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Does Social Sampling Differ Between Online and Offline Contacts? A Computational Modeling Analysis

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Abstract

Decision makers can infer social statistics (e.g., the relative frequency of health risks or consumer preferences in the population) by drawing on samples from their personal social networks. In light of the growing use of the Internet, much of people's social interactions occur online (e.g., via social media) rather than offline (e.g., via face-to-face contact). Here, we examine to what extent sampling of social network members from memory (social sampling) is affected by whether one usually has online vs. offline contact to a person. In our study, participants judged the popularity of holiday destinations and recalled people in their own online and offline social networks who had vacationed at each destination. Additionally, participants indicated the respective contact mode (offline, online, or mixed) and social category (self, family member, friend, or acquaintance) of each recalled person. We used a hierarchical Bayesian modeling approach to contrast two variants of a cognitive model that assumes sequential and limited search—the social-circle model. The variants assumed the search process underlying social sampling to be guided by either contact mode (online vs. offline) or social category. The model comparison further included an exhaustive sampling strategy and guessing. The majority of participants was best described by a limited rather than an exhaustive search strategy or guessing. Additionally, more than a third of participants were best described by the variant of the social-circle model assuming search to be guided by contact mode. Interestingly, participants who followed this search strategy also relied more strongly on their own experiences than participants who probed their memory by social category. Overall, these results provide the first evidence that contact mode affects social sampling from memory.

Keywords: sampling; online networks; decisions under uncertainty; probabilistic inference; heuristics

Introduction

In navigating their everyday lives, people often need to judge unknown frequencies. For example, do more people adhere to or ignore social distancing regulations? Which political candidate is most popular? There are several approaches to inferring these social statistics—for instance, by integrating affective responses (e.g., judging risks with a high emotional response as more frequent; Pachur, Hertwig, & Steinmann, 2012), or by relying on recognition (e.g., judging a political candidate one has heard of as more popular than a candidate one has not heard of; Goldstein & Gigerenzer, 2002). Another approach that has been found to capture people's judgments is to assume that they use knowledge about samples drawn from their personal social network, such as family, friends, and coworkers—and thus rely on *social sampling* (e.g., Galesic, Olsson, & Rieskamp, 2018; Schulze, Hertwig, & Pachur, 2021).

A prominent example of a social sampling strategy is the availability heuristic, according to which people infer the frequencies or probabilities of events by the ease with which instances or occurrences can be retrieved from memory (Tversky & Kahneman, 1973). In fact, several studies have demonstrated a link between people's judgments of population-level statistics and recalled instances of the respective events (e.g., Galesic, Olsson, & Rieskamp, 2012; Hertwig, Pachur, & Kurzenhäuser, 2005). Furthermore, research has examined the search space (i.e., which social contacts are consulted) and the processes underlying recall from social memory (e.g., whether there is a specific search order) in more detail. Findings suggest that search is sequential and limited and that the underlying search process exploits structures of the social environment (e.g., Pachur, Hertwig, & Rieskamp, 2013; Schulze et al., 2021). Specifically, memory recall has been shown to be guided by the social category of, or contact frequency with a recalled person (Pachur et al., 2013; Schulze et al., 2021)—a notion also supported by findings on patch-wise search processes underlying the retrieval of social contacts from memory (Hills & Pachur, 2012). Another factor that has been found to guide the retrieval of social contacts from memory is the level of closeness one feels toward a social contact. In addition to the factors described above, the level of closeness might be associated with ways in which people usually interact with the members of their social networks, such as online versus offline (Töpfer & Hollstein, 2021).

Yet, existing models of social sampling have not distinguished between whether people recall contacts they usually have contact with online or offline. However, the mode of contact represents an important ecological feature of our social environment. In recent years, the number of people using the Internet and social media has been continuously growing (Pew Research Center, 2021). During the COVID-19 pandemic and following social distancing regulations in particular, online contacts became a prominent source of social support and information (Pancani, Marinucci, Aureli, & Riva, 2021).

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Memory research suggests that the mode of contact might indeed serve as an additional retrieval cue for search in social memory. Several studies highlight that the context in which information is encoded plays an important role in how and how well this information is recalled (e.g., Godden & Baddely, 1975). For instance, Russian-English bilinguals recall more autobiographical memories from times during which they spoke Russian when being interviewed in Russian (and, correspondingly, more from their English-speaking past when being interviewed in English; Marian & Neisser, 2000). In addition to the environmental context, the modality of encoded information plays an important role in recall performance. For instance, several studies found that, in delayed recall, people recognize objects more accurately when they were presented visually as opposed to auditorily (e.g., Bigelow & Poremba, 2014; Kirkpatrick, 1894). Interacting with people either online or offline not only represents two different physical environments, but may also be associated with different modalities that influence the recall of social information from memory.

Social sampling has previously been used to explain the cognitive mechanisms behind societal, network-level effects such as polarization and social contagion (Brown, Lewandowsky, & Huang, 2022). In light of the vast amount of information available on social media, which may lead to misinformation and polarization (Hills, 2019; Lazer et al., 2018), it is important to assess to what extent people's cognitive processes underlying social sampling might be influenced by whether they usually have online or offline contact with a person. Hertwig et al. (2005) and Pachur et al. (2012) found little evidence that people make use of samples recalled from the news media to infer risk frequencies. Because online social contact increasingly takes place passively (i.e., by reading others' updates) rather than actively (e.g., by direct messaging or commenting; Burke, Kraut, & Marlow, 2011), samples recalled from interaction via online media might play a similarly small role in social sampling.

The goal of the present study is to investigate whether the contact mode (online vs. offline) might guide internal search in memory in social sampling. In particular, we assess whether a) a search process that explicitly discriminates between online versus offline contacts provides a viable account of people's frequency judgments, and b) which relative weight online versus offline contacts have in people's inferences.

Modeling Social Sampling Based on Contact Mode

To model people's inferences based on recalled (online vs. offline) contacts, we adapted the social-circle model (SCM) developed by Schulze et al. (2021). In contrast to social sampling models that capture how people infer continuous frequencies (e.g., how many people in a certain population have traveled to a specific country; e.g., Galesic et al., 2018), the SCM provides a formalized account of how people infer the relative frequency of two population-level events (e.g., how many people in a certain population have traveled to country A or country B). In doing so, the SCM assumes a sequential and limited search process. According to the SCM, decision makers sequentially inspect social circles defined by social category: the self (circle 1), family members (circle 2), friends (circle 3), and acquaintances (circle 4). The search order in which circles are consulted is assumed to be probabilistic, and defined by circle weight parameters for each social circle $w_i, i \in \{w_{self}, w_{family}, w_{friends}, w_{acquaintances}\}$. Instances of each event recalled from a given social circle (e.g., friends who have traveled to country A or country B) are tallied. The difference between the proportional tallies is contrasted against a difference threshold d that indicates how much evidence is required until a choice is made. If the evidence meets or surpasses this threshold, search is terminated. Otherwise, the next circle (e.g., family members who have traveled to country A or country B) is consulted. The SCM implements a probabilistic version of this process and assumes noise in the comparison of instance knowledge against the difference threshold (see Schulze et al., 2021, for a full formal description of the model).

The SCM parameterizes three aspects of social sampling: It yields parameters for an individual's favored search order (circle weights w_i), a difference threshold (d), and response noise (σ).

We adapted the SCM to capture a search order guided by contact mode (SCM-C). In the SCM-C, the social circles are defined as the self (circle 1), offline contacts (circle 2; people contacted only or mostly face-to-face), mixed contacts (circle 3; people contacted equally often face-to-face and via online platforms), and online contacts (circle 4; people contacted only or mostly via online platforms). The SCM-C thus entails parameters for participants' circle weights $w_j, j \in \{w_{self}, w_{offline}, w_{mixed}, w_{online}\}$, a difference threshold d, and response noise σ.

Experiment

Method

To compare the SCM-C to existing models of social sampling, we conducted an online study using Qualtrics survey software (https://www.qualtrics.com).

Participants Participants were recruited via Prolific (http://prolific.co) and received a reimbursement of 3.10 GBP and an additional performance-contingent bonus payment of 0.04 GBP for each correct inference in the inference task. To ensure that participants would be likely to recall online contacts, they were pre-screened to be between 18–50 years old and to regularly use social media. As the experimental material was targeted toward a UK-based sample, we also pre-screened for nationals from the United Kingdom, with English as their first language. To ensure compliance, participants' approval rate of previous Prolific studies needed to be at least 90%. The experiment was reviewed and approved by the institutional review board of the Max Planck Institute for Human Development. All participants provided informed consent to participate in the study. Overall, 150 participants completed it. We excluded participants who a) failed two or more comprehension and/or attention checks (out of a total of five comprehension and one attention check question), or b) who failed at least one of two seriousness checks. After exclusion, data was analyzed with a sample of $N = 138$ (aged 18—60 years, $M = 31.36$ years, $SD = 8.67$ years; 99 women).[1]

Materials and Procedure After a general introduction to the study, participants completed an inference task. In this inference task, they were asked to judge which of two holiday destinations is more frequently visited by UK residents. The task included comparisons between the 13 countries shown in Table 1 that were retrieved from the travelpac dataset (Office for National Statistics, 2019). We included highly-, medium-, and less-popular holiday destinations, in order to increase differences between popularity rates and thus to facilitate an assessment of how accurately each search strategy discriminates across a broad range of countries. Participants were presented with all possible combinations of these 13 countries over 78 trials. The order in which pairs were presented and the left-right positioning of destinations in each pair were randomized across participants.[2]

Following the inference task, participants answered an attention check question and completed a recall task. In the recall task, participants listed anonymized online and offline contacts from their personal social networks who had traveled to each holiday destination. The order of holiday destinations in the recall task was randomized across participants. For each recalled person, participants indicated the respective a) social category (self, family, friends, acquaintances), and b) contact mode in the preceding 24 months on a five-point scale (only face-to-face, predominantly face-to-face, mixed, mostly social media, or only social media). Additionally, participants were asked for the c) contact frequency with each recalled person during the preceding 24 months on a five-point scale (several times a week, once a week, approximately once a month, around once in six months, less than once in six months). For network members that had been contacted mostly or only via social media, participants additionally indicated d) whether they had ever met the contact in real life and whether the contact knew the participant.

Table 1: Countries presented in the inference task, their ranks in the study, as well as the ranks and visitor numbers from the travelpac sample (Office for National Statistics, 2019).

Rank	Country	Rank according to the full list	Number of visitors (2018-19)
1	Spain	1	6,787
2	France	2	3,179
3	Italy	3	1,375
4	USA	4	1,154
5	Greece	7	853
6	Thailand	22	175
7	Iceland	28	127
8	Canada	31	95
9	Australia	35	77
10	Sweden	40	57
11	Japan	41	56
12	Israel	49	28
13	New Zealand	52	23

At the beginning of the inference task and the recall task, participants were first presented with instructions, followed by comprehension checks (i.e., multiple-choice tests on the study instructions), as well as a practice round. After completing the inference and recall tasks, participants completed two seriousness checks. In these seriousness checks, participants were asked whether a) they had answered the questions faithfully, and whether b) they had googled or looked up any information during the experiment. Finally, participants provided demographic information. The experimental session lasted 22.35 minutes, on average.

The instructions included a definition of social media channels, encompassing platforms such as Facebook, Instagram, Twitter, TikTok, Snapchat, LinkedIn, as well as online forums. Because data collection took place 11 months after the start of the COVID-19 pandemic, we adjusted the study design to minimize potential confounds due to changes in interaction resulting from social distancing regulations. First, our definition of social media channels explicitly excluded Direct Messaging Services (such as WhatsApp), texting, and telephone calls, because we expected that these platforms were commonly used as an alternative for usual face-to-face contact. Second, participants were asked to recall individuals who had travelled to the particular destinations at any time (not only recently). Finally, the questions on contact mode and contact frequency explicitly covered a period of 24 months prior to the study.

Parameter Estimation and Model Evaluation Procedure To test whether a limited search strategy based on contact mode provides a viable account for people's frequency

[1] The age range in the sample deviates from the prescreening criteria, since one participant reported their age inconsistently (i.e., as <= 50 years on Prolific's internal demographic questionnaire and as 60 years in the study demographics).

[2] A technical issue in recording the randomization for two destination pairs lead to missing data on the positioning of these two pairs in the inference data set.

judgments, we compared the SCM-C to limited search based on social category (SCM), availability-by-recall strategy (which assumes exhaustive recall, such that people take into account information from their entire social network rather than from separate social circles), and guessing (i.e., randomly selecting one of two countries with a 50% probability). For this model comparison, a hierarchical Bayesian mixture modeling approach was used (see Bartlema, Lee, Wetzels, & Vanpaemel, 2014). Following this approach, all four models were included in one overarching model, in which a mixture parameter determined for each person, and each decision, which strategy provides a good representation of the respective choice and is used to update the strategy-level and individual-level parameters. This modeling approach yields an estimate of the probability that participants used each of the four strategies tested (posterior distribution of the mixture parameter), as well as a posterior probability of all individual-level parameters.

We followed the same model estimation procedure as Schulze et al. (2021). In particular, we used the same pseudo-priors, priors, and Gibbs sampling approach, implemented in JAGS (Plummer, 2003). Gelman–Rubin statistics confirmed adequate chain convergence of the mixture parameter estimates and all individual-level parameter estimates.[3]

We modeled inferences for all items on which a participant recalled a different number of contacts for the two countries in the comparison, allowing all social sampling strategies to make a prediction. On average, social sampling strategies made predictions in 73.28% of all 78 country comparisons.

Results

Inferential Accuracy and Number of Recalled Instances

On average, participants made correct inferences (according to the official statistics) in $M = 63.11$ of the 78 comparisons in the inference task ($SD = 4.56$). Across all countries presented in the recall task, 93.48% of participants remembered offline instances (i.e., contacts that they interact with only or mostly face-to-face), 84.06% recalled mixed instances (i.e., contacts they interact with equally offline and online), and 88.41% recalled online instances (i.e., contacts they interact with only or mostly via online channels). The total number of recalled contacts as well as the relative distribution of offline, mixed, and online contacts, varied largely between individuals (see Figure 1).

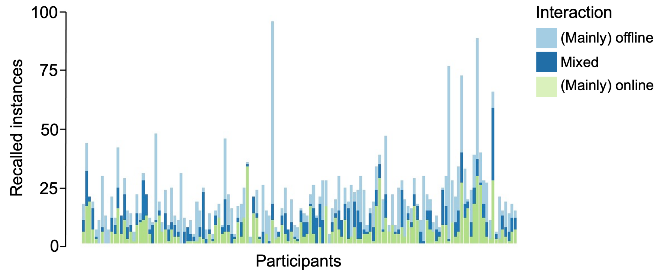

Figure 1: Recalled instances per participant.

There was very strong evidence for a positive rank correlation between the average number of reported instances and the actual number of visitors in the respective countries ($\tau_b(11) = .74$, $p < .001$, $BF_{10} = 95.06$). Thus, participants reported more instances for more frequently visited holiday destinations, suggesting that social sampling is a useful strategy for inferring relative frequencies in the traveling domain.

Model Comparison

To assess model performance for each participant, we examined the posterior distribution of the latent mixture parameter from the hierarchical Bayesian mixture analysis. Figure 2 depicts the individual membership probability of each participant for each of the four strategies.

As can be seen, most participants were clearly assigned to one of the four strategies. Both variants of the social-circle model described the performance of participants better than the availability-by-recall model and a guessing strategy: 36.23% of participants were best described by the SCM-C, 30.43% by the SCM, 26.81% by availability-by-recall, and 6.52% by a guessing strategy. Importantly, the SCM-C provided a better account for a slightly higher number of participants than did the SCM.

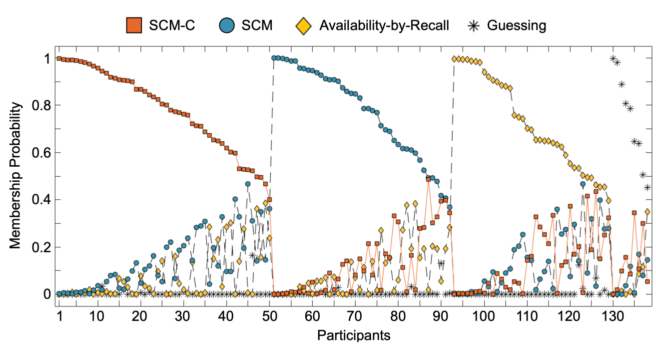

Figure 2: Membership probabilities for SCM-C, SCM, availability-by-recall, and guessing.

[3] According to Gelman-Rubin statistics, three group-level parameter estimates did not converge: variance estimates of w_{self}, w_{mixed} (SCM-C) and w_{family} (SCM). This might have resulted from the smaller number of samples available for estimating the variance for each group of strategy users. Because of the focus of this study on individual-level parameter weights and the global mixture parameter, we did not conduct further analyses with a larger number of chains.

Individual Parameter Estimates

To capture individual differences between users of the same strategy, we analyzed the individual-level model parameters. Figure 3 depicts the medians of the individual-level parameter estimates of individuals for whom the SCM-C or the SCM provided the best account.

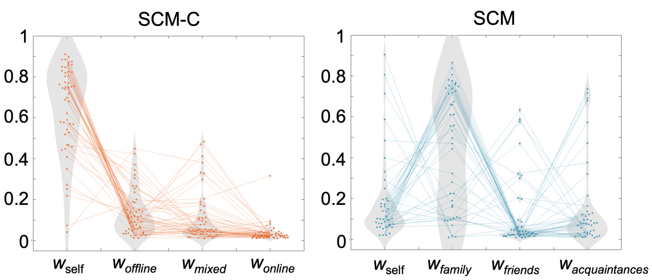

Figure 3: Distributions of the medians of each individual's posterior distribution of SCM-C and SCM weight parameter estimates.

Among participants best described by the SCM, the relative weight of social groups influencing participants' inferences varied widely between participants. Interestingly, participants best described by the SCM-C relied most strongly on their own experience—that is, they seemed to engage in egocentric search. In the next section, we consider the plausibility of participants' high weights for the self-circle (including potential confounding factors).

Distribution of Instance Knowledge

Did SCM-C strategy users rely more strongly on their own experience because they could not recall any other contacts who had traveled to the respective countries? This did not seem to be the case: Irrespective of their classified search strategy, only 8% of all participants recalled only themselves as an instance for at least one country. Additionally, the average number of circles from which contacts were recalled per country was relatively equal for SCM-C and SCM users (see Table 2).

In addition, we examined the correlation between SCM-C users' w_{self} parameter estimates and the relative frequency of correct predictions by the self-circle.[4] There was decisive evidence for such a link ($r(48) = .70$, $p < .001$, $BF_{10} = 816{,}291.08$), indicating that participants with a high weight on w_{self} could have made correct inferences by merely relying on their own experience.

Table 2: Average number of circles from which instances were recalled per country.

Country	SCM-C users	SCM users
Spain	2.22	2.21
France	2.36	2.19
Italy	1.64	1.79
USA	2.02	1.90
Greece	1.50	1.52
Thailand	0.96	1.26
Iceland	0.88	0.81
Canada	0.98	0.86
Australia	1.10	1.19
Sweden	0.78	0.74
Japan	0.76	0.83
Israel	0.40	0.52
New Zealand	0.80	0.57

Discussion

We examined the role of contact mode in sequential and limited social sampling. To that end, SCM-C—an inference strategy that assumes search in memory to be sequential, limited, and guided by contact mode—was compared to sequential and limited search guided by social category (SCM), an exhaustive availability-by-recall strategy, and guessing. Our results suggest that the mode of contact might serve as an additional retrieval cue during social sampling. In particular, the SCM-C provided the best account for more participants' inferences than did the SCM, availability-by-recall, or guessing. These results are in line with previous research showing that limited and sequential search strategies outperform exhaustive and guessing strategies (e.g., Schulze et al., 2021). In addition, our findings shed light on whether people's search through social memory is affected by contact mode (i.e., online vs. offline). Thus, our results add to the literature on context-dependent encoding, highlighting that whether one usually has contact to a person online or offline functions as an additional contextual cue that can affect retrieval from memory.

In contrast to participants who were best described by the SCM, SCM-C users most strongly relied on their own experience. The reasons for this egocentric search need to be scrutinized further in future research. One possible explanation is that people implicitly corrected for potential biases resulting from integrating information about online contacts.

In addition, the results from this study apply only to the investigated judgment domain; a search process as formalized by the SCM-C might not necessarily hold in other domains. For instance, when determining which search strategies to use in a given environment, heuristic inference requires experience and a relevant knowledge base (Horn, Ruggeri, & Pachur, 2016). Thus, topics frequently discussed online (such as mental illness; Jones et al., 2011) might

[4] To assess the relative frequency of correct predictions, we examined the number of correct predictions (based on knowledge about the self) relative to all possible predictions (based on knowledge about the self).

represent a domain where search based on contact mode performs particularly well. Moreover, it is likely that in such domains, online contacts will receive a higher weight, as a sufficient number of instances might not be available from one's offline circle alone. Contrasting parameter weights estimated with the SCM-C in different domains could provide insights into when reliance on online contacts may be adaptive.

Additionally, contact members might jointly vary on contact mode and social category (such that certain friends, for example, are predominantly contacted online) and other retrieval cues, such as the frequency of interaction, or the closeness to a social contact, might also play an important role for cuing social memory (Hills & Pachur, 2012; Töpfer & Hollstein, 2021). Future research should therefore simultaneously incorporate several characteristics of social contacts to examine their relative role in social sampling.

The SCM has previously been used to shed light on developmental differences in social sampling, such as differences between children's and adults' use of social sampling to infer population-level frequencies (Schulze et al., 2021). Further research could examine potential developmental differences in the use and performance of social sampling from online contacts. In particular, such differences seem plausible between adolescents and adults, due to differences in their online environments (e.g., differences in what they use social media for; Koiranen, Keipi, Koivula, & Räsänen, 2020; or differences in which platform is used and the amount of time spent on social media; Pew Research Center, 2018, 2021). One factor influencing how well social sampling strategies perform and thus can be used in an adaptive way is the correlation between recalled contacts and the judgment domain (Horn et al., 2016). Since adolescents have more information from online contacts available than adults, they might use this information to a greater extent.

Overall, although social sampling strategies can undoubtedly lead to inaccurate judgments about the world, in general they seem to be a good guide in gauging relative frequencies in the environment. In our study, participants made correct inferences in more than 80% of comparisons. Additionally, structured and limited social sampling strategies have an important ecological advantage over exhaustive search strategies: they can achieve similar accuracy, while requiring less time to terminate search in certain environments. Following the notion of ecological rationality, structured and limited search in social sampling can perform well when search aligns with the structure of people's external social networks (Todd, Gigerenzer, & the ABC Research Group, 2012). Adding to the literature on the importance of environmental context for memory retrieval, our study sheds light on a new factor that might guide people's retrieval from social memory—whether they have contact to a person online or offline. In particular, our findings suggest that the mode by which one usually interacts with a social network member serves as a retrieval cue that seems to guide internal social sampling from memory, enabling people to navigate effectively in an uncertain world.

References

Bartlema, A., Lee, M., Wetzels, R., & Vanpaemel, W. (2014). A Bayesian hierarchical mixture approach to individual differences: Case studies in selective attention and representation in category learning. *Journal of Mathematical Psychology*, *59*, 132–150. https://doi.org/10.1016/j.jmp.2013.12.002

Bigelow, J., & Poremba, A. (2014). Achilles' ear? Inferior human short-term and recognition memory in the auditory modality. *PLoS ONE*, *9*(2), e89914. https://doi.org/10.1371/journal.pone.0089914

Brown, G. D. A., Lewandowsky, S., & Huang, Z. (2022). Social sampling and expressed attitudes: Authenticity preference and social extremeness aversion lead to social norm effects and polarization. *Psychological Review*, *129*(1), 18–48. https://doi.org/10.1037/rev0000342

Burke, M., Kraut, R., & Marlow, C. (2011). Social capital on Facebook: Differentiating uses and users. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 571–580. https://doi.org/10.1145/1978942.1979023

Galesic, M., Olsson, H., & Rieskamp, J. (2012). Social sampling explains apparent biases in judgments of social environments. *Psychological Science*, *23*(12), 1515–1523. https://doi.org/10.1177/0956797612445313

Galesic, M., Olsson, H., & Rieskamp, J. (2018). A sampling model of social judgment. *Psychological Review*, *125*(3), 363–390. https://doi.org/10.1037/rev0000096

Godden, D. R., & Baddely, A. D. (1975). Context-dependent memory in two natural environments: On land and underwater. *British Journal of Psychology*, *66*, 325–331. https://doi.org/10.1111/j.2044-8295.1975.tb01468.x

Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review*, *109*(1), 75–90. https://doi.org/10.1037/0033-295x.109.1.75

Hertwig, R., Pachur, T., & Kurzenhäuser, S. (2005). Judgments of risk frequencies: Tests of possible cognitive mechanisms. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(4), 621–642. https://doi.org/10.1037/0278-7393.31.4.621

Hills, T. T. (2019). The dark side of information proliferation. *Perspectives on Psychological Science*, *14*(3), 323–330. https://doi.org/10.1177/1745691618803647

Hills, T. T., & Pachur, T. (2012). Dynamic search and working memory in social recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(1), 218–228. https://doi.org/10.1037/a0025161

Horn, S. S., Ruggeri, A., & Pachur, T. (2016). The development of adaptive decision making: Recognition-based inference in children and adolescents. *Developmental Psychology*, *52*(9), 1470–1485. https://doi.org/10.1037/dev0000181

Jones, R., Sharkey, S., Ford, T., Emmens, T., Hewis, E.,

Smithson, J., … Owens, C. (2011). Online discussion forums for young people who self-harm: User views. *The Psychiatrist*, *35*(10), 364–368. https://doi.org/10.1192/pb.bp.110.033449
Kirkpatrick, E. A. (1894). An experimental study of memory. *Psychological Review*, *1*(6), 602–609. https://doi.org/10.1037/h0068244
Koiranen, I., Keipi, T., Koivula, A., & Räsänen, P. (2020). Changing patterns of social media use? A population-level study of Finland. *Universal Access in the Information Society*, *19*(3), 603–617. https://doi.org/10.1007/s10209-019-00654-1
Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., … Zittrain, J. L. (2018). The science of fake news. *Science*, *359*(6380), 1094–1096. https://doi.org/10.1126/science.aao2998
Marian, V., & Neisser, U. (2000). Language-dependent recall of autobiographical memories. *Journal of Experimental Psychology: General*, *129*(3), 361–368. https://doi.org/10.1037/0096-3445.129.3.361
Office for National Statistics. (2019). *Travelpac: Travel to and from the UK (data collection)*. Retrieved from https://www.ons.gov.uk/peoplepopulationandcommunity/leisureandtourism/datasets/travelpac
Pachur, T., Hertwig, R., & Rieskamp, J. (2013). Intuitive judgments of social statistics: How exhaustive does sampling need to be? *Journal of Experimental Social Psychology*, *49*(6), 1059–1077. https://doi.org/10.1016/j.jesp.2013.07.004
Pachur, T., Hertwig, R., & Steinmann, F. (2012). How do people judge risks: Availability heuristic, affect heuristic, or both? *Journal of Experimental Psychology: Applied*, *18*(3), 314–330. https://doi.org/10.1037/a0028279
Pancani, L., Marinucci, M., Aureli, N., & Riva, P. (2021). Forced social isolation and mental health: A study on 1006 Italians under COVID-19 lockdown. *Frontiers in Psychology*, *12*, 1–10. https://doi.org/10.3389/fpsyg.2021.663799
Pew Research Center. (2018). Teens, social media and technology 2018. Retrieved from https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/
Pew Research Center. (2021). Social media fact sheet. Retrieved from https://www.pewresearch.org/internet/fact-sheet/social-media/
Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. *Proceedings of the 3rd International Workshop on Distributed Statistical Computing*, *124*(125.10), 1–10.
Schulze, C., Hertwig, R., & Pachur, T. (2021). Who you know is what you know: Modeling boundedly rational social sampling. *Journal of Experimental Psychology: General*, *150*(2), 221–241. https://doi.org/10.1037/xge0000799
Todd, P. M., Gigerenzer, G., & the ABC Research Group. (2012). *Ecological rationality: Intelligence in the world*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195315448.001.0001
Töpfer, T., & Hollstein, B. (2021). Order of recall and meaning of closeness in collecting affective network data. *Social Networks*, *65*, 124–140. https://doi.org/10.1016/j.socnet.2020.12.006
Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive Psychology*, *5*(2), 207–232. https://doi.org/10.1016/0010-0285(73)90033-9