

# Using the internet “raises the bar” for precision in self-produced question answering

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## Abstract

When responding to queries for information, people control the *grain size* (precision-coarseness) of the information they communicate based on competing goals of accuracy and informativeness (Goldsmith & Koriat, *Behavioral and Brain Sciences*, 1999, 19, 167). Two experiments examined whether the act of searching for answers using the internet influences the granularity of the information people later choose to report. Participants who searched the internet for answers to general information questions later provided more precise (granular) estimates to questions in the absence of the internet when compared to participants who initially answered questions from memory and participants who initially were not asked any questions. These results indicate that searching the internet influences metacognitive processes underlying decisions about the granularity of the information we choose to communicate. The internet may “raise the bar” with respect to the informativeness of the information we feel obliged to offer.

## KEYWORDS

cognitive control, grain size, internet use, memory, metacognition

## 1 | INTRODUCTION

As the preeminent source of the world's knowledge, the internet provides users near-constant access to information with little cost to utilize. Digital media users interact extensively with the internet to satisfy intellectual, social, and behavioral goals. Rather than face the relatively effortful task of querying memory, which is fallible in many ways, a savvy internet user can rapidly generate effective cues for searching the internet to obtain a precise and reasonably reliable answer to questions on the order of seconds. Nonetheless, to reap the benefits of internet search, the user must play an important role in monitoring the accuracy of accessed information and controlling the report and use of that information in a broader social environment. The internet has the peculiar quality of being highly precise but not always accurate.

Control over the precision of reports is essential to efficient memory and communication. Being “precisely right” is only infrequently

viable for reporting from memory. Instead, people have a great deal of freedom to decide what information to report, what aspects to emphasize or skip, and how much detail to provide. Many real-life memory scenarios demand that the individual control the *grain size* (precision-coarseness) of the information they report based on goals of accuracy and informativeness (Goldsmith & Koriat, 1999). If a professor asks a student to define a concept in front of their peers, the student may respond with a simple answer while withholding information that they feel unsure about in order to increase their accuracy. If a friend, on the other hand, asks the same question, the student may choose to volunteer more information with the goal of being as informative as possible. In other words, decisions about the relative precision of the information we communicate will naturally depend on personal and situational goals that are salient when the question is asked. How does using the internet to access information influence the precision of information we choose to offer from our own memory?

In the current experiments, we sought to determine whether searching the internet influences metacognitive processes underlying

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decisions about the precision of the information we choose to report. Because the internet is often understood as an omniscient source of knowledge, we suspect the internet may “raise the bar” with respect to the informativeness of the information we feel obliged to offer. Specifically, we test the hypothesis that people who initially search the internet for answers to general information questions will report more precise (granular) ranges of estimates from memory to new questions than people who initially answer questions from memory or people who do not initially answer any questions.

There are several plausible mechanistic pathways that could lead to the effect that individuals who initially search for answers on the internet provide more granular estimates to questions in the absence of the internet. Internet users may feel *overconfident* in their own ability to precisely report an interval width following internet search. People tend to feel overconfident in their own knowledge when they are tethered to a familiar device (Hamilton & Yao, 2018; Ward, 2013) and engage in an act of deliberate search (Fisher et al., 2015). Higher confidence is known to lead to more precise responding (Koriat & Goldsmith, 1996); if enhanced confidence persists after Internet use, individuals may apply a higher standard for precision for their own reports based on that inflated confidence.

A final reason individuals may exhibit increased precision in reporting standards is that users who initially relied on the internet for answers may conform to the prevailing norms of their digital counterpart, resulting in more granular estimates to questions in the absence of the internet. This effect is evident in human communication (cf. Collins, 1996; Festinger, 1954; Gerber et al., 2018), and the possibility that internet users are adapting to a standard of precision that they come to expect from the internet gave light to our interpretation that the internet is “raising the bar” for precision.

## 2 | CONTROL OVER GRAIN SIZE IN MEMORY REPORTING

In contrast to traditional empirical investigations of memory, which tend to favor strict experimental control, we are primarily concerned with self-controlled processes that govern our memorial decisions (cf. Benjamin, 2007; Koriat & Goldsmith, 1996). In other words, our investigation concerns influences on strategic regulation in memory reporting, rather than memory itself. A reasonable first place to look for instances of strategic control of memory retrieval is eyewitness memory. As an example, consider a fictitious eyewitness scenario where a law official is asking a witness to recall details of an incident:

Q: Can you tell me what you saw as you were leaving the event?

A: I was walking through the park when I heard someone yelling on the other side of the street. As I looked up, a person holding a cardboard sign ran down an alley and several people chased after her. One man seemed to be holding a weapon.

Q: What type of weapon was it?

A: I'm not sure. I think it was a bat or a baton—something with a black, rubber grip.

Q: Do you remember what time it was?

A: Around 11 o'clock, maybe 11:30.

Q: Could you be more specific?

A: Umm [thinks for a moment]. Between 11:15 and 11:30.

Q: Did you see anything else?

A: No, nothing that seems important.

This transcript illustrates the flexibility in memory reports in the context of conversation (e.g., Brown-Schmidt & Benjamin, 2018), as well as the fact that the level of precision can vary with the demands of the moment.

Open-ended questioning, such as in the above example, offers the responder two common means for enhancing the accuracy and informativeness of the information that they communicate. Those are: (1) the option to volunteer or withhold information (i.e., to respond “I don't know”; Koriat & Goldsmith, 1996) and (2) the ability to choose the level of detail or generality, also known as the *grain size*, at which to provide responses (Goldsmith et al., 2002). To date, empirical work on the influence of internet search on personal control over memory reporting has focused on how access to answers via the internet influences a person's willingness to volunteer information. In a general knowledge question-answering task, Ferguson et al. (2015) found that individuals who had access to the internet were less willing to volunteer answers from memory (i.e., more likely to answer “do not know”) than those who did not have access to the internet. This translated into fewer correct answers, but also into superior accuracy for the answers that were offered. Here, we see the ways in which availability of the internet influences the way we come to regulate the accuracy and quantity of the information we decide to communicate.

In other real-world scenarios, individuals make decisions about the grain size of information they choose to offer from memory. Receivers of information prefer answers that are sufficiently informative and appropriately accurate for the nature of the question asked (Yaniv & Foster, 1995). In doing so, the communicator must make a compromise between competing objectives of accuracy and informativeness. We see, for example, the way the witness described above narrowed their estimate of the time of the incident (i.e., “Between 11:15 and 11:30”) when confronted with pressure to be as precise as possible.

## 3 | PRESENT INVESTIGATION

Prominent search engines like Google are able to return answers in the order of milliseconds and with accuracy rates that far exceed a human. A recent study found that Google Home was able to answer 77.4% of 5000 information questions with a 89.7% accuracy rate (Perficient, 2019). It is no surprise that we consider the internet as an omniscient source of knowledge (Nestojko et al., 2013; Ward, 2013)—despite obvious threats of gross misinformation (Hamilton & Benjamin, 2019). We expect that reliance on the internet to answer questions will lead people to produce more precise estimates from memory (i.e., increase informativeness). Our current experimental

paradigm evaluates the hypothesis that reliance on the internet to answer questions will influence the precision of information people later choose to offer from memory when their goal is to provide an accurate and informative response. Specifically, we predict that:

**H1.** Participants who initially search for answers to informational questions will report more precise ranges of estimates on a final round of questions compared to participants who initially answer questions from memory and participants who initially are not asked any questions.

The precision of an estimate, in the context of our study, was communicated by participants in terms of the size of an interval estimate to general information questions. For each question (e.g., “How many oceans make up the world?”), participants provided a low and a high estimate with instructions to be “reasonably certain that the correct answer is captured within the lower and upper bounds of the estimate.” Because a primary goal of this research was to study the self-controlled processes that govern our memory decisions in a digital environment, we chose to operationalize our measure of grain size to reflect the flexibility that people tend to have while making decisions about the granularity of information they choose to offer from memory. This contrasts with instructions in the decision science literature that ask participants to construct confidence intervals that have, for example, a 90% chance of including the correct answer (e.g., Teigen & Jørgensen, 2005). Because differences in grain size following internet search could be driven in part or in whole by individuals' perception of what it means to be “reasonably certain,” asking participants to report an explicit size for the interval would likely undermine our manipulation. We elaborate on possible limitations of this decision in the general discussion.

## 4 | EXPERIMENT 1

### 4.1 | Method

Methods, procedures, target sample size, exclusion rules, and analysis plan were pre-registered before data collection for this experiment (<https://osf.io/u659r/>).

#### 4.1.1 | Participants

We developed a sampling plan to collect data from 120 participants or further until we achieved a Bayes Factor of 3 (or 0.33), a threshold for qualifying evidence as convincing according to Jeffreys (1961). We recruited 180 undergraduates in introductory advertising classes at a large midwestern university to participate for partial course credit between March 2018 to May 2018. All participants were required to be 18 or older to participate. After each session, an experimenter checked the website history to confirm that individuals in the Memory and

Baseline conditions never used the internet in either phase and individuals in the Internet condition never used the internet in the second phase. We originally planned to only exclude participants who failed to follow instructions (e.g., who looked up answers when instructed not to or did not look up answers when instructed to do so).<sup>1</sup> Upon reviewing raw responses and prior to data analysis, we noticed that several participants provided arbitrary answers to meet the participation requirements and therefore we included exclusion procedures beyond those described in the preregistration.<sup>2</sup> These additional procedures were implemented without evaluating their influence of the conditional effects of interest. We excluded 7 people for failing to follow instructions, 13 people for providing arbitrary answers, and 34 people for failing to complete the survey. The final sample included 126 participants (91 women, 35 men) between 18 and 23 years old ( $M = 19.81$ ,  $SD = 1.16$ ). The majority of participants (96.03%) communicated in English with professional proficiency or better.

#### 4.1.2 | Materials

Research assistants gathered 40 informational questions on topics related to history, geography, and pop culture (see Appendix A for the list of questions). All questions contained answers with numerical values (e.g., “What year did Princess Diana of Wales die?”). The value of the answers ranged from 2 to 2,705,000. Questions were chosen to be easily “Google-able” such that answers would easily be found on the first page of search results. We pretested questions for fairness and difficulty with a separate participant sample ( $n = 26$ ) using the questions, “Rate the fairness of this question (1 = *extremely unfair* to 5 = *extremely fair*),” and “Rate the difficulty of this question (1 = *easy* to 3 = *difficult*).” The selected questions ranged from 2.42 to 4.04 on fairness ( $M = 3.36$ ,  $SD = 0.43$ ), indicating that questions were fair, but not entirely obvious. Questions ranged from 1.54 to 2.75 on difficulty ( $M = 2.15$ ,  $SD = 0.38$ ).

#### 4.1.3 | Design and procedure

Participants answered general information questions across two phases. In the *manipulation* phase, participants were randomly assigned to one of three between-subjects conditions: Internet ( $n = 44$ ), Memory ( $n = 41$ ), or Baseline ( $n = 41$ ). In the *test* phase, all participants answered a new set of questions entirely from memory. In both phases, the randomly selected questions were displayed on the computer screen one question at a time. Participants answered questions by providing an upper and lower estimate such that they were “reasonably certain” that the correct answer fell between their estimates. The correct answer was provided immediately after participants submitted their estimates. Participants were told that their answers would be “scored based on accuracy (i.e., whether the answer is captured within your estimate) and precision (i.e., the distance between your lower and upper estimates).” These instructions were intentionally vague in order to allow individuals to freely respond to the manipulation.

During the manipulation phase, participants in the Internet and Memory conditions answered 20 (of 40) informational questions. In the Internet condition, participants used Google in a separate window on the computer screen to search for answers. Participants were instructed to use Google regardless of whether they knew the answer. In the Memory condition, participants answered questions from memory without help from any external information sources. We asked participants to give their best guess even if they did not know an answer. Participants were given the correct answer as feedback after each question, regardless of condition or whether their initial response was correct. In the Baseline condition, participants completed a filler task that took approximately the same amount of time to complete as the question-answering in the other conditions. Participants used the computer mouse to find “Waldo,” a puzzle book character, in eight separate images displayed one after another on the screen.

During the test phase, all participants answered a new set of 20 questions from memory without help from any external information sources. Participants reported an upper and lower estimate such that they were reasonably certain the correct answer laid between their estimates. Their goal was to provide estimates that were as accurate and precise as possible. Feedback was provided after each question.

## 4.2 | Results

All data are available on our OSF project page (<https://osf.io/u659r/>). The pre-registered analysis plan described our intention to analyze our data by Bayes factor for one-way ANOVA (memory vs. internet vs. baseline). Experiment 1 data were assessed for violation of normality and equal variance assumptions—a test of homogeneity of variance on the three groups demonstrated that our data violated the assumption that the variances of the three groups were equal (Levene's Test;  $p < .001$ ). We, therefore, deemed nonparametric analysis more appropriate for our data and deviated from our original plan, using a new strategy described below.

We assessed our data using Bayesian inference to allow for evaluations in favor of both the null and alternative hypotheses. Specifically, these Bayesian analyses evaluated the likelihood of a point null hypothesis (i.e., Cohen's  $d = 0$ ) to that of a JZS alternative prior. We report Bayes factors that provide ratios of evidence in favor of our alternative hypotheses. Following recommendations by Jeffreys (1961), Bayes factors greater than 3 and less than 0.33 are interpreted as substantial evidence in favor of the alternative or null, respectively. Comparable analyses using null hypothesis significance testing are included at an alpha level of 5% (two-tailed) for heuristic value.

### 4.2.1 | Analysis of grain size

We calculated each participant's grain size for each question answered during the test phase as (grain size = upper estimate – lower estimate). Then we determined the median grain size for each item (across subjects), separately for each condition. Therefore, each condition was

represented by one median per item ( $n_{\text{item}} = 40$ ). We employed a sign test to evaluate if the median grain size for an item in one condition was substantially different from the median grain sizes for an item in another condition. Under the null hypothesis, the asymptotic probability of one condition having a higher score than another is 0.5; the actual observed proportions are presented in Table 1 with Bayes factors for a test contrasting a null hypothesis in which the condition effect is nil and variance on the observed proportions is only due to chance, with an alternative hypothesis in which the probability of observing a narrower median grain size on one of two compared conditions is greater than 0.5 (i.e., a Bayesian equivalent of binomial test; Morey & Rouder, 2022). Figure 1 shows the distribution of these outcomes across the item set, separately for the three pairwise comparisons. Across the 40 questions, there was a pattern in which participants who initially searched the internet for answers reported more precise ranges of estimates on a final test ( $M_{\text{median grain size}} = 37,521$ ,  $SD = 167,700$ ) than participants who initially answered questions from memory ( $M_{\text{median grain size}} = 50,826$ ,  $SD = 227,188$ ) and than those who initially did not answer questions at all ( $M_{\text{median grain size}} = 50,025$ ,  $SD = 223,601$ ; see Appendix B for descriptive statistics by item). The critical inferential test involved a comparison of the Internet and Memory conditions, which revealed that median grain size was narrower in the Internet condition compared to the Memory condition for 23 of 40 items, with only nine items eliciting a narrower median grain size in the Memory condition,  $BF_{10} = 5.58$ ,  $p < .05$  (and eight ties). Median grain size was also narrower in the Internet than in the Baseline condition for 23 of 40 items, with only nine items having a narrower median grain size in the Baseline condition,  $BF_{10} = 5.58$ ,  $p < .05$  (and eight ties). Finally, median grain size was narrower in the Memory than the Baseline condition for 18 of 40 items, with 12 items narrower in the Baseline condition, which qualifies as ambiguous evidence,  $BF_{10} = 0.68$ .

### 4.2.2 | Mean accuracy

Responses in the test phase were considered accurate if the correct answer was captured between their upper and lower estimates (inclusive). Figure 2 depicts mean accuracy scores across conditions during the test phase. An analysis of condition on mean accuracy during the test phase yielded evidence in favor of the null model,  $F(2, 123) = .068$ ,  $p > .05$ ,  $BF_{10} = 0.08$ . Mean accuracy scores were approximately the same across memory ( $M = 0.196$ ,  $SD = 0.162$ ), internet ( $M = 0.186$ ,  $SD = 0.181$ ), and baseline ( $M = 0.199$ ,  $SD = 0.162$ ) conditions. The support we cite of the null hypothesis is only revealed by the Bayesian analysis—traditional NHST can only reveal whether the alternative hypothesis should be rejected; it can never weigh on the plausibility of the null hypothesis.

## 4.3 | Discussion

Individuals who used the internet to search for answers to an initial set of informational questions gave narrower estimates on a final set

**TABLE 1** Proportion of items that elicited a narrower median grain size in each pairwise comparison of conditions.

		Experiment 1 (N = 126)		Experiment 2 (N = 118)		Combined (N = 244)	
		Obs. (N <sup>b</sup> )	BF <sub>10</sub>	Obs. (N <sup>c</sup> )	BF <sub>10</sub>	Obs. (N <sup>a</sup> )	BF <sub>10</sub>
Internet–Memory	Internet	0.72 (23)	5.58	0.68 (17)	1.65	0.70 (40)	22.58
	Memory	0.28 (9)		0.32 (8)		0.30 (17)	
Internet–Baseline	Internet	0.72 (23)	5.58	0.73 (19)	4.37	0.68 (42)	70.34
	Baseline	0.28 (9)		0.27 (7)		0.28 (16)	
Memory–Baseline	Memory	0.60 (18)	0.68	0.70 (16)	1.88	0.64 (34)	2.19
	Baseline	0.40 (12)		0.30 (7)		0.36 (19)	

Note: The Bayes Factor for each comparison indicates the odds of that difference reflecting a true population difference rather than a chance outcome. Obs. (N) = Observed Proportion (Number of Successes) <sup>a</sup>N of 70; <sup>b</sup>N of 40; <sup>c</sup>N of 30.

**FIGURE 1** Informativeness of responses provided during the test phase. A visual illustration of the proportion of narrower median grain size between two conditions across each item in Experiments 1 ( $n_{\text{item}} = 40$ ) and 2 ( $n_{\text{item}} = 30$ ).



of questions answered from memory than those who initially answered questions from memory or those who initially completed an unrelated task. Our data also provide convincing evidence that accuracy did not vary across conditions. Although it may be the case that using the internet raises the bar for precision in question-answering, our findings do not reveal a cost in accuracy to this higher standard.

## 5 | EXPERIMENT 2

Experiment 1 provides initial evidence that using the internet to search for answers influences the precision of information people later choose to report. The goal of Experiment 2 was to assess the replicability of the

observed effect in a design that provided superior control over the heterogeneity of ranges of answers present in Experiment 1.

Experiment 2 used a nearly identical design, except that participants answered an alternative set of 30 informational questions, to which all answers were in units of chronological years (e.g., “When did Boris Becker last win the Wimbledon men’s tennis finals?” Answer: 1989). This adjustment allowed better control over aspects of the individual’s decision criterion. We worried that the huge range of values in Experiment 1 (e.g., “How many oceans make up the world?” Answer: 5 vs. “How many minutes are in a year?” Answer: 525,600) would reduce the degree to which the bias in precision transferred across questions and across phases of the experiment.

## 5.1 | Method

### 5.1.1 | Participants

Our starting point for sample size planning was the same as in Experiment 1. Because our research team conducted several experiments using informational questions, we planned to collect data from as many participants as possible between November 2018 to December 2018. We recruited 135 undergraduates in introductory advertising classes at a large midwestern university to participate for partial course credit. All participants were required to be 18 or older to participate. We planned to only exclude participants who failed to follow instructions (e.g., look up questions when instructed not to or did not look up questions when instructed to do so). Only integers between 1000 and 2018 were accepted as valid entries. We excluded 12 people for failing to follow instructions and 5 people for failing to complete the survey. Our final sample included 118 participants (90 women, 28 men) between 18 and 24 years old ( $M = 20.24$ ,  $SD = 1.17$ ). The majority of participants (93.22%) communicated in English with professional proficiency or better. Participants were randomly assigned to one of three between-subject conditions: Internet ( $n = 30$ ), Memory ( $n = 42$ ), and Baseline ( $n = 46$ ).

### 5.1.2 | Materials

In Experiment 2, a new set of questions replaced those used in Experiment 1 (see Appendix C for the list of questions). Instead of questions with answers containing any possible numerical value, participants answered questions with answers in years. The value of the answers

ranged from 1644 (“What year was the Great Wall of China completed?”) to 2012 (“What year was Gangnam Style by PSY released?”).

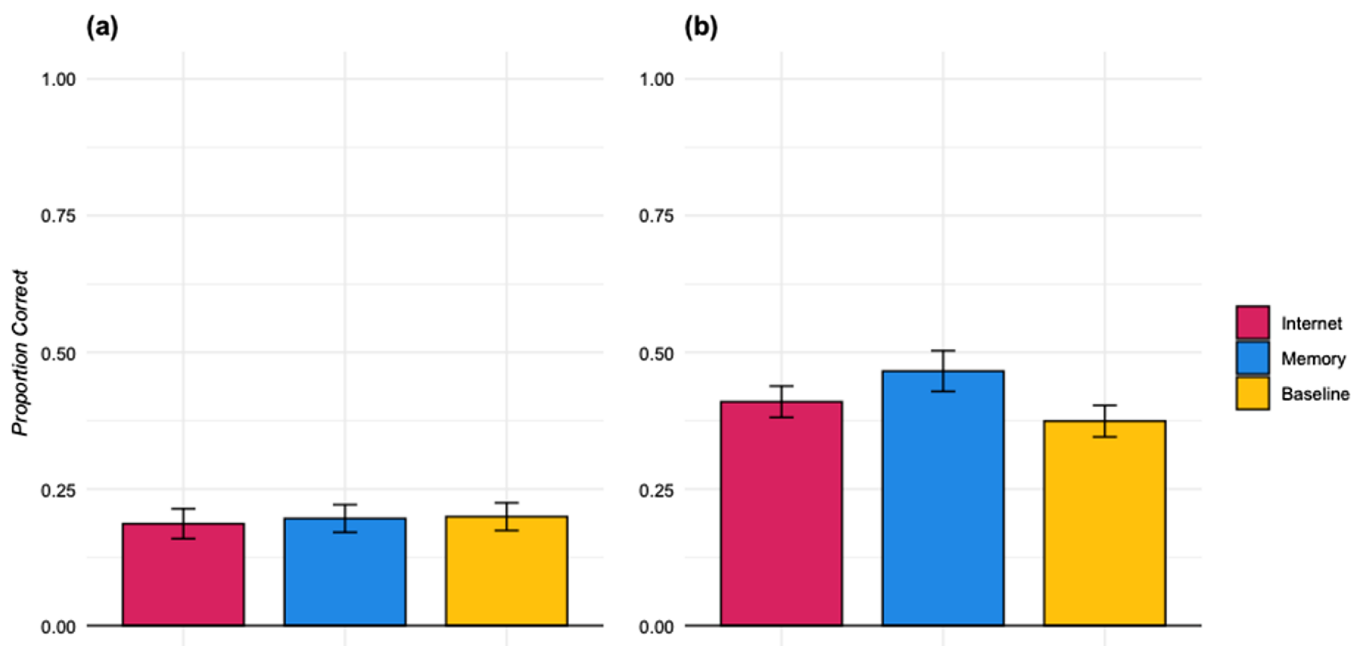
### 5.1.3 | Design and procedure

The design and procedure were identical to Experiment 1.

## 5.2 | Results

### 5.2.1 | Analysis of grain size

We determined the median grain size for each item in the same manner as we did in Experiment 1. Figure 1 shows the distribution of these outcomes across the item set, separately for the three pairwise comparisons. Table 1 presents observed proportions and Bayes factors for a Bayesian equivalent of a binomial test. The overall pattern was identical to that evinced in Experiment 1: participants who initially searched the internet for answers reported more precise ranges of estimates ( $M_{\text{median grain size}} = 25.3$ ,  $SD = 17.6$ ) on a final test than participants who initially answered questions from memory ( $M_{\text{median grain size}} = 26.4$ ,  $SD = 16.3$ ) or who initially did not answer questions at all ( $M_{\text{median grain size}} = 32.6$ ,  $SD = 23.4$ ; see Appendix D for descriptive statistics by item). Specifically, median grain size was narrower in the Internet condition compared to the Baseline condition for 19 of 30 items, with only seven items having a narrower median grain size in the Baseline condition,  $BF_{10} = 4.37$ ,  $p < .05$  (and four ties). Median grain size was narrower in the Internet condition compared to the



**FIGURE 2** Accuracy of responses provided during the test phase in Experiment 1 (a) and Experiment 2 (b). Error bars represent standard error of the mean.

Memory condition for 17 of 30 items, with eight items having a narrower median grain size in the Baseline condition,  $BF_{10} = 1.65$  (and five ties). Median grain size was narrower in the Memory condition compared to the Baseline condition for 16 of 30 items, with seven items having a narrower median grain size in the Baseline condition,  $BF_{10} = 1.88$  (and seven ties). The NHST equivalent for the latter two tests failed to reject the null hypothesis, but higher-powered tests that we will discuss shortly reveal a clear effect in which people in the Internet condition provided more precise answers.

### 5.2.2 | Mean accuracy

Figure 2 depicts mean accuracy scores across conditions during the test phase. An analysis of condition on mean accuracy during the test phase yielded ambiguous evidence in favor of the null model,  $F(2, 115) = 1.948, p > .05, BF_{10} = 0.392$ . Mean accuracy scores were approximately the same across memory ( $M = 0.374, SD = 0.187$ ), internet ( $M = 0.466, SD = 0.204$ ), and baseline ( $M = 0.409, SD = 0.194$ ).

## 5.3 | Discussion

Experiment 2 replicated the pattern observed in Experiment 1: using the internet to search for answers influences the precision of information people choose to report. Individuals who used the internet to search for answers to an initial set of informational questions gave narrower estimates on a final set of questions answered from memory than those who initially answered questions from memory or a control group.

## 6 | COMBINED RESULTS

### 6.1 | Combined analysis of grain size

We observed a similar pattern across nearly identical experiments, and therefore combined data to draw more precise inferences from a larger sample. These data are also shown in Table 1 and Figure 1. Across all 70 informational questions, there was a consistent pattern in which participants who initially searched the internet for answers reported more precise ranges of estimates on a final set of questions compared to participants who initially answered questions from memory and participants who initially were not asked any questions. Median grain size was substantially narrower in the Internet condition compared to the Memory condition for 40 of 70 items, with only 17 items having a narrower median grain size in the Memory condition,  $BF_{10} = 22.58, p < .05$  (and 13 ties). Median grain size was also substantially narrower in the Internet condition compared to the Baseline condition for 42 items, with only 16 items having a narrower median grain size in the Baseline condition,  $BF_{10} = 70.38, p < .05$  (with 12 ties). The Bayes Factors for these two comparisons indicate

strong support for the conclusion that using the internet to answer questions “raises the bar” of one’s internal standards for precision in question-answering.

### 6.2 | Mean accuracy

An analysis of condition on mean accuracy during the test phase yielded evidence in favor of the null model,  $F(2, 241) = .212, p > .05, BF_{10} = 0.052$ . Mean accuracy scores were about the same across memory ( $M = 0.289, SD = 0.194$ ), internet ( $M = 0.300, SD = 0.234$ ) and baseline ( $M = 0.310, SD = 0.208$ ).

## 7 | GENERAL DISCUSSION

People expect reliable information even under conditions where the responder is uncertain of the truth or has only partial information. The best a responder can do to meet the demands of this request is often to communicate answers as judgments or predictions about quantities shaped by goals of informativeness and accuracy (Yaniv & Foster, 1995). In our studies, participants communicated the precision of an estimate in terms of the size of an interval estimate to general informational questions. A coarse-grained response maximizes the chance that the answer is correct at the expense of informativeness.

Across two experiments, participants instructed to use the internet to answer a set of questions later provided narrower ranges for answers drawn from memory to a new set of questions than participants instructed to initially answer a set of questions from memory and participants who did not initially answer a set of questions. The internet may “raise the bar” with respect to the informativeness of the information we feel obliged to communicate, but, in this study, we found no evidence that this change came at the expense of accuracy. Pervasive internet use may enable biases, whether accurate or not, that tempt the media user to be more informative.

## 8 | OVERCONFIDENCE IN INTERVAL ESTIMATES

Interval estimation is a widely used task, and there are aspects from our procedure that share commonalities with the tasks used in that literature, as well as prominent differences that reflect the different focus one brings from the metacognitive perspective. One prominent feature of our results is the low accuracy of the intervals constructed by decision-makers; that low accuracy might reflect in part the well-known tendency to exhibit overconfidence in interval estimates (Soll & Klayman, 2004). When decision-makers are asked to generate subjective confidence intervals that contain an answer to a question with some predetermined probability, people often generate intervals that are too narrow (in other words, that are overly precise). In one classic example, Alpert and Raiffa (1982) asked students to generate interval estimates such that they believed there

was only a 2% chance the correct answer would fall outside their estimate. If confidence judgments were simply a product of accurately assessed probabilities, then answers should indeed fall within estimates 98% of the time. Instead, only 58% of interval estimates contained the correct answer.

One might expect the grain size of reports to correspond exclusively to a reporter's confidence in the specific answer that they provide, but in fact the magnitude of overconfidence depends additionally on the expectations and beliefs individuals hold about themselves and about various other aspects of the decision scenario. From that perspective, it can be easier to understand how experiences seemingly extraneous to the actual accuracy of individual estimates—like a recent history with search from one's memory or from the Internet—can influence the size of generated intervals.

One relevant detail from the study of interval estimation is that different domains of questions are systematically associated with different degrees of overconfidence. Soll and Klayman (2004) found that the degree of confidence elicited through subjective confidence intervals varied across domains (which included such variable topics as fertility rates, invention dates, and July temperatures). For this reason, researchers often advocate for randomly sampling across domains to produce sets of questions that reveal a degree of overconfidence that is not artificially inflated or deflated by the arbitrary selection of a single topic (e.g., Gigerenzer et al., 1991; Klayman et al., 1999). The work reported here includes questions from multiple domains (including history, geography, science and popular culture), suggesting that the generally poor accuracy we report is not an artifact of a poorly chosen domain.

Yet, other evidence suggests that more overconfidence is evident when questions with widely varying interval widths are used (e.g., 1200 miles, 30 years, 6°F; Soll & Klayman, 2004). This certainly may have occurred in the current Experiment 1, and motivated our choice to use a nonparametric analytic approach. In Experiment 2, we aimed to control the heterogeneity of ranges of answers more directly by selecting questions with answers in units of chronological years, but still from a variety of topical domains (e.g., “When did Boris Becker last win the Wimbledon men's tennis finals?” Answer: 1989). Across both cases, we observed more granular responses following unremitting internet search. The generality of the effect across these two experiments suggests that the effect we report is general across question domain choice and the variability of intervals elicited by questions.

Accuracy rates in subjective confidence interval construction tasks allow us to speculate a bit as to how participants interpreted the task. In both experiments, accuracy scores were quite low (39% across two experiments) for a task in which individuals are asked to provide an interval (i.e., not an exact response). In many of the interval estimation studies in the decision science literature, subjects are chosen to have some topical expertise with the matter at hand. In this study, they were not and, in addition, the questions were designed to be difficult. So, in addition to the well-noted problems people exhibit with estimating confidence intervals (e.g., Soll, 1996; Soll & Klayman, 2004; Teigen & Jørgensen, 2005), here we also have a number of cases where individuals are actually bringing little

or no substantive knowledge to bear on the problems. Some research suggests that overconfidence is a function of question difficulty (Gigerenzer et al., 1991; Juslin, 1993), but others have concluded that question difficulty does not produce systematic differences in overconfidence (Klayman et al., 1999; Soll & Klayman, 2004). In either case, question difficulty does not vary across conditions in our experiments and so can not play a role in the effect we report.

With infinite precision of measurement, changes in informativeness must translate into changes in accuracy—that is, conditions that increase precision (like the Google condition here) must also decrease accuracy. However, the specific trade-off will depend on where individuals naturally place themselves on that trade-off function; if they are naturally conservative in tasks like this one, it may be possible to gain a substantial amount of informativeness for only a small reduction in accuracy—so small, in fact, that it might not be detectable in the designs we have implemented here. So the absence of a clear reduction in accuracy in this task should not be taken to indicate any behavior outside of the realm of normal accuracy/informativeness tradeoffs evident in any task.

Lastly, the degree of overconfidence often depends on how ranges of interval estimates are solicited. In our studies, participants selected two exact numbers to describe their confidence as a range estimate to be treated as a single judgment. This contrasts other elicitation procedures that ask participants to report an interval that corresponds to a certain level of confidence (e.g., “Provided high and low estimates such that you are 80% sure that the correct answer lay between them”) or that ask participants to report an interval in two questions (“I am 80% sure that the answer is after \_\_” and “I am 80% sure that the answer is before \_\_”). Two-choice questions tend to produce less overconfidence in interval estimates than single range estimates (Klayman et al., 1999; Soll & Klayman, 2004). Compared to range estimates, the two-point method encourages people to sample their knowledge twice, which tends to make these estimates less prone to cognitive bias. Because we were interested in understanding a social phenomenon by which people set their standard for precision on the basis of prior internet search, we chose a measure that reflected the flexibility that people tend to have while making decisions about grain size in the real-world. Asking participants to report an explicit size for the interval (e.g., a 90% chance of including the correct answer) may undermine the possibility that these differences are produced by changes in a person's perception of what it means to be reasonably certain following internet search. Nonetheless, the decision to ask participants to be “reasonably certain” that answers fall within their estimates makes it impossible to know whether participants defined this phrase consistently. In other words, we can not know if the effect here reflects an undue inflation of confidence, or if it reflects a change in one's standards for accurate responding. Manipulations of these instructions will be instrumental in elaborating the mechanism that underlies our result. Possible mechanisms are elaborated in the following section.



## 9 | POSSIBLE THEORETICAL MECHANISMS

What is being communicated by the decision to report more precise responses? There are a number of mechanisms that may explain the finding that individuals who initially searched for answers on the internet provided more granular estimates to questions in the absence of the internet than individuals who did not initially search the internet. Those are (1) confidence inflation, (2) a failure to accurately maintain valid memory of our own accuracy (vs. the computer), and (3) social adaptation.

### 9.1 | Confidence inflation

Using the internet to find answers contributes to the blurring of boundaries between internal knowledge and external information, resulting in undue confidence in one's own knowledge. Several researchers have suggested that people tend to overestimate their cognitive abilities when they experience near-ubiquitous access to information via internet search. Ward (2013) demonstrated that on-demand access to external information, enabled by internet search, causes people to believe they could—or did—remember what they just found. Fisher et al. (2015) found that the internet inflates estimates of internal knowledge in domains specific to search content and general knowledge domains. This feeling of confidence in one's own knowledge tends to occur when people are tethered to a familiar device (Hamilton & Yao, 2018; Ward, 2013) or engage in an act of deliberate search (Fisher et al., 2015). Flanagin and Lew (2023) demonstrated that people tend to conflate external information as self-produced when users experience cognitive fluency while obtaining answers through internet search. In our experiments, individuals in the internet condition initially had unremitting and reliable access to answers through internet search. Uninterrupted access to the internet may have led those participants to feel (unduly) confident in their own abilities while answering questions without the internet, resulting in more granular responses.

### 9.2 | Failure of source memory

Second, users may have failed to accurately maintain valid memory of their own accuracy (vs. the computer). Recent research demonstrates that it is difficult for individuals to monitor whether information has been retrieved internally, from our own memory, or externally, as from another person or a device. In a question-answering task, individuals exhibit poorer source memory for answers retrieved from a device and have a cognitive bias to appropriate external knowledge as their own (Siler et al., 2022). It is possible that individuals in the internet condition lost track of which items were estimated with the aid of the internet and which were not, leading to a misappropriation of some very precise estimates as their own and an attendant inflated sense of one's own accuracy.

### 9.3 | Social adaptation

It is possible that users who initially relied on the internet for answers treat the internet as “partner” and unwittingly attempt to conform to the norms established by their digital counterpart, resulting in more granular estimates to questions in the absence of the internet than individuals who did not initially search the internet. In this case, the relentless precision of the internet may change the tenor of the conversations we have with it, whereby we hope to provide answers with roughly the same accuracy it provides to us. This would be analogous to similar findings in research on teams of humans (cf. Collins, 1996; Festinger, 1954; Gerber et al., 2018).

There may also be a component of social desirability that plays a role here. People often choose to compare themselves to others whose abilities are similar to, or slightly better than, their own for self-enhancing purposes (Collins, 1996; Wood, 1989). Bridge players asked to nominate people with whom they have similar ability in the game gave the names of peers whose lifetime record of play was objectively superior to their own (Nosanchuk & Erickson, 1985). In our experiments, those who initially had reliable access to the internet may have been enticed to believe they had similar abilities as their digital counterpart to answer questions precisely and accurately. Because none of our participants received feedback about whether their answers to the second round of questions were correct, the act of reporting precise grain sizes may have satisfied the desire of those in the internet condition to enhance or maintain their self-esteem.

Investigations concerning the influence of internet access on report option—which allows the responder to screen out incorrect information (e.g., “do not know” or “do not remember” responses) to regulate the accuracy of the information they communicate to others—reveals a similar effect to our own findings. Ferguson et al. (2015) found that access to the internet raised standards with respect to the amount of partial information subjects demanded before providing answers from internal knowledge stores. Such an effect led individuals to be more conservative in deciding the detail of information to report, while raising the bar led those in our experiment to become more liberal in the level of detail of memory reports. What remains clear is that the ways people remember and solve problems have and will continue to be impacted by aspects of our digital environment. The present results suggest that unremitting internet search influences metacognitive processes underlying decisions about the precision of the information we choose to report. In this case, the internet may “raise the bar” with respect to the informativeness of the information we feel obliged to communicate.

### AUTHOR CONTRIBUTIONS

Kristy A. Hamilton, Jessica Siler, and Aaron S. Benjamin jointly planned and designed the experiments. Kristy A. Hamilton drafted the manuscript and all authors critically edited the manuscript.

### CONFLICT OF INTEREST STATEMENT

We have no other conflicts of interest to disclose.

## DATA AVAILABILITY STATEMENT

All materials are available at <https://osf.io/u659r/>.

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## ENDNOTES

- <sup>1</sup> A research assistant checked participants' search history after the experiment to verify that participants followed instructions to look up answers when told to do so. All participants passed this initial manipulation check.
- <sup>2</sup> Two research assistants (RAs) blind to condition and our experimental hypotheses flagged all lower or upper estimated values except "non negative integers." In other words, we accepted only whole numbers that were either positive or zero. The RAs also flagged suspicious numbers or values (e.g., 121212, 1000000000000000, "infinity"). We excluded participants who recorded at least 10 values flagged by both RAs across both phases.

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**How to cite this article:** Hamilton, K. A., Siler, J., & Benjamin, A. S. (2023). Using the internet “raises the bar” for precision in self-produced question answering. *Applied Cognitive Psychology*, 1–15. <https://doi.org/10.1002/acp.4072>

## APPENDIX A: ITEMS FOR EXPERIMENT 1

Item	Question
1	In weeks, on average, how long does a human pregnancy last?
2	How many oceans make up the world?
3	How many countries are there in North America?
4	Approximately how many miles make up a marathon?
5	How many pairs of chromosomes do humans have?
6	What is the boiling point of water in degrees Fahrenheit?
7	How many fluid ounces are in a gallon?
8	What year did World War 2 start?
9	What year was the first Superbowl?
10	How many bones does an adult human have?
11	What year did the Titanic sink?
12	What year did the U.S. Constitution grant women the right to vote?
13	How old was the youngest person to ever win an Olympic Gold medal?
14	How many floors make up the Empire State Building?
15	What year did the first two monkeys survive the flight into space?
16	How many countries make up Africa?
17	How many countries are there in the world?
18	What was the population of Chicago, IL in 2016?
19	What year did Spain give Florida to the United States?
20	When was the Eiffel Tower built?
21	What is the equivalent of 0 degrees Celsius in degrees Fahrenheit?
22	Which US amendment gave the right to bear arms?
23	What year did Columbus discover America?
24	How many white stripes are on the American flag?
25	How many colors (main divisions) are in the color wheel?
26	During games, how many soccer players from one team are on the field at any given time?
27	What year did the first person land on the moon?
28	How many lobes does the human brain have?
29	What year was the US Constitution written?
30	How many elements are in the periodic table?
31	How many minutes are in a year?
32	How many letters are there in the Greek alphabet?
33	What year was Apple founded?
34	What year did the "Berlin Wall" that divided East and West Berlin fall?
35	How many calories are in a pound of fat?
36	What year was the first telephone call made?
37	How old was Marilyn Monroe when she died?
38	How many feet above sea level is Mt. Everest?
39	How long is the Great Wall of China (in miles)?
40	What year were the Olympics first held in London?

## APPENDIX B: INTERVAL WIDTHS FOR EXPERIMENT 1

Item	Internet (N = 44)				Memory (N = 41)				Baseline (N = 41)			
	M	SD	Mdn	IQR	M	SD	Mdn	IQR	M	SD	Mdn	IQR
1	4.5	4.7	3.0	3.8	5.0	5.3	4.0	8.0	5.7	6.5	4.0	5.0
2	11.5	41.1	2.0	4.8	3.8	4.3	2.0	4.0	6.3	11.1	2.0	5.0
3	9.4	16.0	2.5	7.0	5.5	8.3	3.0	6.0	12.1	25.9	5.0	9.0
4	4.8	8.5	1.5	5.3	10.1	18.4	4.0	9.3	10.2	12.4	5.0	16.5
5	71.0	196.7	2.0	9.8	4.0	5.9	2.0	5.0	18.7	49.0	2.0	6.0
6	50.9	90.0	20.0	40.0	27.6	30.8	20.0	32.0	20.7	22.9	11.0	40.0
7	14.1	16.5	12.0	19.5	11.2	13.5	8.0	15.0	46.0	121.2	8.0	10.0
8	18.6	25.7	10.0	15.0	12.9	13.5	10.0	6.0	18.8	25.4	10.0	21.0
9	33.0	33.1	20.0	37.5	21.5	21.2	20.0	10.0	22.1	22.5	20.0	21.0
10	71.3	104.1	30.0	88.5	54.8	44.4	50.0	90.0	41.8	36.6	37.0	32.0
11	37.3	47.4	20.0	42.3	40.1	50.4	24.0	25.0	43.4	43.4	30.0	38.0
12	38.0	57.4	16.5	41.0	25.4	33.1	10.0	35.8	33.9	34.8	22.5	33.5
13	4.3	3.5	3.5	3.0	4.0	2.5	4.0	4.0	4.3	4.2	3.0	3.0
14	38.4	43.6	30.0	35.0	42.5	37.1	40.0	35.0	45.4	34.6	40.0	40.0
15	29.2	29.7	20.0	20.0	34.8	39.0	15.0	20.0	21.6	13.9	20.0	20.0
16	18.3	21.1	13.5	10.0	19.6	16.2	17.0	10.0	20.7	21.7	15.0	10.0
17	180.4	331.0	75.0	155.8	129.0	149.4	100.0	70.0	105.9	185.6	50.0	48.0
18	1.28e+06	1.48e+06	6.25e+05	1.88e+06	2.62e+06	4.40e+06	1.00e+06	2.50e+06	5.22e+07	2.23e+08	1.45e+06	4.55e+06
19	53.5	31.5	50.0	47.5	55.9	51.2	38.0	80.0	54.0	48.0	50.0	40.0
20	99.5	80.4	100.0	112.5	76.2	75.4	50.0	80.0	57.7	36.2	50.0	60.0
21	12.6	18.2	8.5	10.8	15.1	33.3	5.0	12.0	7.3	10.2	1.0	12.3
22	3.5	2.9	3.5	5.8	9.8	21.5	4.0	6.5	4.4	4.2	3.0	4.8
23	3.3	5.5	1.5	3.0	5.2	6.8	2.0	9.0	5.2	9.5	2.0	4.3
24	1.0	1.6	0.0	2.0	8.4	22.7	2.0	4.8	1.9	3.2	0.0	2.3
25	7.0	10.8	3.0	8.5	10.2	14.0	2.5	11.5	8.2	12.6	4.0	5.0
26	14.4	18.4	10.0	15.0	33.2	87.3	10.0	13.3	16.7	12.1	10.0	21.5
27	797.7	1926.0	200.0	500.0	829.2	1373.7	250.0	655.0	1365.8	2739.7	450.0	1041.3
28	44.4	65.6	20.0	29.3	45.3	85.8	20.0	10.0	68.3	62.5	45.0	80.0
29	18.8	20.7	15.0	12.0	27.3	34.0	20.0	16.3	28.4	33.5	17.5	23.0
30	11.1	11.5	8.0	12.3	13.5	14.3	7.0	16.8	29.2	66.4	10.0	11.8
31	39.3	66.2	12.5	32.0	52.5	131.1	15.5	33.8	77.2	116.9	40.0	82.5
32	44.9	69.5	15.0	80.0	78.9	104.0	48.0	90.3	53.0	73.1	3.0	104.5
33	1.8	1.8	2.0	3.0	2.5	2.4	2.0	4.0	3.4	3.4	3.5	3.3

Item	Internet (N = 44)				Memory (N = 41)				Baseline (N = 41)			
	M	SD	Mdn	IQR	M	SD	Mdn	IQR	M	SD	Mdn	IQR
34	21.2	16.4	19.0	20.0	31.4	26.5	24.0	39.3	35.5	27.9	35.5	40.5
35	24.7	42.7	10.0	15.0	16.3	11.8	12.5	10.0	21.8	15.5	20.0	22.0
36	5819.8	2.35e+04	200.0	950.0	5.42e+04	2.23e+05	500.0	4575.0	3.82e+04	1.12e+05	295.0	1.19e+04
37	1.87e+04	4.71e+04	3000.0	4826.0	1.11e+05	2.49e+05	3275.0	4.46e+04	1.10e+05	2.30e+05	2.00e+04	7.04e+04
38	1.72e+10	7.85e+10	9.70e+05	9.98e+06	1.08e+08	3.12e+08	1.75e+06	4.47e+06	1.05e+13	3.15e+13	5.00e+05	3.96e+07
39	45.1	54.5	23.0	40.8	54.4	68.8	22.5	48.5	88.0	100.4	50.0	85.0
40	38.0	60.4	13.0	40.5	64.9	109.6	21.0	52.3	101.0	132.3	71.0	88.0

## APPENDIX C: ITEMS FOR EXPERIMENT 2

Item	Question
1	What year were the Olympics first held in the United Kingdom?
2	What year did WWI begin?
3	What year did the United States abolish slavery?
4	What year was Facebook created?
5	What year was the Treaty of Versailles signed?
6	What year was the Eiffel Tower built?
7	What year did Princess Diana of Wales die?
8	What year did the first person land on the moon?
9	What year was the Great Wall of China completed?
10	What year was Coca Cola founded?
11	What year did Bill Gates and Paul Allen found the Microsoft corporation?
12	What year did the Berlin Wall go up?
13	What year was the first telephone call made?
14	What year was the Sears (Willis) Tower opened?
15	What year was Gangnam Style by PSY released?
16	What year were the Olympics first held in the United States?
17	What year did WWI end?
18	What year did Rosa Parks refuse to give up her bus seat to a white passenger?
19	What year was Google created?
20	What year was Machu Picchu discovered?
21	What year was Yellow Fever discovered?
22	What year did Marilyn Monroe die?
23	What year was the first dog launched into space?
24	What year was the Taj Mahal completed?
25	What year was Pepsi founded?
26	What year did Steve Jobs and Stephen Wozniak found Apple Computers?
27	What year did the Berlin wall come down?
28	What year was Morse Code invented?
29	What year was the John Hancock Center opened?
30	What year was Call Me Maybe by Carly Rae Jepsen released?

## APPENDIX D: INTERVAL WIDTHS FOR EXPERIMENT 2

Item	Internet (N = 30)				Memory (N = 43)				Baseline (N = 46)			
	M	SD	Mdn	IQR	M	SD	Mdn	IQR	M	SD	Mdn	IQR
1	43.6	34.7	37.0	40.5	46.4	41.2	30.0	52.0	91.8	110.6	50.0	80.0
2	19.1	32.5	8.0	17.3	9.6	9.8	10.0	8.0	26.3	25.7	18.0	25.0
3	29.9	38.8	17.5	16.0	33.2	38.1	20.0	54.0	45.4	46.6	30.0	33.5
4	4.1	3.3	4.0	3.8	12.4	22.1	5.0	5.0	6.2	4.7	5.0	5.5
5	36.1	37.3	20.0	52.5	45.3	50.7	20.0	60.0	90.2	149.0	30.0	80.0
6	53.9	52.1	44.5	43.8	44.5	38.3	35.0	48.0	94.2	77.3	80.0	132.5
7	33.3	49.0	10.0	34.8	25.7	26.3	20.0	29.0	26.3	27.7	20.0	22.0
8	33.2	50.1	10.0	32.5	18.2	16.4	10.0	24.0	17.1	20.6	10.0	10.0
9	60.4	73.4	22.5	82.5	67.8	72.5	50.0	82.5	120.7	114.7	75.0	159.5
10	37.1	36.4	20.0	40.0	30.3	27.4	23.0	21.0	42.4	29.2	40.0	35.0
11	20.7	23.9	17.5	10.0	16.1	12.0	10.0	12.0	21.7	19.2	15.0	20.0
12	44.9	66.9	15.0	57.0	41.1	40.8	25.0	48.0	42.3	36.2	35.0	34.0
13	39.1	40.6	26.0	21.3	23.9	17.9	20.0	30.0	44.3	46.9	20.0	31.5
14	19.6	24.3	14.0	10.0	20.5	19.6	13.0	31.0	41.4	40.5	30.0	32.5
15	4.5	4.9	4.0	4.5	2.5	2.1	2.0	3.0	3.9	3.8	3.0	4.0
16	39.0	34.3	32.5	48.3	54.7	45.2	45.5	46.3	58.0	83.5	25.0	65.0
17	12.6	27.4	2.0	11.0	22.0	40.1	10.0	19.3	37.8	47.6	20.0	50.0
18	33.1	25.7	28.0	21.3	37.9	43.0	20.5	33.3	41.4	64.4	20.0	20.0
19	19.2	24.0	12.5	13.5	26.0	39.0	12.5	19.5	30.2	28.3	20.0	35.0
20	81.3	77.1	55.5	72.5	101.0	94.6	96.0	100.0	116.9	137.4	80.5	71.3
21	88.7	78.8	60.0	102.0	84.3	78.8	80.0	97.5	123.3	216.2	46.0	88.5
22	31.7	28.7	20.0	27.5	43.6	58.8	20.0	36.8	40.8	51.8	20.0	30.0
23	30.1	30.5	18.0	22.5	30.5	25.5	20.0	18.3	46.5	60.3	20.0	35.0
24	128.8	151.5	60.0	161.8	137.9	153.8	100.0	142.5	141.9	134.4	100.0	150.0
25	34.7	26.0	30.0	35.0	47.3	38.9	40.0	64.0	46.8	47.9	30.0	26.0
26	27.4	41.4	10.0	20.0	19.4	23.1	10.0	19.3	30.8	32.6	19.0	29.5
27	40.6	52.3	20.0	36.3	40.7	48.4	22.0	25.0	45.6	55.5	20.0	55.5
28	93.1	82.8	90.0	52.5	104.5	118.2	69.5	110.3	91.9	114.4	50.0	70.0
29	50.9	56.5	23.5	49.5	38.5	36.0	24.0	34.5	48.7	49.2	38.0	54.5
30	5.6	6.4	4.0	3.5	10.7	23.1	4.5	4.5	19.3	46.9	5.0	8.5