social-circle heuristic first considers information about the self. If this circle does not distinguish between the options (because it provides no evidence or the same amount of evidence for each alternative), the search process follows a hierarchy of circles, from family (i.e., kin relationships) to friends and finally acquaintances (i.e., nonkin relationships).

Pachur, Hertwig, and Rieskamp (2013) tested the social-circle heuristic against a search strategy that assumes limitless search—that is, that all instances of an event in a person's social network are taken into consideration. In these analyses, the social-circle heuristic was the best model for the inferences of a similar number of participants as the exhaustive strategy, suggesting that limited search in social sampling (embodied by the social-circle heuristic) might be a viable modeling assumption. Moreover, Pachur and colleagues showed that limiting the sampling space is not necessarily detrimental to judgment accuracy. Using computer simulations, they found that under environmental conditions that are arguably common in the real world—a clustered occurrence of events in the population and a skewed distribution of event frequencies—the social-circle heuristic can achieve a similar level of accuracy as an exhaustive search strategy. Thus, it seems possible that the mind may curtail social sampling to reduce cognitive processing costs. This possibility echoes ideas about search in memory in cognitive architectures: Anderson and Milson (1989), for instance, suggested that search in memory should terminate once the expected gain from retrieving more information is less than the cost of retrieving that information (weighted by the probability that it will be needed in the current context). Because information is often subject to diminishing returns (see, e.g., Hertwig & Pleskac, 2010), even a small sample of observations can sometimes enable accurate inferences (see also Ambady & Rosenthal, 1992; Gigerenzer & Goldstein, 1996; Kareev, 1995).

Overall, the evidence thus suggests that the notion of boundedly rational social sampling—encompassing search that probes social memory in a structured fashion and ignores some of the available information—may be useful for conceptualizing how people make inferences about social statistics in the world. Previous models of social sampling have, however, largely ignored two important aspects of decision making. First, both search and choice behavior are fundamentally probabilistic in nature, meaning that they are unlikely to consistently unfold in the same way every time a person faces the same information. Second, there are considerable individual differences in how decision makers search for information and how they process the sampled evidence. We next review research on other types of judgments and decisions that has highlighted these aspects.

The Probabilistic Nature of Search and Choice

Behavior in many domains of decision making is often assumed to be fundamentally probabilistic in nature (e.g., Luce, 1959; Thurstone, 1927; Tversky, 1972). In their seminal study, Mosteller and Nogee (1951) found that people do not deterministically follow their preferences in an "all-or-none" manner, but rather gradually increase the frequency of choosing a particular option. This insight is formalized in various mathematical models of risky choice (e.g., Birnbaum & Chavez, 1997; Busemeyer & Townsend, 1993), and probabilistic variants of choice models have been shown to outperform their deterministic relatives (e.g., Rieskamp, 2008). Likewise, computational modeling supports a probabilistic rather than a deterministic perspective in domains such as intertemporal choice (Dai & Busemeyer, 2014; Regenwetter et al., 2018) and multi-attribute decision making (Bergert & Nosofsky, 2007; Heck, Hilbig, & Moshagen, 2017). Incorporating probabilistic search and choice processes into a model of social sampling thus closes an important gap.

Who You Know Is Not Who I Know: Individual Differences in Social Sampling

Cognitive models that allow for individual heterogeneity in the search processes involved in judgment and decision making are often better able to account for people's behavior than are models assuming that search unfolds uniformly. For instance, in multiple-cue inference, people differ considerably in the order in which they search available cues (Bergert & Nosofsky, 2007). That is, most people do not consistently base their search order on estimates of objective cue validities, as is assumed in Gigerenzer and Goldstein's (1996) model of the take-the-best heuristic. Similarly, by generalizing the priority heuristic—a boundedly rational model for choosing between risky prospects by sequentially comparing the prospects' attributes (e.g., the magnitude of their minimum outcome; Brandstätter et al., 2006)—Rieskamp (2008) found that people differ in the order in which they inspect these attributes.

Further, people are likely to differ in the criterion they set for terminating sampling from social memory. Research with sequential sampling models has shown that response criteria are contingent on individual difference variables such as age (e.g., Ratcliff, Thapar, & McKoon, 2010, 2011) as well as on external situational factors such as sleep deprivation (Ratcliff & van Dongen, 2009). Finally, the level of noise or error varies across decision makers and seems to be associated with variability in fluid intelligence, numeracy, and affect (e.g., Pachur, Mata, & Hertwig, 2017). Individual factors have also been found to impact social recall from memory (Hills & Pachur, 2012). Allowing for individual differences in the order in which social memory is searched as well as in the stopping and decision stages of the inference process is therefore likely to provide a better account of the cognitive mechanisms of social sampling than is assuming an invariable process.

Although the fixed search sequence assumed by the social-circle heuristic (proceeding from the self, to kin relationships, to nonkin relationships) reflects a natural hierarchy of social relations, alternative orders are plausible. Newell et al. (2004), for instance, suggested that the order in which candidate pieces of information are considered is influenced by their "usefulness" in discriminating between options and thus keeping search costs low. By extension, the order in which (some) people inspect their social circles might be sensitive to the circles' ability to discriminate between events. For example, the smallest social circle, the self, will rarely discriminate between events and may therefore be inspected later. Alternatively, search may be guided by the representativeness of social circles for the inference domain. In some domains, acquaintances may be prioritized over family members or the self may be discounted as an unrepresentative source of information (e.g., when judging the commonness of one's own family name; see Oppenheimer, 2004). Moreover, the judged relevance or importance of information from different social sources may differ as a function of the decision maker's age (e.g., Knoll, Magis-Weinberg, Speekenbrink, & Blakemore, 2015).

To conclude, previous work has established systematic individual differences in cognitive search and decision making, suggesting that it might also be important to acknowledge heterogeneity in a conceptualization of social sampling. We next develop a generalized cognitive process model of social sampling that (a) integrates the assumptions of bounded rationality, (b) captures differences between individuals in the search for instances in memory, and (c) acknowledges the probabilistic nature of choice.

The Social-Circle Model

The social-circle model is a process account of how people infer which of two events is more frequent in a population when summary information about social statistics is not available. For instance, suppose you want to determine which of two holiday destinations, Italy or France, is more popular. The social-circle model assumes that people search their social memory for relevant instances and that this sampling exploits the natural structures of social environments that delineate groups differing in social closeness to the individual (see, e.g., Hill & Dunbar, 2003; Milardo, 1992). The model assumes that the distinct social circles of self, family, friends, and acquaintances are probed sequentially for relevant instances (see Pachur, Hertwig, & Rieskamp, 2013). The evidence, e_i, in each inspected circle i is represented as the difference in the proportion of instances recalled for each event (i.e., the difference in the proportion of people one knows who have holidayed at either destination):

$$e_i = \frac{n_{iA}}{n_{iA} + n_{iB}} - \frac{n_{iB}}{n_{iA} + n_{iB}}. \tag{1}$$

Using a proportional evidence score takes differences in the size of the circles into account. The order in which the circles are inspected is probabilistic (see, e.g., Bergert & Nosofsky, 2007; Tversky, 1972) and is represented by circle-weight parameters, one for each circle (w_i; constrained by $\sum w_i = 1$; Bergert & Nosofsky, 2007). The weight for each circle can be estimated from the data and represents the probability that a circle is inspected as

$$p(inspect\ \ circle_i) = \frac{w_i}{\sum_i^N w}. \tag{2}$$

Once a circle has been inspected, it is not considered further (i.e., the denominator is calculated only over circles that have not yet been inspected). The probability of following a particular search order $p(order_j)$ is given by the product of the individual probabilities of circle inspection in that order. For example, for the order $j = 1,2,3,4$:

$$p(order_{j=1,2,3,4}) = \prod_{i=1}^{4} p(inspect\ \ circle_i). \tag{3}$$

The social-circle model further assumes that the proportional evidence obtained from each circle is compared against a difference threshold, d (see, e.g., Busemeyer & Townsend, 1993; Dai et al., 2018; Rieskamp, 2008; Thurstone, 1927). If the evidence from the recalled instances reaches or exceeds the threshold, a decision is made; otherwise, the next circle is inspected. Because the evidence from the recalled instances is expressed as a proportional difference score, this difference threshold indicates a person's sensitivity to the difference in the proportion of instances recalled for each event. The social-circle model implements a probabilistic version of this process, assuming stochasticity in the comparison of proportional evidence against the difference threshold. Various functional forms of stochasticity have been proposed (see, e.g., Stott, 2006). In Appendix A, we report the results of an analysis in which we systematically compared the descriptive performance of three functional forms of probabilistic responding for the social-circle model: probit, logit, and a constant application error. Probit and logit performed similarly well and clearly outperformed the constant application error. For convenience, in the following, we will focus on a probit instantiation of the social-circle model. The probit variant assumes normally distributed error for each circle, denoted as ε_i, generated from a normal distribution with mean zero and standard deviation σ. Thus, it is assumed that if the proportional evidence score in a given circle, with added random error, meets or exceeds d, search is stopped and a decision is made (i.e., event A is selected if $e_i + \varepsilon_i \geq d$ and event B is selected if $e_i + \varepsilon_i \leq -d$). The probability of making a decision after inspecting circle i is given by

$$\begin{aligned} p_i(choice) &= p(|e_i + \varepsilon_i| \geq d) \\ &= p(e_i + \varepsilon_i \geq d) + p(e_i + \varepsilon_i \leq -d) \\ &= \Phi\left(\frac{e_i - d}{\sigma}\right) + \Phi\left(\frac{-e_i - d}{\sigma}\right), \end{aligned} \tag{4}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

The probability of inferring that event A (holidaying in Italy) is more popular given a particular search order, $p_j(A|AB)$, follows from combining the choice probabilities resulting from inspecting the circles in that order (see Rieskamp, 2008). For example, for the order $j = 1,2,3,4$:

$$p_{j=1,2,3,4}(A|AB) = p_1(A|AB) + [1 - p_1(choice)] \times p_2(A|AB) + [1 - p_1(choice)] \times [1 - p_2(choice)] \times p_3(A|AB) + [1 - p_1(choice)] \times [1 - p_2(choice)] \times [1 - p_3(choice)] \times p_4(A|AB). \quad (5)$$

The total probability of inferring that event A occurs more frequently is defined as the sum of all $p_j(A|AB)$, each weighted by the probability that the individual follows order j (see Equation 3):

$$p(A|AB) = \sum_{j=1}^{N!} p_j(A|AB) \times p(order_j). \quad (6)$$

In sum, the social-circle model parameterizes three key components of social sampling: a person's preferred search order through social memory (circle-weight parameters, w_i), their sensitivity to differences in the proportional evidence for each event (difference threshold, d), and response noise (σ). The model can thus capture different variants of structured and limited search and quantify to what extent individuals differ in these processes underlying social sampling.

Of course, the flexibility of the social-circle model in accounting for individual differences comes at the price of increased model complexity. To test whether the model's descriptive validity justifies this complexity relative to that of simpler models which either ignore individual differences in search and decision making or assume exhaustive instead of limited search, we use a hierarchical Bayesian latent-mixture approach. The key assumption in hierarchical mixture modeling is that participants' inferences arise from a mixture of discrete cognitive strategies and from more gradual variation within each group of strategy users (see, e.g., Bartlema, Lee, Wetzels, & Vanpaemel, 2014; Lodewyckx et al., 2011). This approach therefore combines the advantages of pooling continuous individual differences hierarchically and assuming discrete differences among classes of individuals. It yields a posterior distribution of a classification (or latent-mixture) parameter that has a natural interpretation in terms of Bayes factors (Kass & Raftery, 1995) and thus balances goodness-of-fit with all forms of model complexity. Moreover, approaches utilizing latent-mixture models and Bayesian inference have recently been shown to be well suited for examining developmental differences in strategy use (e.g., Steingroever, Jepma, Lee, Jansen, & Huizenga, 2019). We apply the hierarchical latent-mixture modeling approach in a reanalysis of published data (Study 1) and with new experimental data from children and adults (Study 2); finally, we use the approach to demonstrate the recoverability of the social-circle model and its parameters (Study 3).

Study 1: Individual Differences in a Reanalysis of Pachur, Hertwig, and Rieskamp (2013)

Pachur, Hertwig, and Rieskamp (2013) conducted two studies in which participants judged either the mortality from various types of cancer or the popularity of various sports in Germany in two-alternative choice tasks. The studies tested which of three strategies best described participants' inferences in each domain: (a) the social-circle heuristic, which assumes a boundedly rational, limited search process (that is the same across all participants); (b) a variant of the availability heuristic called *availability-by-recall*, which assumes that all instances of an event are tallied across the entire social network and that the option with the larger tally is chosen (Hertwig et al., 2005; Pachur et al., 2012); or (c) random guessing. The authors classified each individual as a user of one of these strategies based on participants' inferences and their reports of any cases of death from cancer or any sports club memberships in their own social networks. In both studies, the social-circle heuristic and availability-by-recall provided the best account for the inferences of similar proportions of people.

In our reanalysis, the key question was how well the social-circle model, which captures individual differences in search and evidence accumulation, performs relative to the three more constrained models tested by Pachur, Hertwig, and Rieskamp (2013), while taking into account its higher complexity. We modeled the data in their Study 2, in which participants made inferences about the popularity of 25 different sports in Germany.[1] To ensure comparability with the original analysis, we assumed a constant error mechanism for the social-circle heuristic and availability-by-recall. This mechanism assumes that a participant uses a given strategy with probability $1 - g$ and otherwise guesses with probability g, where g is a free parameter that is estimated from the data (see also Appendix A). For the guessing strategy, we assumed that participants randomly selected one of the two sports in each pair (i.e., with probability .50).

Parameter Estimation and Model Evaluation Procedure

We modeled inferences for all items on which a participant's instance knowledge allowed all strategies to make an unambiguous prediction. On average, instance-based strategies made predictions in 53.25% of all 300 pair comparisons; they did not make a prediction if a participant recalled no or equal numbers of instances for both sports in a pair. The reason for focusing on cases where all models made a prediction is that the present models are mute when instance knowledge cannot be used. We used a hierarchical Bayesian latent-mixture approach to estimate parameters for each participant and, simultaneously, their probability of using each strategy. In this approach, all strategies are included in a single general model as candidate accounts of people's decisions, and a categorical classification parameter determines which strategy is applied to model a person's decisions. The posterior probability of the classification parameter reflects the probability, given the data, that the participant used each strategy. In Bayesian estimation, prior probability distributions over models and their parameters are updated according to Bayes' rule into posterior probability distributions based on the observed data.

The posterior distributions of model parameters were estimated via Gibbs sampling methods implemented in JAGS (Plummer, 2003). We used reasonably uninformative priors: For the w_i and d parameters of the social-circle model and for the g parameter of availability-by-recall and the social-circle heuristic, we assumed uniform priors on the group-level mean and gamma priors (with a shape parameter of 1.1051 and a rate parameter of 0.01051; see Bartlema et al., 2014) on the group-level precision. For the σ

[1] We focused on Study 2 in Pachur, Hertwig, and Rieskamp (2013) because their Study 1 examined participants' inferences regarding cancer mortality, a domain where participants retrieved only few instances of each risk, resulting in lower applicability of social sampling-based strategies.

parameter of the social-circle model, we assumed uniform distributions constrained between [0.0001–100] on the group-level mode and standard deviation. For the latent-mixture classification parameter, we assumed a categorical prior that assigned equal weight to each strategy.[2] To ensure efficient mixing, we used pseudo-priors that approximated the posterior density for the individual-level parameters (see, e.g., Lodewyckx et al., 2011). These pseudo-priors were parameter estimates from initial hierarchical Bayesian analyses that were performed separately for each model (i.e., without a mixture component). In the model estimation, 40 chains—each with 50,000 samples drawn from the posterior distributions—were run after an initial burn-in period of 2,000 samples. Gelman–Rubin statistics and visual inspections of the chains indicated adequate chain convergence.

Results

Model comparison. Figure 1 shows the probability that each participant in Study 2 of Pachur, Hertwig, and Rieskamp (2013) used each of the strategies tested (i.e., membership probability), as derived from the posterior distribution of the classification parameter. For most participants, membership probability was highest for the social-circle model. Only a few participants were best captured by the other strategies considered by Pachur, Hertwig, and Rieskamp (2013). Specifically, four of the 40 participants were best described by availability-by-recall, two by the social-circle heuristic, and one by a guessing strategy.[3] By contrast, in Pachur, Hertwig, and Rieskamp's (2013) original analysis, availability-by-recall and the social-circle heuristic proved to be the best models for similar numbers of participants. As Figure 1 shows, moreover, in most cases the assignment of participants to latent groups was based on strong evidence: most membership probabilities unambiguously favored one model. In Pachur, Hertwig, and Rieskamp (2013), in contrast, the evidence for availability-by-recall and the social-circle heuristic was equally strong (and thus ambiguous) for a substantial subset of participants.

Parameter estimates. Figure 2 shows the individual-level parameter estimates of the social-circle model for those participants identified as more likely to have used this model than the other models. Considerable individual differences emerged on the search, stopping, and decision aspects of the model. For example, as the somewhat bimodal distribution of the w_{family} parameter estimates indicates, some individuals for whom the social-circle model provided the best account strongly weighted the "family" circle and consulted it early in the search process, whereas others entirely disregarded this source of instance knowledge. Overall, most participants for whom the social-circle model provided the best account first consulted instances in their "family" or "friends" circles, followed by their "acquaintances" or "friends" circles; most participants paid little heed to the "self" circle. In other words, participants often used a different search order than that assumed in the social-circle heuristic, which is based on the notion of relatedness. This is also apparent in the results of the model comparison summarized above, which showed that only few participants were best described by the social-circle heuristic. Figure 2 also shows that few participants gave equal weight to all four social circles (which would be represented by flat lines across all circle-weight parameters at .25) but instead preferred particular sources of instance knowledge over others. Importantly, as will be shown in the parameter recovery analyses below (Study 3), these individual differences in the weighting of social circles are unlikely to be due to poor parameter identifiability, as the parameters of the social-circle model were well recovered by the hierarchical Bayesian latent-mixture procedure. Moreover, the variability in the weighting of circles is not an artifact of variability in how often participants' recalled instances in a particular circle discriminated between the events. In Appendix B, we report supplemental simulation analyses showing that the circle weights estimated by the social-circle model are not primarily driven by differences in the discrimination rate of the circles.[4]

Discussion

In sum, our findings support the idea that, for most people, social sampling is not exhaustive but limited. In addition, the good performance of the social-circle model relative to the more constrained social-circle heuristic highlights the importance of individual differences and of probabilistic aspects of search for instances in memory. The higher flexibility of the social-circle model was matched by a substantial increase in explanatory power. Moreover, relative to Pachur, Hertwig, and Rieskamp (2013), our analysis diagnosed considerably fewer participants as users of availability-by-recall. In other words, some of the participants previously identified as engaging in an exhaustive search may, in fact, have relied on limited search, but with a search direction (or difference threshold) that deviated from that assumed in the social-circle heuristic. Overall, a "one-size-fits-all" approach—in terms of either a single exhaustive search or a single limited order of search—was not consistent with people's inferences. Rather, the substantial variability in the distribution of the social-circle model's individual-level parameter estimates indicates individual differences in the search, stopping, and decision mechanisms involved in social sampling.

To test the robustness and generalizability of these results, we next turn to a different judgment domain: the relative popularity of holiday destinations. In addition, we illustrate how the social-circle model can be used to capture age-related individual differences by

[2] For a few participants, this approach resulted in the mixture converging entirely on the social-circle model. For these participants, we therefore used a prior that assigned low initial weight to the social-circle model (e.g., .001) and equal weight to the other strategies. To ensure unbiased estimation of latent group membership, we took these unequal priors into account when calculating membership probabilities.

[3] We obtained similar results when we equipped the social-circle heuristic and availability-by-recall with the same error mechanism implemented in the social-circle model (i.e., a probit error mechanism). Specifically, the majority of participants (65%) were still best described by the social-circle model. These results indicate that the substantial support for the social-circle model is not due to its particular error mechanisms but to its ability to account for individual differences in the search and decision processes underlying social sampling.

[4] Although we found individual variability in all parameter estimates of the social-circle model (see Figure 2), assuming individual differences in the cognitive processes underlying social sampling may have been more important for some of these processes than others. Additional analyses, in which parameters were fixed to their group-level posterior mean estimates, showed that allowing for individual differences in response noise but not in the difference threshold parameter of the social-circle model improved the model's ability to account for the data, account taken of the higher complexity of models that allow for individual differences. Depending on domain and sample, it might thus sometimes be possible to simplify the social-circle model.

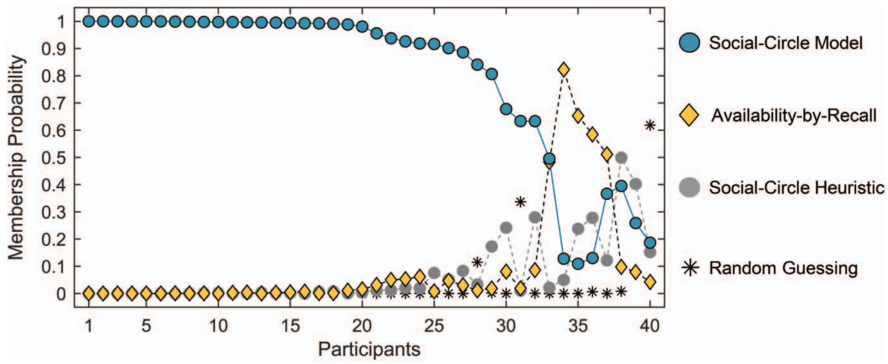

Figure 1. Membership probabilities of participants in the four latent subgroups in Study 1: the social-circle model, availability-by-recall, the social-circle heuristic, and random guessing. Modeled are the inferences of the 40 participants in Study 2 by Pachur, Hertwig, and Rieskamp (2013). See the online article for the color version of this figure.

applying it to two age groups: adults and children. This developmental application is interesting for two reasons. First, it provides a framework for disentangling and pinpointing the cognitive processes on which children and adults might differ (e.g., search vs. noise). Second, relatively little is known about how search for information in social memory develops ontogenetically. Do children also consult their social memories to draw inferences about everyday social statistics? Does social sampling perhaps play an especially important role in childhood? After all, children have relatively little conceptual or episodic knowledge that they could recruit to estimate social statistics. And do children already implement sequentially structured and limited search—perhaps, given their cognitive constraints, to an even greater extent than adults? Research on the development of cognitive search in multiattribute choice, cue-based inference, and risky choice suggests conflicting predictions for search in social sampling. One possibility is that children's working memory limitations restrict them to relying on frugal strategies, as processing large amounts of evidence would be too taxing (e.g., Bereby-Meyer, Assor, & Katz, 2004). Another possibility is that limitations in the ability to selectively focus attention on relevant information result in young children using more exhaustive but unsystematic search strategies (e.g., Davidson, 1991; Mata, von Helversen, & Rieskamp, 2011). A final possibility is that children and adults do not differ in their search efforts, as has been found for exploration-based risky choice (e.g., van den Bos & Hertwig, 2017). In sum, it is conceivable that children rely on the social-circle model to a greater, lesser, or equal extent than adults. Study 2 aims to determine which of these possibilities is supported empirically.

Study 2: Boundedly Rational Social Sampling in Children and Adults

Judgments of the popularity of holiday destinations constitute an inference domain for which children and adults may have comparably valid instance knowledge. The holiday destinations of children tend to be selected by their parents; we therefore expected

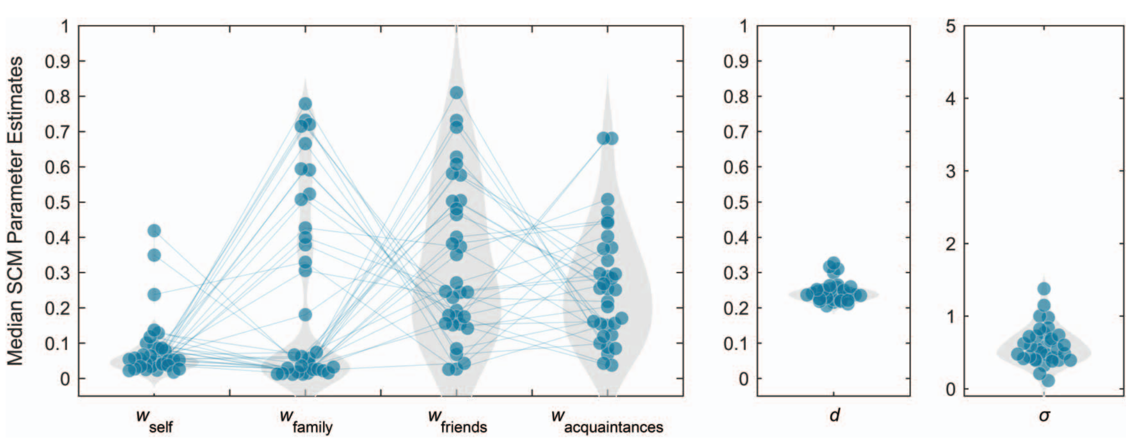

Figure 2. Distributions of the medians of each individual's posterior distribution of social-circle model (SCM) parameter estimates in Study 1. The lines link the estimated circle-weight parameters of each participant. Medians were computed over samples for which the classification parameter indicated membership of the social-circle model. Modeled are the inferences of the 33 participants in Study 2 of Pachur, Hertwig, and Rieskamp (2013) for whom the social-circle model provided the best fit (82.5%). See the online article for the color version of this figure.

children's and adults' instance knowledge to be comparable across their respective social samples, and we expected this knowledge to trace the objective social statistics in the overall population rather well. Moreover, it could reasonably be expected that participants would recall instances in each social circle, ensuring that models assuming exhaustive search would make sufficiently many diverging predictions from models assuming limited search. A final advantage of this inference domain is that large-scale real-world data on the actual frequency distribution of holiday destinations in the German population are available, enabling us to evaluate the ecological validity of participants' social memory.

Method

Participants. Fifty-six adults (aged 20–35 years, mean age 26.30 years, 32 female) and 56 children (aged 8–11 years, mean age 9.79 years, 31 female) were recruited from the subject pool of the Max Planck Institute for Human Development. The data of four additional adults and six children were excluded because of software failure; the data of one further child were excluded because they reported instances for only a single destination, causing ambiguous predictions for instance-based models on approximately 90% of trials. The sample size was determined via power calculation (using G*Power software) to give sufficient statistical power (at least .80) to detect a medium effect of age group on strategy use. Participants received a performance-based payment for their responses in the inference task (see below; earning €0.04 for each correct inference but losing the same amount for each incorrect inference) and an additional flat fee of €10. The experiment was reviewed and approved by the institutional review board (IRB) of the Max Planck Institute for Human Development.

Materials. We selected holiday destinations based on a frequency ranking of data from a market research study conducted in Germany from 2014 to 2016 (Institut für Demoskopie Allensbach, 2017). In that study, each year, a large representative sample of approximately 24,000 German-speaking residents aged 14 years or older was interviewed about their attitudes, consumption habits, and media consumption across a variety of domains (e.g., holidays and travel, financial investments, health, fashion). One question was: "Where have you been on holiday in the last 12 months?" In a face-to-face interview, respondents were provided with a list of 32 possible destinations and could choose multiple options. From this list, we selected the 19 destinations shown in Table 1, which we could reasonably expect children aged 8–11 years to have heard of. The 19 destinations were ranked based on the results of the market research study (averaged across years 2014–2016).[5] For Study 2, we constructed the set of all possible 171 paired comparisons of the 19 destinations. Participants were informed that the accuracy of their inferences would be assessed based on the available statistics. Inferences on comparisons between destinations with the same ranks (e.g., Switzerland vs. England, Ireland, and Scotland; see Table 1) were always scored as correct, irrespective of participants' responses.

Procedure. The experiment consisted of three tasks: inference, recognition, and retrieval. All participants first completed the *inference task*. They were asked to judge for each of the 171 paired comparisons which of the two destinations is visited by more German holiday makers (Figure 3a). Items were presented in 10 blocks of 17 pairs (18 pairs in the final block). Blocks were separated by a self-paced pause. The order in which pairs of destinations were presented was randomized across participants; the left–right positioning of destinations in each pair was predetermined so that correct and incorrect inferences (according to the available statistics) were equally distributed across the two positions. Each trial started with a fixation cross being displayed at the center of the screen, followed by two labeled, pictorial representations of the holiday destinations (Figure 3a). Participants made a decision by pressing one of two designated keys on the keyboard. After each choice, a gray frame marked the selected destination for 1.5 s to confirm its selection. Participants were instructed to make all inferences as accurately as possible. They were financially incentivized based on accuracy (see *Participants* section) but received no trial-by-trial feedback.

In the *recognition* and *retrieval tasks*, completed after the inference task, all participants were presented with each of the 19 destinations shown in Table 1 in randomized order. They first indicated whether they had previously heard of the destination. If so, the retrieval task for that item followed; if not, the next destination followed.[6] In the retrieval task, participants reported how many people they knew personally who had recently holidayed at the respective destination or planned to go there soon (see Figure 3b). To make responses, they dragged and dropped pictorial representations of family members, friends, and acquaintances onto an image of the holiday destination. They were also asked to indicate their contact frequency with each recalled person on a scale from one (less than once every 6 months) to five (several times per week).[7] Additionally, participants could drag and drop a pictorial representation labeled "myself" to indicate they had recently visited the destination or planned to go there soon. Each

[5] Note that the item labeled "staycation" not only covered responses indicating that respondents had not been on holiday in the past year, but may also have been selected by respondents to indicate that they preferred not to say where they had been. Nevertheless, other data likewise suggest that not going away is the most frequent holiday option in the German population. For example, approximately one-fifth of the German population could not afford a holiday in 2012 (Statistisches Bundesamt, 2014). Several other reasons may also result in people not taking a holiday in a particular year (e.g., illness, relocation, change of jobs).

[6] We assessed participants' familiarity with each holiday destination because existing models of social sampling, such as the social-circle heuristic, assume that both event categories need to be recognized for an instance-based strategy to be applied (see Pachur, Hertwig, & Rieskamp, 2013). If only one category is recognized, the inference is typically assumed to be based on the recognition heuristic (see Pachur, 2011; Pachur, Todd, Gigerenzer, Schooler, & Goldstein, 2011); if none is recognized, an inference is made by guessing. However, post-experiment discussions with our participants indicated that some children may have misunderstood the recognition task and these data were therefore not considered further.

[7] This measure was used by Pachur, Hertwig, and Rieskamp (2013) to evaluate a model of boundedly rational social sampling that assumes that the search for instances in memory is guided by frequency of contact with the recalled person rather than by their social category, the social-circle heuristic$_F$ (where "F" stands for frequency). This model performed considerably less well in accounting for people's inferences than did the social-circle heuristic or availability-by-recall. We also examined an instantiation of the social-circle model that assumes search to be determined by frequency of contact. This model, however, performed less well in accounting for participants' inferences than did a social-circle model that assumes search to be guided by social category and was therefore not considered further.

Table 1
The 19 Holiday Destinations Used in Study 2, Their Frequency and Rank in the German Population (Institut für Demoskopie Allensbach, 2017), and Total Number of Instances Recalled From the Social Networks of Child and Adult Participants

Holiday destination	Popularity (indicated by % of respondents)	Rank	Total number of recalled instances	
			Children	Adults
Staycation (no holiday in the last 12 months)	40.13	1	298	276
Baltic and North Sea coast	15.30	2	305	336
Austria and Bavaria	15.13	3	166	159
Spain	8.70	4	168	237
Italy	7.93	5	146	188
Turkey	6.37	6	94	133
France	3.70	7	136	179
Northern Europe (Denmark, Sweden, Norway, Finland, Iceland)	3.17	8	153	182
Benelux Countries (Netherlands, Belgium, Luxembourg)	3.10	9	70	162
Greece	2.57	10	104	158
Switzerland	2.27	11.5	72	82
England, Ireland, and Scotland	2.27	11.5	110	184
North America (US, Canada, Alaska)	2.03	13	130	188
North Africa (Morocco, Tunisia, Egypt)	1.83	14	95	116
Asia	1.77	15	45	197
Portugal	1.53	16	61	127
Central and South America	1.17	17	63	144
Middle East (e.g., Israel, Jordan)	0.57	18.5	32	92
East, South, and Central Africa (e.g., Kenia, South Africa)	0.57	18.5	33	79

Note. Respondents in the market research study could choose multiple options; therefore, the sum of the percentage responses exceeds 100%.

recalled person was represented on the screen and counted toward an overall tally of people who holidayed at the destination in question that was displayed on the screen. Participants were familiarized with all phases of the experiment in brief training periods before the start of each task. At the end of the experiment, participants were informed about their overall accuracy on the inference task (proportion of correct inferences) and received their payment.

Model comparison. Drawing on the instances recalled by each participant in the retrieval task, we used hierarchical Bayesian latent-mixture modeling to model each participant's decisions in the inference task. The mixture component covered three inference strategies: (a) the social-circle model, (b) availability-by-recall, and (c) random guessing (i.e., selecting one of the two destinations in each pair with probability .50). We no longer considered the social-circle heuristic because Study 1 showed that it was clearly outperformed by the social-circle model and because our focus was on age-dependent and individual differences in limited and structured search. For better comparability between strategies, we applied the same response noise mechanism for availability-by-recall that is implemented in the social-circle model. Accordingly, the probability that event A is inferred to be more frequent is

$$p_{AbR}(A|AB) = \Phi\left(\frac{n_A - n_B}{\sigma_{AbR}}\right), \quad (7)$$

where n_A denotes the number of instances recalled for event A across all circles (and n_B for event B) and σ_{AbR} is a response noise parameter. This is a departure from Study 1, in which, to ensure comparability with the original analysis, we assumed a constant error component for availability-by-recall (see Pachur, Hertwig, & Rieskamp, 2013). We again modeled inferences for all items on which a participant's instance knowledge allowed all strategies to make an unambiguous prediction; the instance-based strategies now made predictions in, on average, 81.95% and 75.50% of all 171 pair comparisons for adults and children, respectively. The parameter estimation procedure was identical to that in Study 1, and we used the same priors on the group-level mode and standard deviation of σ_{AbR} as for the response noise parameter in the social-circle model. Gelman–Rubin statistics and visual inspections of the chains indicated adequate chain convergence.

Results

In addition to conventional methods of null-hypothesis significance testing, we conducted Bayesian inference based on Bayesian t tests (Rouder, Speckman, Sun, Morey, & Iverson, 2009), Bayesian hypothesis tests for correlations (Wetzels & Wagenmakers, 2012), and Bayesian contingency analyses using independent multinomial sampling (Jamil et al., 2017). For these analyses, we report Bayes factors, denoted as BF_{10}, that quantify the strength of evidence in favor of the alternative hypothesis; $BF_{10} > 1$ indicates support for the alternative hypothesis and $BF_{10} < 1$ indicates support for the null hypothesis. All Bayes factors were estimated in JASP (v.0.11.1; JASP Team, 2019).

Behavioral data. The age groups differed in their accuracy in the inference task, $t(110) = 5.42$, $p < .001$, $d = 1.02$, $BF_{10} = 35{,}789.18$. On average, adults picked the more popular holiday destination on a higher proportion of trials than children (Ms = .76 vs. .68), but both age groups performed at well above chance level, $t(55) = 23.53$, $p < .001$, $d = 3.14$, $BF_{10} = 1.26 \times 10^{27}$ for adults and $t(55) = 17.48$, $p < .001$, $d = 2.34$, $BF_{10} = 9.38 \times 10^{20}$ for children. Adults also recalled more instances in the retrieval task (Ms = 57.48 vs. 40.73; see also Table 1), $t(102.38) = 3.36$, $p = .001$, $d = 0.64$, $BF_{10} = 27.60$. Finally, the distributions of both children's and adults' number of recalled instances were valid indicators of the actual frequency distribution of holiday destina-

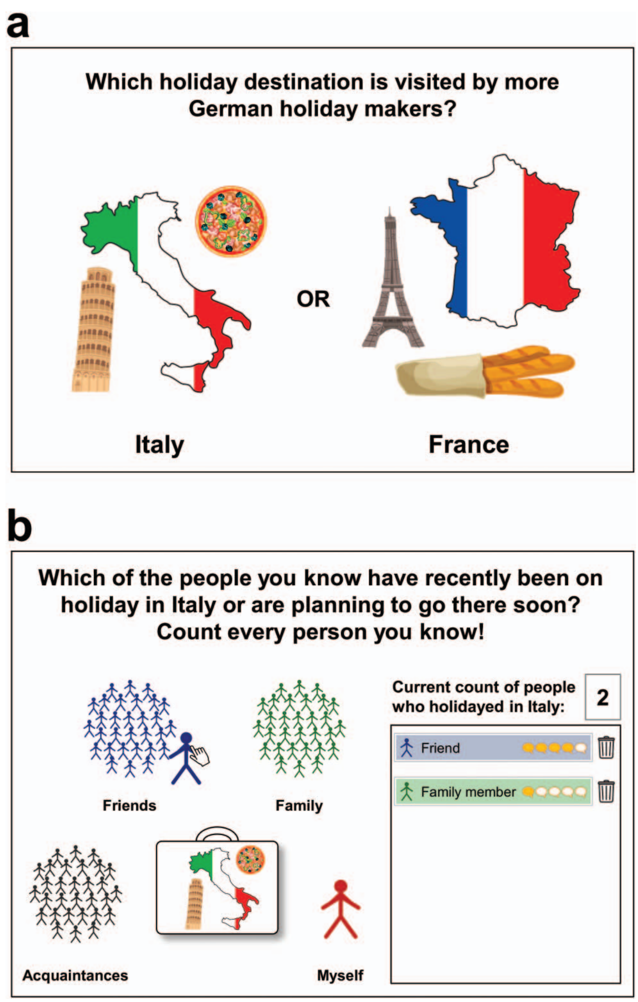

Figure 3. Illustration of the task screen used in the (a) inference task and (b) retrieval task in Study 2. See the online article for the color version of this figure.

tions in the population, as indicated by significant rank correlations between the total sum of the reported instances and actual frequency for adults, $r_S(17) = .65$, $p = .003$, $BF_{10} = 17.83$, and children, $r_S(17) = .89$, $p < .001$, $BF_{10} = 43{,}447.21$.

Model comparison. Figure 4 shows the membership probability of each adult (left panel) and each child (right panel) for each of the strategies, as derived from the posterior distribution of the classification parameter. The figure shows that the judgments of most adults and most children were best described by the social-circle model (64.29% of adults and 78.57% of children). The proportion of participants best described by availability-by-recall (25.00% of adults and 12.50% of children) or the guessing strategy (10.71% of adults and 8.93% of children) was considerably lower. The differences in strategy use between the two age groups were not significant, $\chi^2(2) = 3.22$, $p = .199$, $BF_{10} = 0.24$; in fact, the Bayesian analysis provided positive evidence against an effect of age on strategy use (see, e.g., Kass & Raftery, 1995).

Parameter estimates. An important advantage of hierarchical latent-mixture modeling is that, in addition to distinguishing between discrete classes of participants who used different inference strategies, it allows us to estimate the model parameters within each group. Inspecting the distributions of the social-circle model's parameters at the group and individual level gives insights into the search and decision processes underlying adults' and children's inferences. As the group-level means of the parameters reported in Table 2 show, children and adults weighted the different circles in their social network in similar ways, applied similar difference thresholds, and did not differ on the response noise parameter (for all parameters, the 95% highest density intervals overlapped).

Turning to the individual-level parameter estimates of participants for whom the social-circle model provided the best account, Figure 5 reveals substantial individual differences in the mechanisms underlying social sampling in the two age groups. There were also some differences between the age groups in the relative weighting of instances represented in, for example, the "family" and "friends" circles: More adults put a high weight on instances among family members, whereas children seemed to pay more attention to instances among their friends. Overall, however—and in line with the group-level means—there were more similarities than differences between children and adults in their search for instances in memory.

Discussion

In Study 2—as in Study 1, but in a different domain—we found strong support for structured and limited search in social sampling. Using the social-circle model to study children's and adults' social sampling revealed striking similarities in the search and decision processes of the two age groups. This finding suggests that children are already able to systematically exploit their knowledge of instances to make inferences about social statistics and that they often harness their instance knowledge in a structured and limited fashion. Finally, we obtained evidence for considerable individual differences in these processes, which the social-circle model allows to represent and measure.

Study 3: Recovery of the Social-Circle Model and Its Parameters

Studies 1 and 2 used the social-circle model to capture individual differences in various aspects of boundedly rational social sampling. The results suggest that it is important to allow for such heterogeneity if the aim is to capture the cognitive processes involved in social sampling. But do the estimated parameters of the social-circle model indeed reflect the characteristics of the cognitive process assumed to underlie social sampling? And do they lead to patterns in decisions that are specific enough to correctly diagnose the parameter values that generated the data? Finally, can decision patterns generated by the social-circle model be reliably differentiated from decision patterns generated by other models? To address these questions, we conducted model and parameter recovery analyses using computer simulations. Specifically, we used the instance knowledge and parameter estimates obtained for participants in Study 1 and Study 2 to simulate decision makers who used each of the instance-based strategies examined. The question was how well the generating models, as well as the parameter values generating the models' decisions, could be recovered.

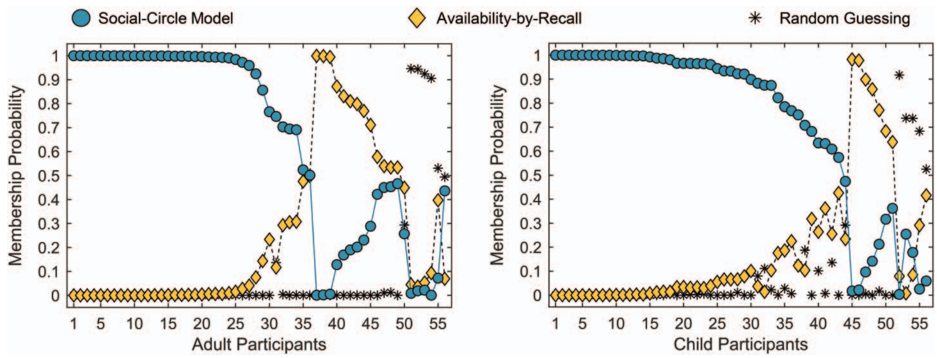

Figure 4. Membership probabilities of adult (left panel) and child participants (right panel) in the three latent subgroups in Study 2: the social-circle model, availability-by-recall, and random guessing. See the online article for the color version of this figure.

Method

We conducted three sets of recovery analyses, one for each of the participant samples in Studies 1 and 2 (i.e., $N = 40$ for Study 1, and $Ns = 56$ for both samples in Study 2), again analyzing the social-circle model, availability-by-recall, and the social-circle heuristic for the Study 1 data, and the social-circle model and availability-by-recall for the Study 2 data. For the Study 1 data, we again assumed a constant error mechanism for the social-circle heuristic and availability-by-recall; for the Study 2 data, we assumed the same response noise mechanism for availability-by-recall as is implemented in the social-circle model (i.e., a probit error mechanism). We also used the same inference problems (and number of trials) as previously, as well as the instance knowledge reported by each participant. Using the posterior group-level mean parameter estimates for each strategy as reported above, we determined, for each participant (based on the instance knowledge they reported), the choice probabilities predicted by the respective strategy across each trial of the inference task. Based on the predicted choice probabilities, binary decisions were generated. To control for sampling error, we repeated this procedure 15 times for each participant. In total, there were thus 600, 840, and 840 simulated decision makers for each strategy in the first, second, and third simulation analysis, respectively.

We modeled the simulated decisions using a hierarchical Bayesian latent-mixture modeling approach, treating each of the 15 simulated data sets as one experiment. This procedure allowed us to assess parameter recovery on the group level (across the 15 simulated data sets) as well as at the individual level (within each data set). The latent-mixture structure used in the recovery analyses again included a baseline model representing a guessing strategy. For parameter estimation and model evaluation procedures, we used the same priors on the parameters as were used in Studies 1 and 2, ensured efficient mixing with pseudo-priors that approximated the posterior density for the individual-level parameters, and ran multiple chains to estimate the posterior distributions of model parameters via Gibbs sampling methods implemented in JAGS (Plummer, 2003). In the analyses, 20 chains—each with 5,000 samples drawn from the posterior distributions—were run after an initial burn-in period of 500 samples.

Table 2
Posterior Means and 95% Highest Density Intervals (HDIs; in Brackets) of the Group-Level Estimates for Parameters of the Social-Circle Model, Separately for Adults and Children in Study 2

	Posterior *M*s and 95% HDIs	
Group-level parameters	Adults	Children
w_{self}	.27 [.00, .57]	.24 [.00, .52]
w_{family}	.29 [.00, .56]	.26 [.06, .51]
$w_{friends}$	.35 [.02, .63]	.41 [.07, .70]
$w_{acquaintances}$	.10 [.00, .21]	.09 [.00, .19]
Difference threshold (d)	.18 [.03, .32]	.21 [.11, .31]
Response noise (σ)	0.70 [0.51, 0.88]	0.66 [0.42, 0.88]

Results

Model recovery. Drawing on the membership probabilities estimated for each simulated decision maker, we classified decision makers as users of one of the strategies under consideration (the one for which membership probability was highest). Table 3 summarizes the percentages of simulated decision makers classified as users of each strategy for the three data sets, as a function of the model generating the simulated choices. For the large majority of simulated decision makers in all three sets, the generating mechanism was correctly recovered. Nevertheless, there was some variability in recoverability across sets, with recoverability being highest for the adult sample in Study 2 and lowest for Study 1. This pattern may be attributable to differences in the amount of instance knowledge across data sets, which determined the number of inferences on which the strategies can make (diverging) predictions; the number of reported instances was highest for the adult sample in Study 2 (median of 51 instances across all holiday destinations) and lowest for Study 1 (median of 21 instances across all sport types). In sum, the results show that use of the social-circle model can be reliably discriminated from the other tested strategies, but also that the general recoverability of the strategies depended on how many instances were reported.

Parameter recovery. To assess parameter recovery, we compared the recovered group-level and individual-level parameter estimates with the values that were used to generate the data. As Figure 6 shows, both the individual-level posterior median param-

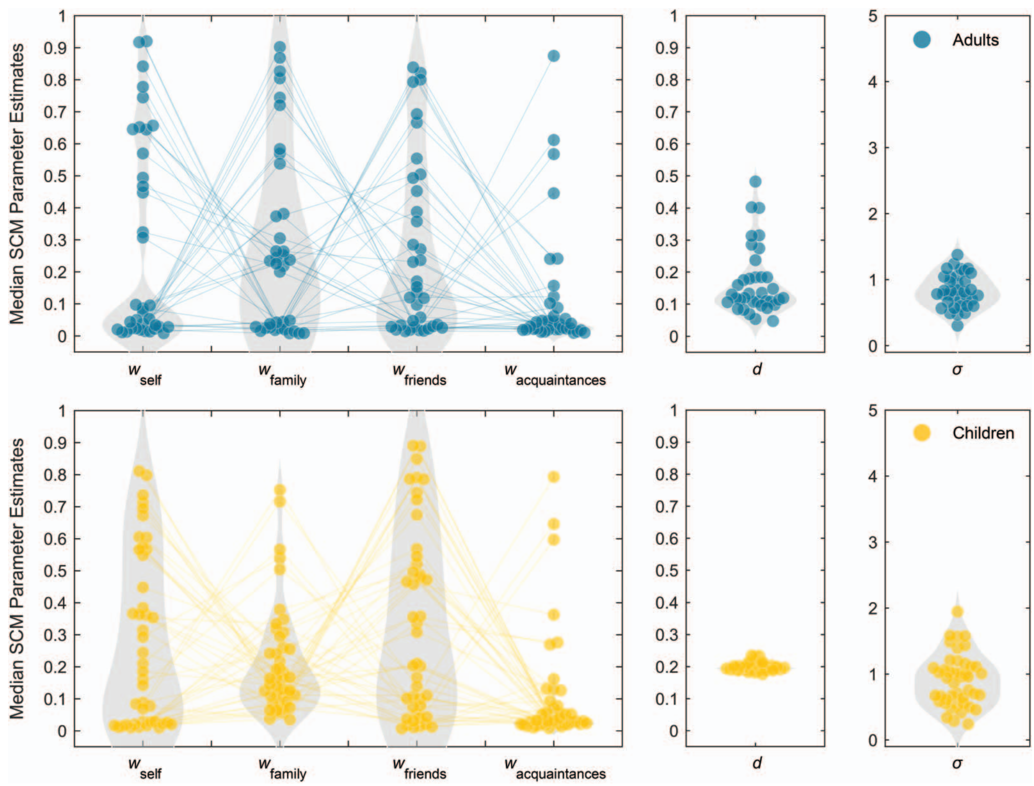

Figure 5. Distributions of the medians of each individual's posterior distribution of social-circle model (SCM) parameter estimates in Study 2, separately for adults (top) and children (bottom) for whom the social-circle model provided the best fit. Colored lines link the estimated circle-weight parameters of each participant. Medians were computed over samples for which the classification parameter indicated membership of the social-circle model. See the online article for the color version of this figure.

eter estimates of the social-circle model (density plots) and its group-level posterior mean parameter estimates (gray circles) recovered the generating parameter values (dashed lines) rather well.

Discussion

The recovery analyses presented in this section demonstrate that the computational framework of the social-circle model is able to disentangle and measure aspects of the cognitive processes assumed to underlie boundedly rational social sampling. For all data sets, the hierarchical Bayesian model comparison method recovered the large majority of simulated strategy users. Specifically, 79% to 95% of the simulated decision makers were correctly assigned to the strategy that had generated their choices; the social-circle model was correctly recovered in no fewer than 85% of cases. Importantly, these analyses also showed adequate parameter recovery, on both the group and the individual level. These results thus indicate that the cognitive processes assumed by the social-circle model are identifiable—at least when using the hierarchical Bayesian modeling approach.

General Discussion

People can make inferences about social statistics in the population by drawing on observations sampled from their proximate social networks. Through their behaviors and characteristics, network members provide indications about social statistics—that is, the frequency distribution of those behaviors and characteristics in the population at large. But how exactly do people sample members of their social network from memory? Both theoretical and empirical work on multi-attribute and risky choice has highlighted that search for attributes, reasons, and cues often proceeds sequentially, and that it is terminated when sufficient evidence has been accumulated. To date, little attention has been paid to the possibility that social sampling might be governed by the same principles of bounded rationality, namely, sequential, structured, and limited search. In addition, a large literature suggests that there is considerable heterogeneity across decision makers in search and decision-making processes, as well as individual variability in terms of probabilistic responding. In this article, we proposed a computational model that represents one way in which boundedly rational social sampling can be conceptualized. This model goes beyond previous work on social sampling (e.g., Galesic et al., 2012, 2018; Hertwig et al., 2005; Pachur et al., 2012; Pachur, Hertwig, & Rieskamp, 2013; Tversky & Kahneman, 1973) by considering three key aspects of search and decision making. First, the social-circle model captures the idea that search is sequentially structured and limited; second, it permits individual differences to

Table 3
Results of the Model Recovery Analyses in Study 3: Percentages of Simulated Decision Makers Classified as Users of Each Strategy, Separately for the Three Sets of Recovery Analyses (Using the Reported Instance Knowledge of Participants in Study 1 or the Adult and Child Sample in Study 2, Respectively)

	Generating model		
Classified strategy	Social-circle model	Availability-by-recall	Social-circle heuristic
Based on Study 1			
Social-circle model	**85.17%**	5.00%	5.00%
Availability-by-recall	5.83%	**83.17%**	15.67%
Social-circle heuristic	8.17%	11.83%	**78.83%**
Random guessing	0.83%	0.00%	0.50%
Based on Study 2 (adult sample)			
Social-circle model	**93.21%**	5.00%	—
Availability-by-recall	6.67%	**95.00%**	—
Random guessing	0.12%	0.00%	—
Based on Study 2 (child sample)			
Social-circle model	**92.98%**	11.31%	—
Availability-by-recall	6.31%	**86.90%**	—
Random guessing	0.71%	1.79%	—

Note. The percentage of correctly recovered strategy users in each analysis is marked in bold.

be represented and measured; third, it acknowledges the probabilistic nature of human judgment and decision making.

Our analyses, which used hierarchical Bayesian latent-mixture modeling, provided considerable support for the social-circle model. We found that people often limited their search through social memory when judging event frequencies on the basis of instance knowledge, rather than engaging in exhaustive search. Our analyses also supported the idea that people exploit regularities of the external social environment to structure and terminate the internal search in memory. These results thus echo past research findings of links between the cognitive processes underlying search in physical space and search in abstract cognitive space (e.g., Hills et al., 2008). We also observed considerable individual differences in how, and how extensively, people searched for instances in social memory. This applied to both adults and children—although children generally reported fewer instances than adults did. Using cognitive modeling to formalize and quantitatively analyze individual differences in the use of social sampling strategies enabled us both to detect differences in the use of discrete strategies and to parameterize the mechanisms underlying search for instances in memory. Moreover, our results offer insights into developmental aspects of the search for social information in memory. Children seem to consult their social memories to draw inferences about social statistics and to rely on sequentially structured and limited search. This developmental dimension illustrates how the proposed modeling framework can be used to formalize and discern properties of the underlying cognitive processes (e.g., search order, sensitivity to sampled information, response noise) across development. More generally, the social-circle model offers a measurement tool for disentangling and quantifying aspects of the cognitive processes in social sampling and, on that basis, for studying individual differences and differences across age groups and domains. Next, we discuss the implications and future directions of our work.

Individual Differences and the Development of Social Sampling

Our findings echo previous results highlighting the importance of individual differences in the cognitive search associated with decision making (e.g., Davidson, 1991; Garcia-Retamero & Dhami, 2009; Mata & Nunes, 2010; Pachur & Marinello, 2013; Rakow et al., 2010). There seems to be quite some heterogeneity in the order in which people search their social memories, and in how extensive their social sampling is. An important avenue for future research is to understand the origins of these differences in people's search processes (e.g., age, gender, or expertise) and to relate them to cognitive abilities (e.g., executive control or working memory) but also to differences in the representation and structure of social environments.

The social-circle model assumes that people exploit a manifest regularity of their social environment to structure and search their social memory, namely, the natural segmentation of the social environment into groups of differing proximity to the individual (see, e.g., Hill & Dunbar, 2003; Milardo, 1992). This assumption is supported by research on the cognitive mechanisms underlying search in social memory, which has shown that social contacts are recalled in clusters of individuals that share a common feature (e.g., Bond & Brockett, 1987; Bond et al., 1985; Brewer, 1995; Fiske, 1995; Hills & Pachur, 2012). Various factors have been shown to contribute to this clustering—physical or personality characteristics (e.g., Bond & Brockett, 1987; Bond et al., 1985), social context (e.g., Bond et al., 1985; Fiske, 1995), and phonetic similarity of names (e.g., Fiske, 1995)—and there is considerable evidence that structuring in terms of social relations and social proximity accounts well for people's recall patterns (e.g., Brewer, Rinaldi, Mogoutov, & Valente, 2005; Hills & Pachur, 2012). Clustering in terms of social groups has also been shown to play an important role in structuring children's recall of their classmates

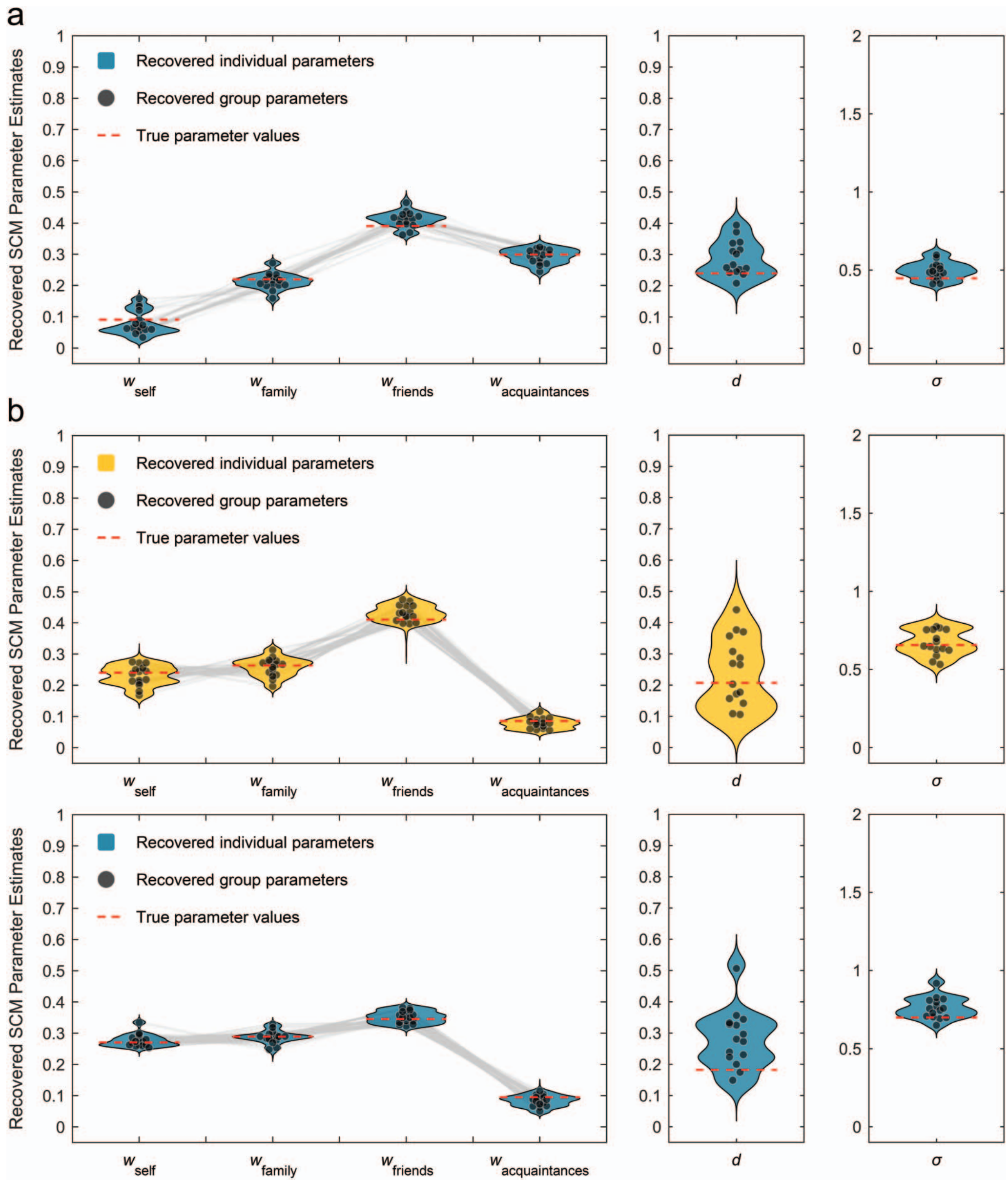

Figure 6. Recovery results for the parameters of the social-circle model (SCM) in Study 3 using the instance knowledge of (a) participants in Study 1, (b, top) children in Study 2, and (b, bottom) adults in Study 2. The density plots show the distributions of the medians of each simulated individual's posterior distribution of social-circle model parameter estimates; solid gray lines link the estimated circle-weight parameters of each simulated individual. Medians were computed over samples for which the classification parameter indicated membership of the social-circle model. Gray circles indicate the recovered group-level posterior mean parameter estimates, and red dashed lines show the true, generating parameter values. See the online article for the color version of this figure.

(e.g., Bjorklund & Zeman, 1983). Nonetheless, search in social memory is likely to rest on more than one type of retrieval cue and may differ as a function of the internal representation of the social environment. Another important retrieval cue that may guide social sampling from memory is the frequency of contact with a person. Frequency of occurrence has been shown to be a key factor in determining the retrieval probability of information stored in memory (e.g., Anderson & Milson, 1989) and, in free social recall, people name individuals with whom they have more contact earlier (e.g., Hills & Pachur, 2012). In the two empirical studies we presented here, participants' frequency of contact with each person recalled during the retrieval task was elicited along with their social category. However, assuming the search for instances in memory to be guided by frequency of contact with the recalled person did not account as well for participants' inferences as did assuming search to be structured by social category (see Footnote

7 and Pachur, Hertwig, & Rieskamp, 2013). It is possible that frequency of contact plays a more important role in other domains or samples.

To examine developmental similarities and differences in social sampling, Study 2 applied the social-circle model to the inferences of both adults and children (see also Schulze, Pachur, & Hertwig, 2017). This analysis expands on a previous study in which we asked children and adults to judge the relative frequency of common first names in Germany (Schulze et al., 2017). In that study, a substantial subset of children exploited their instance knowledge in a structured and limited way—in line with the present findings. In contrast to the present findings, however, there were also many children who applied an exhaustive search mechanism. One limitation of the decision domain used in Schulze et al. (2017) was that children had relatively sparse instance knowledge on which to base their judgments (after all, the reference class of possible first names is larger than that of possible holiday destinations), leading to a lower discriminability between inference strategies in children than in adults. In the present study, with a richer inference domain, there were similar levels of discriminability between inference strategies in children and adults. As the simulations in Study 3 showed, the recoverability of computational models describing a participant's strategy use improved with increasing amounts of instance knowledge available to that participant.

Overall, an important insight from our comparison of children's and adults' social sampling is the striking similarity between age groups in the underlying search and decision processes and the individual differences therein. These results echo previous findings from risky choice, suggesting that children do not necessarily differ from adults in their search efforts (see van den Bos & Hertwig, 2017).

Social Sampling Across Domains

Together with our previous work (Schulze et al., 2017), the present results also point to an important aspect of social sampling that can be addressed using the social-circle model: the domain specificity of people's use of instance knowledge in their social circles. Comparing the distributions of individual participants' social-circle weight parameters in the two domains we investigated—the popularity of sports (Study 1) and holiday destinations (Study 2)—suggests that participants weighted the various sources of their instance knowledge somewhat differently in these domains. Instance knowledge from friends and acquaintances was given priority for sports, whereas participants' own experiences were factored in more strongly for holiday destinations. These findings might indicate an adaptive use of instance knowledge, reflecting domain-specific differences in the relative reliability and density of instance knowledge. Although knowledge about the activities, preferences, and opinions of others is likely to be less certain and reliable than knowledge about oneself, acquaintances may be the only available source of information in domains where instance knowledge is sparse (e.g., the relative popularity of sports or first names; see Schulze et al., 2017). As a consequence, information from acquaintances might receive higher weight in domains where instance knowledge is sparse than in domains where it is more densely distributed (e.g., the relative popularity of holiday destinations).

Advantages and Potential Downsides of Boundedly Rational Social Sampling

Sampling from one's local social network provides only a snapshot of the distribution of characteristics in the population at large. Conceptualizing social sampling as boundedly rational—that is, as characterized by structured and limited search—implies even smaller samples of information. Inferences based on social sampling can thus also lead to inaccurate impressions of the world (see also Schulze & Pachur, 2019). People may perceive their own beliefs and behaviors to be more prevalent in the population than behaviors they would not endorse (false-consensus effect; Ross et al., 1977). Similarly, because social network ties are not distributed randomly, but people tend to associate with others who have much in common with them, proximate social samples can be unrepresentative of the population at large (e.g., McPherson, Smith-Lovin, & Cook, 2001). Although people may strive to correct for such unrepresentative information (see, e.g., Galesic et al., 2018; Oppenheimer, 2004), they may not always succeed in gauging to what extent they need to adjust their personal experience. Nonetheless, relying on small samples is not *necessarily* detrimental to inferential accuracy; it can also empower accurate inferences (e.g., Pachur, Hertwig, & Rieskamp, 2013; see also Ambady & Rosenthal, 1992; Hertwig & Pleskac, 2010; Kareev, 1995). Moreover, although sampling from the proximate social environment can result in apparent social distortions—including self-enhancement or self-deprecation—the underlying social judgments reflect the structure of the immediate social environment rather well (Galesic et al., 2012, 2018). To the extent that the proximate social environment is a more relevant frame of reference for social comparisons than is the social environment at large, judgments being well calibrated to the frequency distributions in the relevant social circles may be considered adaptive.

In an increasingly digitalized world where people have access to unprecedented amounts of (social) information, however, the reliance on personal social information may pose additional challenges, or even shift the balance between the positive and negative consequences of boundedly rational social sampling. Information proliferation through social media and other digital communication technologies may have detrimental consequences such as polarization, herding, and misinformation (e.g., Hills, 2019). Under competition for attentional resources in information-rich environments, people tend to prefer information that is consistent with their prior beliefs or decisions over inconsistent information (e.g., Fischer, Schulz-Hardt, & Frey, 2008). Reduced exposure to information diversity through formats such as personalized online information, recommender systems, or in-group selection can create communication paths that resemble "echo chambers" (e.g., Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). Thus, another important direction for future research is to examine whether these characteristics of information-rich online environments also impact the cognitive mechanisms underlying social sampling from online relative to offline social networks. Previous research has shown that online and offline social networks are highly comparable in size and structure and that both follow the predictions of the social brain hypothesis (Dunbar, 2016; Dunbar, Arnaboldi, Conti, & Passarella, 2015). Whether this generalizability from external offline to online social networks also holds for the cognitive mechanisms that harvest information from internal social memory is an open question.

Conclusion

Let us recall the challenges faced by contestants in *Family Feud* (or, indeed, by anyone making judgments about the social texture of everyday life). In an uncertain world void of objective information about social statistics, people can exploit observations sampled from their personal social networks to make inferences about frequencies in many domains of life. The enjoyment that people appear to derive from considering their social environment may therefore be a consequence of adaptive social learning strategies. Our findings suggest that such boundedly rational social sampling is guided by the structure of the external social environment, that search is limited, that the underlying search and decision processes vary across individuals, and that—like many other cognitive processes—social sampling is probabilistic in nature. The present work thus contributes to a better understanding of how people exploit their social ecologies when making boundedly rational judgments about the world, and how individual differences in these processes can be mapped.

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Appendix A

Bayesian Model Selection

The social-circle model described in this article makes it possible to measure individual differences in three key aspects of social sampling: an individual's search order through social memory, the difference threshold required to stop search at a given circle, and response noise. In developing the social-circle model, we evaluated the necessity of having these aspects as free parameters in the model by systematically comparing models that either constrain or freely estimate each aspect (see Table A1). Additionally, we compared different functional forms of stochasticity commonly implemented in computational models of human judgment and decision making to estimate response noise. Probabilistic models have a long history in research on judgment and decision making (e.g., Luce, 1959; Thurstone, 1927; Tversky, 1972); here, we contrasted three prominent functional forms of probabilistic responding for the social-circle model: probit, logit, and a constant application error.

Model Specifications for Different Error Mechanisms

Probit

As described in the main text, this variant assumes stochasticity in the comparison of proportional evidence against the difference threshold in the form of normally distributed error for each circle; the probability of making a choice after inspection of a particular circle is specified in Equation 4.

Logit

Here, the probability of selecting an event based on the comparison between evidence and threshold at a particular circle is assumed to follow a logistic function:

$$p_i(A|AB) = \frac{1}{1 + e^{-\theta(e_i - d)}}. \tag{A1}$$

The slope of the function is governed by the sensitivity parameter θ. If $\theta = 0$, search is stopped at random, whereas high sensitivity parameter values ($\theta \rightarrow \infty$) result in strictly deterministic stopping decisions when the comparison of evidence against the threshold favors one option over the other.

Constant Application Error (or "Trembling Hand")

In this variant, search is stopped deterministically based on the comparison between evidence and threshold. Stochasticity in responding is introduced by assuming that an individual sometimes makes application errors that are independent of the amount of evidence in a given circle. If the evidence within a circle exceeds the threshold, the probability of stopping equals 1. When making a decision, individuals are assumed to guess with a constant probability g ($0 < g < 1$) between the events in any comparison. If a person does not guess, they are assumed to use the social-circle model with $1 - g$ instead, such that

$$p^*(A|AB) = \frac{g}{2} + (1 - g) \times p(A|AB). \tag{A2}$$

Hierarchical Bayesian Model Evaluation

To evaluate the relative importance of having each of the model's aspects as free parameters and to compare the performance of different error functions, we used the Deviance Information Criterion (DIC) statistic, which balances a model's goodness-of-fit and complexity (Spiegelhalter, Best, Carlin, & van der Linde, 2002). We performed hierarchical Bayesian modeling analyses separately for each model. For models that assumed a probit or constant application error mechanism, we used the same priors on the group-level parameters as described in the main text. For models implementing the logit variant, we assumed uniform distributions constrained between [0.0001–100] on the group-level mode and standard deviation of the θ parameter. In each model estimation, 20 chains—each with 50,000 samples drawn from the posterior distributions—were run after an initial burn-in period of 2,000 samples to estimate the posterior distributions of model parameters via Gibbs sampling methods implemented in JAGS (Plummer, 2003). Gelman–Rubin statistics and visual inspections of the chains indicated adequate chain convergence. Table A1 summarizes the assumptions, constraints, and DIC values of the 12 models compared. The models were applied to the inferences of 40 participants in Study 2 of Pachur, Hertwig, and Rieskamp (2013). As the table shows, each freely estimated aspect of the social-circle model sufficiently improved the model's ability to account for the data to justify the higher model complexity—irrespective of the assumed error mechanism. Nonetheless, there were differences between the three error mechanisms, with the constant application error showing the poorest performance, irrespective of the other aspects considered (difference threshold and search order). Logit and probit showed very similar performances.

(*Appendices continue*)

Table A1
Deviance Information Criterion (DIC) for 12 Models Assuming That the Difference Threshold and Search Order Are Fixed Versus Freely Estimated and Where the Assumed Error Mechanism Consists of a Constant Application Error, a Logit Function, or a Probit Function (With Number of Free Parameters and Assumptions Made for Each Model)

Model name	Number of parameters	Difference threshold	Search order	Error mechanisms (DIC)		
				Constant error	Logit	Probit
Social-circle heuristic[a]	1	Fixed	Fixed	15,448.20	15,394.60	15,398.01
SCM with threshold only	2	Free	Fixed	15,376.97	15,372.70	15,374.93
SCM with circle weights only	4	Fixed	Probabilistic	15,335.82	15,032.88	14,960.76
SCM full model	5	Free	Probabilistic	15,308.32	14,911.81	14,915.76

Note. SCM = social-circle model. For models assuming a fixed difference threshold, this parameter was set to zero (or a very low value to allow models with a probabilistic search order and an error mechanism that operates on the instance evidence to continue search beyond circles with zero instance evidence).
[a] The social-circle heuristic developed in Pachur, Hertwig, and Rieskamp (2013) assumes a constant application error. Here, we compare different error mechanisms but preserve all other constraints (fixed search order and no difference threshold).

Appendix B

Relation of the Social-Circle Model's Circle-Weight Parameter Estimates to a Circle's Discrimination Rate

Are the estimated circle weights of the social-circle model distorted by the amount of instance knowledge the respective circle contains—such that the estimated weight is higher for a circle with more instances that thus discriminates more frequently between events? To address this possibility, we ran additional simulations in which we generated decisions based on a specific circle and then modeled the decisions with the social-circle model. The amount of instance knowledge available for a particular circle and which circle determined an inference were manipulated orthogonally. The goal of this simulation was to test whether the estimated circle weights for the social-circle model were indeed primarily indicators of a circle's importance in determining a decision, or rather of the distribution of instances across circles—that is, of the *discrimination rate* of the circle, defined as the frequency with which the number of instances in a circle differentiates between the events.

Method

We factorially manipulated the number of instances in a circle and whether a circle was decisive—that is, on which circle a decision was based. One circle contained the largest number of instances and the three other circles contained considerably fewer instances. To make a decision, the simulated decision maker examined only instances in the decisive circle: If the number of instances for each event discriminated between the alternatives, a decision was made; otherwise a random guess was implemented.

We ran three sets of analyses, separately for our three data sets in Studies 1 and 2. In each analysis, the number of instances for circles with high and low levels of instance knowledge was based on the distribution of instance knowledge in one of the participant samples in Studies 1 and 2. This procedure allowed us to gauge whether the validity of the estimated circle weights depended on the amount of instance knowledge, which varied across data sets (see also Study 3). In the simulations, the number of instances in the circle with the high number of instances was set to equal (approximately) the third quartile of instances per circle in the adult sample in Study 2 (19 instances), the child sample in Study 2 (13 instances), and the Study 1 sample (eight instances). The number of instances in the other circles was set to equal approximately the first quartile of instances per circle in the respective sample (six, four, and one instance, respectively). In all conditions, the number of instances was distributed randomly across 19 possible events. For each of the 16 conditions (high instance knowledge in each of the four circles × decisiveness of each of the four circles) in each of the three sets of analyses, we simulated 40 decision makers who made 171 inferences about all possible paired comparisons of 19 events.

The decisions of each simulated decision maker were determined as follows. For each decision problem, the instance knowledge in the decisive circle was examined. If the number of instances for the event discriminated, a decision was made; otherwise, the simulated decision maker guessed randomly. The simulated decision makers' inferences were then modeled with the social-circle model using a hierarchical Bayesian approach (with the same priors as described above) implemented in JAGS (Plummer, 2003). In each analysis, 20 chains—each with 5,000 samples drawn from the posterior distributions—were run after an initial burn-in period of 500 samples.

(*Appendices continue*)

Table B1
Posterior Means of the Group-Level Estimates for the Social-Circle Model's Circle-Weight Parameters of the Decisive Circle, Averaged Across Circles for Which the Manipulated Instance Amount and Decisiveness Coincided (n = 4) and Those for Which the Decisive Circle Did Not Pool the Majority of Instances (n = 12)

	Average posterior means	
Simulation	Decisive circle has highest number of instances (n = 4)	Decisive circle has a low number of instances (n = 12)
Low instance knowledge (based on Study 1)	.996	.984
Medium instance knowledge (based on Study 2, child sample)	.996	.993
High instance knowledge (based on Study 2, adult sample)	.996	.995

Results

Would the estimated circle weights in the different conditions consistently indicate which circle was decisive, or would they be distorted by the number of instances in a circle? The simulations showed that, even when instance knowledge was low, the circle-weight parameters of the social-circle model correctly reflected a decision maker's search order rather than the discrimination rate of that circle. Table B1 summarizes the means of the posterior distributions of the group-level circle weight parameter for the decisive circle, separately for cases where that circle contained the majority of instances and those cases where that circle contained only few instances. Across all three simulation analyses (with different overall levels of instance knowledge), the decisive circle was accurately recovered (with an estimated circle weight close to 1), irrespective of whether or not it contained the majority of instances.

In sum, the simulations showed that the circle-weight parameters of the social-circle model correctly reflected a decision maker's search order, rather than the discrimination rate of that circle (i.e., the frequency with which the number of instances in a circle differs between the events). This held even when the amount of instance knowledge was rather low.

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