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The Confidence Database

Dobromir Rahnev, Kobe Desender, Alan Lee, William Adler, David Aguilar-Lleyda, Başak Akdoğan, Polina Arbuzova, Lauren Atlas, Fuat Balci, Ji Won Bang, et al.

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HAL Authorization

1 The Confidence Database

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129 **Abstract**

130 **Understanding how people rate their confidence is critical for characterizing a wide range of**
131 **perceptual, memory, motor, and cognitive processes. To enable the continued exploration of these**
132 **processes, we created a large database of confidence studies spanning a broad set of paradigms,**
133 **participant populations, and fields of study. The data from each study are structured in a common,**
134 **easy-to-use format that can be easily imported and analyzed in multiple software packages. Each**
135 **dataset is further accompanied by an explanation regarding the nature of the collected data. At the**
136 **time of publication, the Confidence Database (available at osf.io/s46pr) contained 145 datasets**
137 **with data from over 8,700 participants and almost 4 million trials. The database will remain open**
138 **for new submissions indefinitely and is expected to continue to grow. We show the usefulness of**
139 **this large collection of datasets in four different analyses that provide precise estimation for several**
140 **foundational confidence-related effects.**

141

142 **Main**

143 Researchers from a wide range of fields use ratings of confidence to provide fundamental insights
144 about the mind. Confidence ratings are subjective ratings regarding one's first-order task
145 performance. For instance, participants may first decide whether a probe stimulus belongs to a
146 previously learned study list or not. A confidence rating, in this case, could involve the participants'
147 second-order judgment regarding how sure they are about the accuracy of the decision made in that
148 trial (i.e., accuracy of the first-order task performance). Such second-order judgments reflect people's
149 ability to introspect and can be dissociated from the first-order judgment¹. Confidence ratings tend to

150 correlate strongly with accuracy, response speed, and brain activity distinguishing old and new
151 probes² suggesting that they reflect relevant internal states.

152

153 The question of how humans (or other animals) evaluate their own decisions has always been an
154 important topic in psychology, and the use of confidence ratings dates back to the early days of
155 experimental psychology³. In addition, confidence has been used as a tool to, among many other
156 things, determine the number of distinct memory retrieval processes⁴, reveal distortions of visual
157 awareness⁵, understand the factors that guide learning⁶, assess the reliability of eyewitness
158 testimony⁷, test theories of sensory processing⁸ and decision-making^{9,10}, help estimate the fit of
159 parameters of the psychometric function more efficiently¹¹, and characterize various psychiatric
160 conditions¹². The wide application of confidence makes it a fundamental measure in psychological
161 research.

162

163 However, despite the widespread use of confidence ratings, scientific progress has been slowed by
164 the traditional unavailability of previously collected data. In the current system, testing a new idea
165 often requires scientists to spend months or years gathering the relevant data. The substantial cost in
166 time and money associated with new data collection has undoubtedly led to many new ideas simply
167 being abandoned without ever being examined empirically. This is especially unfortunate given that
168 these ideas could likely have been tested using the dozens of datasets already collected by other
169 scientists.

170

171 Typically, when data re-use takes place, it is within a lab or a small scientific group -- that often
172 restricts itself to very specific paradigms -- which potentially limits the formation of a broader
173 understanding of confidence across a wider range of tasks and participants. Therefore, another
174 important advantage of data re-use lies in the diversity of experimental tasks, set-ups, and
175 participants offered by compiling datasets from different labs and different populations.

176

177 Although data sharing can speed up scientific progress considerably, fields devoted to understanding
178 human behavior unfortunately have cultures of not sharing data^{13,14}. For example, Wicherts et al.¹⁵
179 documented their painstaking and ultimately unsuccessful endeavor to obtain behavioral data for re-
180 analysis; despite persistent efforts, the authors were able to obtain just 25.7% of datasets the authors
181 claimed to be available for re-analysis. Nevertheless, recent efforts towards increased openness have
182 started to shift the culture considerably and more and more authors post their data in online
183 depositories^{16,17}.

184

185 There are, however, several challenges involved in secondary analyses of data, even when such data
186 have been made freely available. First, the file type may not be usable or clear for some researchers.
187 For example, sharing files in proprietary formats may limit other researcher's ability to access them
188 (e.g., if reading the file requires software that is not freely or easily obtainable). Second, even if the
189 data can be readily imported and used, important information about the data may not have been
190 included. Third, researchers who need data from a large number of studies have to spend a
191 considerable amount of time finding individual datasets, familiarizing themselves with how each

192 dataset is structured, and organizing all datasets into a common format for analysis. Finally, given the
193 size of the literature, it can be difficult to even determine which papers contain relevant data.

194

195 Here we report on a large-scale effort to create a database of confidence studies that addresses all of
196 the problems above. The database uses an open standardized format (.csv files) that can easily be
197 imported into any software program used for analysis. The individual datasets are formatted using
198 the same general set of guidelines making it less likely that critical components of the datasets are
199 not included and ensuring that data re-use is much less time-consuming. Finally, creating a single
200 collection of confidence datasets makes it much easier and faster to find datasets that could be re-
201 used to test new ideas or models.

202

203 **Details on the database**

204 The Confidence Database is hosted on the Open Science Framework (OSF) website (osf.io/s46pr).

205 Each dataset is represented by two files – a data file in .csv format and a readme file in .txt format.

206

207 The majority of data files contain the following fields: participant index, stimulus, response,
208 confidence, response time of the decision, and response time of the confidence rating. Depending on
209 the specific design of each study, these fields can be slightly different (e.g., if there are two stimuli on
210 each trial or confidence and decision are given with a single button press). Further, many datasets
211 include additional fields needed to fully describe the nature of the collected data.

212

213 The readme files contain essential information about the contributor, corresponding published paper
214 (if the dataset is published and current status of the project if not), stimuli used, confidence scale, and
215 experimental manipulations. Other information such as the original purpose of the study, the main
216 findings, the location of data collection, etc. are also often included. In general, the readme files
217 provide a quick reference regarding the nature of each dataset and mention details that could be
218 needed for future re-analyses.

219

220 The Confidence Database includes a wide variety of studies. Individual datasets recruit different
221 populations (e.g., healthy or patient populations), focus on different fields of study (e.g., perception,
222 memory, motor control, decision making), employ different confidence scales (e.g., binary, n-point
223 scales, continuous scales, wagering), use different types of tasks (e.g., binary judgements vs.
224 continuous estimation tasks), and collect confidence at different times (e.g., after or simultaneous
225 with the decision). Figure 1 gives a broad overview of the types of datasets included in the database
226 at the time of publication. This variety ensures that future re-analyses can address a large number of
227 scientific questions and test them based on multiple methods of evaluating one's own primary task
228 performance.

229

230 Importantly, the database will remain open for new submissions indefinitely. Instructions for new
231 submissions are made available on the OSF page of the database. Carefully formatted .csv and .txt
232 files that follow the submission instructions can be e-mailed to confidence.database@gmail.com.
233 They will be checked for quality and then uploaded with the rest of the database.

234

235 Finally, to facilitate searching the database, a spreadsheet with basic information regarding each
236 study will be maintained (link can be found on the OSF page). The spreadsheet includes information
237 about a number of different details regarding the dataset such as the field of study (e.g., perception,
238 memory, etc.), authors, corresponding publication, number of participants and trials, the type of
239 confidence scale, etc.

240

241 At the time of publication, the Confidence Database contained 145 datasets, bringing together 8,787
242 participants, for a total of 3,955,802 individual trials. The data were collected mostly in laboratory
243 experiments (from 18 different countries over five continents) but also in online experiments. Despite
244 its already large size, the database still contains only a small fraction of the available data on
245 confidence and is expected to continue to grow. We encourage researchers who already make their
246 data available to also submit their data to the Confidence Database. This would make their data
247 easier to discover and re-use, and would multiply the impact of their research.

248

249 Anyone is encouraged to download and re-use the data from the database. The database is shared
250 under the most permissive CC0 license thus placing the data in the public domain. As with the re-use
251 of any other data, publications that result from such re-analysis should cite the current paper, as well
252 as the listed citation for each of the datasets that were re-analyzed. We highly encourage the
253 preregistration of future secondary analyses and refer readers who wish to perform such analyses to
254 an excellent discussion of this process including preregistration templates by Weston et al.¹⁸ (the
255 templates are available at osf.io/x4gzt).

256

257 **Example uses of the Confidence Database**

258 The Confidence Database can be used for a variety of purposes such as developing and testing new
259 models of confidence generation; comparing confidence across different cognitive domains, rating
260 scales, and populations; determining the nature of metacognitive deficits that accompany psychiatric
261 disorders; characterizing the relationship between confidence, accuracy, and response times; and
262 building theories of the response times associated with confidence ratings. Further, the database can
263 also be used to test hypotheses unrelated to confidence due to the inclusion of choice, accuracy, and
264 response time. Different studies can re-use a few relevant datasets (maybe even a single one) or
265 simultaneously analyze a large set of the available datasets thus achieving substantially higher power
266 than typical individual studies.

267

268 Below we present results from four different example analyses in order to demonstrate the potential
269 utility and versatility of the database. These analyses are designed to take advantage of a large
270 proportion of the available data, thus resulting in very large sample sizes. Annotated codes for
271 running these analyses are freely available at the OSF page of the database (osf.io/s46pr). We note
272 that these codes can be used by researchers as a starting point for future analyses. All statistical tests
273 are two-tailed and their assumptions were verified. Measurements were taken from distinct samples.

274

275 Analysis 1: How confidence is related to choice and confidence response times (RTs)

276 One of the best known properties of confidence ratings is that they correlate negatively with choice
277 RT^2 . However, despite its importance, this finding is virtually always treated as the outcome of a
278 binary null-hypothesis significance test, which does not reveal the strength of the effect. At the same

279 time, it is becoming widely recognized that building a replicable quantitative science requires that
280 researchers, among other things, “adopt estimation thinking and avoid dichotomous thinking”¹⁹.
281 Precise estimation, though, requires very large sample sizes and any individual study is usually not
282 large enough to allow for accuracy in estimation. The Confidence Database thus provides a unique
283 opportunity to estimate with unprecedented precision the strength of foundational effects such as
284 the negative correlation between confidence and choice RT, thus informing theories that rely on
285 these effects. Further, the database allows for investigations of lesser studied relationships such as
286 between confidence and confidence RT.

287

288 Using the data from the Confidence Database, we thus investigated the precise strength of the
289 correlation of confidence with both choice and confidence RT. We first selected all datasets where
290 choice and confidence RTs were reported. Note that some datasets featured designs where the
291 choice and confidence were made with a single button press -- such datasets were excluded from the
292 current analyses. In addition, we excluded individual participants who only used a single level of
293 confidence because it is impossible to correlate confidence and RT for such subjects, and participants
294 for whom more than 90% of the data were excluded (which occurred for six participants from a study
295 with very high confidence RTs; see below). In total, the final analyses were based on 4,089
296 participants from 76 different datasets.

297

298 Before conducting the main analyses, we performed basic data cleanup. This step is important as
299 contributors are encouraged to include all participants and trials from an experiment even if some
300 participants or trials were excluded from data analyses in the original publications. Specifically, we

301 excluded all trials without a confidence rating (such trials typically came from studies that included a
302 deadline for the confidence response), all trials without choice RT (typically due to a deadline on the
303 main decision), and all trials with confidence and/or choice RTs slower than 5 seconds (the results
304 remained very similar if a threshold of 3 or 10 seconds was used instead). These exclusion criteria
305 resulted in removing 7.3% of the data. In addition, for each participant, we excluded all choice and
306 confidence RTs differing by more than 3 standard deviations from the mean (resulting in the removal
307 of additional 1.8% of the data).

308
309 We then correlated, for each participant, the confidence ratings with choice RTs. We found that the
310 average correlation across participants was $r = -.24$ ($t(4088) = -71.09$, $p < 2.2e-16$, $d = 1.11$). The very
311 large sample size allowed us to estimate the average correlation with a very high degree of precision:
312 the 99.9% confidence interval for the average correlation value was $[-.25, -.23]$, which should be
313 considered as a medium-to-large effect²⁰. At the same time, it is important to emphasize that the high
314 precision in estimating the average correlation does not imply a lack of variability between individual
315 participants. Indeed, we observed very high individual variability ($SD = .21$), which we visualize by
316 plotting all individual correlation values and corresponding density functions in the form of raincloud
317 plots²¹ (Figure 2A). Still, the effect size is large enough that power analyses indicate that a sample size
318 as small as $N=9$ provides $>80\%$ power and a sample size of $N=13$ provides $>95\%$ power to detect this
319 effect (at $\alpha = .05$).

320
321 We next performed the same analyses for the correlation between confidence and confidence RT. We
322 found that the average correlation across participants was $r = -.07$, $SD = .24$ ($t(4088) = -18.77$, $p <$

323 2.2e-16, $d = .29$) with a 99.9% confidence interval for the average correlation value of $[-.08, -.06]$. This
324 effect should be considered as “very small for the explanation of single events but potentially
325 consequential in the not-very-long run”²⁰. The small but reliable negative association between
326 confidence and confidence RT would have been particularly difficult to detect with a small sample
327 size. Indeed, a study with a sample size of 33 (the median sample size of the studies in the Confidence
328 Database) would have only 37% power of detecting this effect. To achieve power of 80%, one
329 requires a sample size of $N=93$; for power of 95%, $N=152$ is needed.

330

331 It should be noted that existing models of confidence generation (e.g. ²²) predict a lack of any
332 association between confidence and confidence RT (but see ²³). The small but reliable negative
333 correlation thus raises the question about what is causing this negative association. One possibility is
334 that participants are faster to give high confidence ratings because a strong decision-related signal
335 can propagate faster to neural circuits that generate the confidence response (for a similar argument
336 in the case of attention, see ²⁴) but further research is needed to directly test this hypothesis.

337

338 Finally, we also found that the strength of the correlation between confidence and confidence RT was
339 itself correlated with the strength of the correlation between confidence and choice RT, $r(4087) = .20$,
340 $p < 2.2e-16$ (Figure 2B). Future research should investigate whether this correlation is due to
341 variability in individual participants or variability at the level of the datasets.

342

343 Analysis 2: Serial dependence in confidence RT

344 It is well known that perceptual choices²⁵, confidence judgments²⁶, and choice RTs²⁷ are subject to
345 serial dependence. Such findings have been used to make fundamental claims about the nature of
346 perceptual processing such as that the visual system forms a “continuity field” over space and
347 time^{28,29}. The presence of serial dependence can thus help reveal the underlying mechanisms of
348 perception and cognition. However, to the best of our knowledge, the presence of serial dependence
349 has never been investigated for one of the most important components of confidence generation:
350 confidence RT. Therefore, determining whether serial dependence exists for confidence, and if so,
351 estimating precisely its effect size, can therefore provide important insight about the nature of
352 confidence generation.

353

354 To address this question, we considered the data from the Confidence Database. We analyzed all
355 datasets in which confidence was provided with a separate button press from the primary decision
356 and that reported confidence RT. In total, 82 datasets were included, comprising 4,474 participants.
357 Data cleanup was performed as in the previous analysis. Specifically, we removed all trials without
358 confidence RT and all trials with confidence RT slower than 5 seconds (results remained very similar if
359 a threshold of 3 or 10 seconds was used instead), both on the current trial and up to seven trials back,
360 because we wanted to investigate serial dependence up to lag-7 (this excluded a total of 4.3% of the
361 data). Further, as before, we excluded, separately for each participant, all confidence RTs differing by
362 more than 3 standard deviations from the mean (thus excluding additional 9.6% of the data).

363

364 We performed a mixed regression analysis predicting confidence RT with fixed effects for the recent
365 trial history up to seven trials back²⁵ and random intercepts for each participant. Degrees of freedom

366 were estimated using Satterthwaite's approximation, as implemented in the lmerTest package³⁰. We
367 found evidence for strong autocorrelation in confidence RT. Specifically, there was a very large lag-1
368 autocorrelation ($b = 1.346$, $t(1299601) = 153.6$, $p < 2.2e-16$; Figure 3). The strength of the
369 autocorrelation dropped sharply for higher lags but remained significantly positive until at least lag-7
370 (all p 's $< 2.2e-16$).

371
372 These results suggest the existence of serial dependence in confidence RT. However, it remains
373 unclear whether previous trials have a causal effect on the current trial. For example, some of the
374 observed autocorrelation may be due to a general speed up of confidence RTs over the course of
375 each experiment. To address this question, future studies should experimentally manipulate the
376 speed of the confidence ratings on some trials and explore whether such manipulations affect the
377 confidence RT on subsequent trials.

378
379 Analysis 3: Negative metacognitive sensitivity

380 Many studies have shown that humans and other animals have the metacognitive ability to use
381 confidence ratings to judge the accuracy of their own decisions³¹. In other words, humans have
382 positive metacognitive sensitivity³², meaning that higher levels of confidence predict better
383 performance. However, it is not uncommon that individual participants fail to show the typically
384 observed positive metacognitive sensitivity. Until now, such cases have been difficult to investigate
385 because they occur infrequently within a given dataset.

386

387 Using the Confidence Database, we estimated the prevalence of negative metacognitive sensitivity
388 and investigated its causes. We analyzed all datasets that contained the variables confidence and
389 accuracy. In total, 71 datasets were included, comprising of 4,768 participants. We excluded studies
390 on subjective difficulty, because these investigate the relation between confidence and performance
391 *within* correct trials. We further excluded participants who only reported a single level of confidence
392 (since it is impossible to estimate metacognitive sensitivity for such participants), studies with a
393 continuous measure of accuracy, and participants for whom more than 90% of the data were
394 excluded (which occurred for six participants from a study with very high confidence RTs).
395 Metacognitive sensitivity was computed using a logistic regression predicting accuracy by normalized
396 confidence ratings. This measure of metacognition has a number of undesirable properties³² but
397 reliably indicates whether metacognitive sensitivity is positive or negative.

398

399 We found that, across all participants, the average beta value from the logistic regression was .096,
400 $SD = .064$, ($t(4767) = 104.01$, $p < 2.2e-16$, $d = 1.5$; Figure 4A), thus indicating that metacognitive
401 sensitivity was reliably positive in the group. However, 293 of the participants (6.1% of all
402 participants) had a negative beta value, indicating the potential presence of negative metacognitive
403 sensitivity.

404

405 We next explored why such negative coefficients may occur for these 293 participants. We reasoned
406 that the majority of the cases of estimated negative metacognitive sensitivity could be due to several
407 factors unrelated to the true metacognitive sensitivity of each participant. First, the negative beta
408 values could simply be due to misestimation stemming from relatively small sample sizes. Even

409 though the number of trials per participant did not correlate with participants' beta coefficient
410 ($r(4766) = -.021, p = .143$; Figure 4B), 9.9% of all participants with negative beta value completed less
411 than 50 trials in total. Second, a positive relationship between confidence and accuracy can be
412 expected only if performance is above chance (if performance is at chance, this may indicate that
413 there is no reliable signal that could be used by the metacognitive system, although see^{33,34}). We did
414 indeed observe a correlation between the beta values and average accuracy ($r(4766) = .203, p < 2.2e-$
415 16 , Figure 4C) with 19.4% of all participants with negative beta values having an accuracy of less than
416 55%. Third, for those datasets including choice RT or confidence RT, we calculated the overall median
417 choice/confidence RTs and correlated these with the beta coefficients (one dataset was excluded
418 here, because the primary task was to complete Raven's progressive matrices and therefore choice
419 and confidence RTs were within the range of minutes rather than seconds). Again, we observed
420 significant correlations between betas and choice RTs ($r(3076) = -.083, p = 3.6e-06$, Figure 4D) and
421 between betas and confidence RTs ($r(2191) = .071, p = 0.0009$, Figure 4E), but the magnitude of these
422 correlations was very small and only 2.3% and 2.4% of participants with negative betas had median
423 choice or confidence RT of less than 200 ms, respectively. Finally, we reasoned that beta coefficients
424 could be misestimated if a very large proportion of confidence judgments were the same. Therefore,
425 we computed the proportion of the most common confidence rating for each participant ($M=37.9%$,
426 $SD = .22$). We did not observe a significant correlation between the proportion of the most common
427 confidence rating and the beta values ($r(4766) = -.025, p = .086$, Figure 4F), and only 5.4% of all
428 participants with negative betas only used a single confidence rating for more than 95% of the time.

429

430 Overall, 96 participants from the 293 with negative beta values (32.7%) completed less than 50 trials,
431 had overall accuracy of less than 55%, or used the same confidence response on more than 95% of all
432 trials. This means that 197 participants had negative beta values despite the absence of any of these
433 factors (note that for 55 of these participants, no RT information was provided, so a few of them
434 could have had overly fast choice or confidence RT). This result raises the question about the
435 underlying causes of the negative beta values. Follow-up studies could focus on these subjects and
436 determine whether there is anything different about them or the tasks that they completed.

437

438 Analysis 4: Confidence scales used in perception and memory studies

439 One of the strengths of the Confidence Database is that it allows for investigations on how specific
440 effects depend on factors that differ from study to study. For example, for any of the analyses above,
441 one could ask how the results depend on factors like the domain of study (i.e., perception, memory,
442 cognitive, etc.), confidence scale used (e.g., n-point vs. continuous), whether confidence was
443 provided simultaneously with the decision, the number of trials per participant, etc. These questions
444 can reveal some of the mechanisms behind confidence generation, such as, for example, whether
445 metacognition is a domain-specific or domain-general process^{35,36}.

446

447 Here we took advantage of this feature of the Confidence Database to ask a meta-science question:

448 Does the type of confidence scale researchers use depend on the subfield that they work in?

449 Confidence ratings are typically given in one of two ways. The majority of studies use a discrete Likert
450 scale (e.g., a 4-point scale where 1 = lowest confidence, 4 = highest confidence). Such scales typically
451 have a fixed stimulus-response mapping so that a given button always indicates the same level of

452 confidence (though variable stimulus-response mappings are still possible). Likert scales can also have
453 different number of options. Comparatively fewer studies use continuous scales (e.g., a 0-100 scale
454 where 0 = lowest confidence, 100 = highest confidence). Such scales typically do not have a fixed
455 stimulus-response mapping and responses are often given using a mouse click rather than a button
456 press (though it is possible to use a keyboard in such cases too).

457

458 We focused on the domains of perception and memory because these were the only two domains
459 with a sufficient number of datasets in the database (89 datasets for perception and 27 datasets for
460 memory; all other domains had at most 16 datasets; see Figure 1). We categorized each dataset from
461 these two domains as employing a 2-point, 3-point, 4-point, 5-point, 6-point, 7-to-11-point, or a
462 continuous confidence scale (we combined the 7- to 11-point scales into a single category because of
463 the low number of datasets with such scales). Finally, we computed the percent of datasets with each
464 of the confidence scales separately for the perception and memory domains.

465

466 We found that there were several systematic differences between the two domains. Most notably,
467 memory studies used a 3-point confidence scale 48% of the time (13 out of 27 datasets), whereas
468 perception studies used a 3-point confidence scale just 16% of the time (14 out of 89 datasets) with
469 the difference in proportions being significant ($Z = -3.49, p = 0.0005$; Figure 5). On the other hand, a
470 much lower percent of memory datasets (4%, 1 out of 27 datasets) used a continuous scale compared
471 to perception studies (33%, 29 out of 89 datasets; $Z = 3.002, p = 0.003$). Both comparisons remained
472 significant at the .05 level after Bonferroni correction for multiple comparisons was applied. We did

473 not find any difference between perception and memory studies for the rest of the confidence scale
474 types (all p 's > 0.2 before Bonferroni correction).

475

476 These results suggest the presence of systematic differences in how confidence is collected in
477 perception and memory studies with most pronounced differences in the use of 3-point and
478 continuous scales. Since it is unclear why perception and memory research would benefit from the
479 use of different confidence scales, these findings may point to a lack of sufficient cross-talk between
480 the two fields. Future research should first confirm the presence of such differences using an
481 unbiased sample of published studies and then trace the origin of these differences.

482

483 **Data sharing in the behavioral sciences**

484 It is a sad reality that “most of the data generated by humanity’s previous scientific endeavors is now
485 irrecoverably lost”¹³. Data are lost due to outdated file formats; researchers changing universities,
486 leaving academia, or becoming deceased; websites becoming defunct; and lack of interpretable
487 metadata describing the raw data. It is unlikely that much of the data not already uploaded to
488 websites dedicated to data preservation will remain available for future research several decades
489 from now.

490

491 We hope that the Confidence Database will contribute to substantially increased data preservation
492 and serve as an example for similar databases in other subfields of behavioral science and beyond.
493 Many subfields of psychology produce data that can be fully summarized in a single file using a
494 common format and thus can be easily shared. The mere existence of such a database in a given field

495 may encourage data sharing by facilitating the process of preparing and uploading data; indeed lack
496 of easy options for data sharing is among the important factors preventing researchers from sharing
497 their data^{37,38}. A popular database can also provide the benefit of the extra visibility afforded to the
498 studies in it. Databases could serve as invaluable tools for meta-analyses and as a means to minimize
499 false positive rates that may originate from low-powered studies and publication bias (i.e., favoring
500 significant findings) by simply including datasets that also show null effects. Importantly, it is critical
501 that sharing data is done ethically and that participant anonymity is not compromised³⁹⁻⁴¹. We have
502 followed these principles in assembling the Confidence Database: All datasets have received IRB
503 approvals by the relevant local committees (these can be found in the original publications), all
504 participants have provided informed consent, and all available data are de-identified.

505

506 Facilitation of data sharing would benefit from determining the factors that prevent researchers from
507 exercising this important practice as part of their dissemination efforts. One of these factors could be
508 the notion that researchers who spent resources to collect the original dataset should have priority
509 over others in re-using their own data^{37,42}. We argue that sharing data can have positive
510 consequences for individual researchers by increasing the visibility of their research, the citation
511 rate⁴³, and its accuracy by enabling meta-analysis. Another set of factors are those that deter
512 researchers from using shared data in open repositories. One of those factors is the belief that
513 utilizing shared data could limit the impact of the work. Milham et al.⁴⁴ addressed such issues by
514 demonstrating that manuscripts using shared data can, in fact, result in impactful papers in cognitive
515 neuroscience and make a case for a more universal effort for data sharing. We hope the construction

516 and maintenance of the Confidence Database will help address some of these issues in the domain of
517 confidence research.

518

519 Finally, it is important to consider the limitations of the Confidence Database and similar future
520 databases. First, the quality of such databases is determined by the quality of the individual studies;
521 amassing large quantities of unreliable data would be of little use. Second, the datasets included are
522 unlikely to be an unbiased sample of the literature (though the literature as a whole is unlikely to be
523 an unbiased sample of all possible studies). Third, in standardizing the data format across various
524 datasets, some of the richness of each dataset is lost. Therefore, in addition to contributing to field-
525 wide databases, we encourage researchers to also share their raw data in a separate repository.

526

527 **Conclusion**

528 The traditional unavailability of data in the behavioral sciences is beginning to change. An increasing
529 number of funding agencies now require data sharing and individual researchers often post their data
530 even in the absence of official mandates to do so. The Confidence Database represents a large-scale
531 attempt to create a common database in a subfield of behavioral research. We believe that this effort
532 will have a large and immediate effect on confidence research and will become the blueprint for
533 many other field-specific databases.

534

535 **Data availability**

536 The Confidence Database is available at osf.io/s46pr.

537

538 **Code availability**

539 Codes reproducing all analyses in this paper are available at osf.io/s46pr.

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632

633 **Author contributions**

634 The Confidence Database was conceived and organized by D.R. who also drafted the paper. Analyses
635 were performed by K.D., A.L., and D.R. All contributors at the time of publication are listed as authors
636 in alphabetical order except for the first three authors. All authors also edited and approved the final
637 version of the manuscript.

638

639 **Competing interests**

640 The authors declare no competing interests.

641

642 **Figure legends**

643 **Figure 1. Datasets currently in the Confidence Database.** Pie charts showing the number of datasets
644 split by category, publication year, number of participants, number of trials per participant, type of
645 judgment, and rating scale. The label “Multiple” in the first pie chart indicates that the same
646 participants completed tasks from more than one category. The maximum number of participants
647 was 589 and the maximum trials per participant was 4,320 (“variable” indicates that different
648 participants completed different number of trials).

649

650 **Figure 2. Correlating confidence with choice and confidence RT.** (A) We found a medium-to-large
651 negative correlation ($r = -.24, p < 2.2e-16, n = 4,089$) between confidence and choice RT, as well as a
652 small negative correlation ($r = -.07, p < 2.2e-16, n = 4,089$) between confidence and confidence RT.
653 Box shows the median and the interquartile (25-75%) range, whereas the whiskers show the 2-98%
654 range. (B) The strength of the two correlations in panel A were themselves correlated across subjects
655 ($r = .23, p < 2.2e-16, n = 4,089$).

656

657 **Figure 3. Serial dependence in confidence RT.** We observed a large lag-1 autocorrelation ($b = 1.346,$
658 $t(1299601) = 153.6, p < 2.2e-16, n = 4,474$). The autocorrelation decreased for higher lags but
659 remained significant up to lag-7 (all p 's $< 2.2e-16, n = 4,474$). Error bars indicate SEM. Individual
660 datapoints are not shown because the plots are based on the results of a mixed model analysis.

661

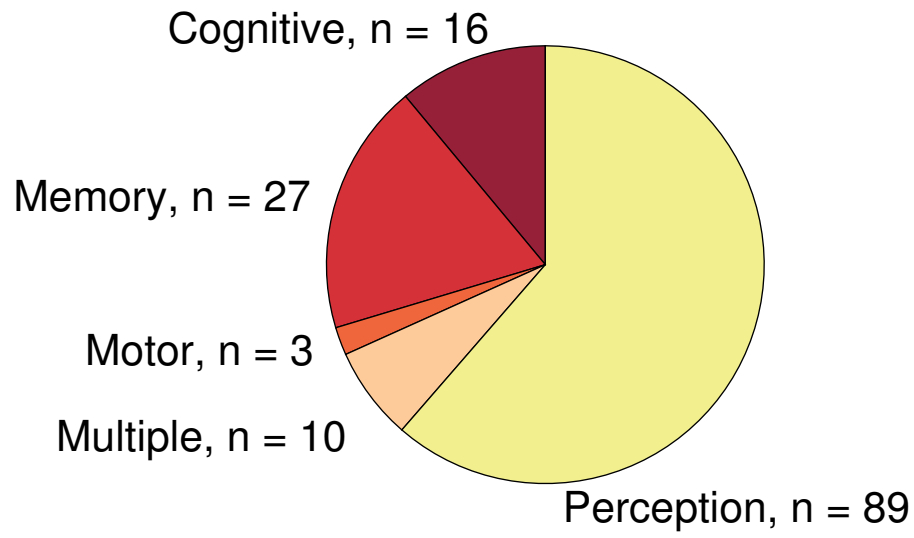
662 **Figure 4. The prevalence of estimates of negative metacognitive sensitivity.** (A) Individual beta
663 values and beta values density plot for the observed relationship between confidence and accuracy.
664 Box shows the median and the interquartile (25-75%) range, whereas the whiskers show the 2-98%
665 range. (B-F) Scatter plots, including lines of best fit, for the relationships between the beta value for
666 confidence-accuracy relationship and the number of trials (B), average accuracy (C), median choice RT
667 (D), median confidence RT (E), and the proportion of trials where the most common confidence
668 judgment was given (F).

669

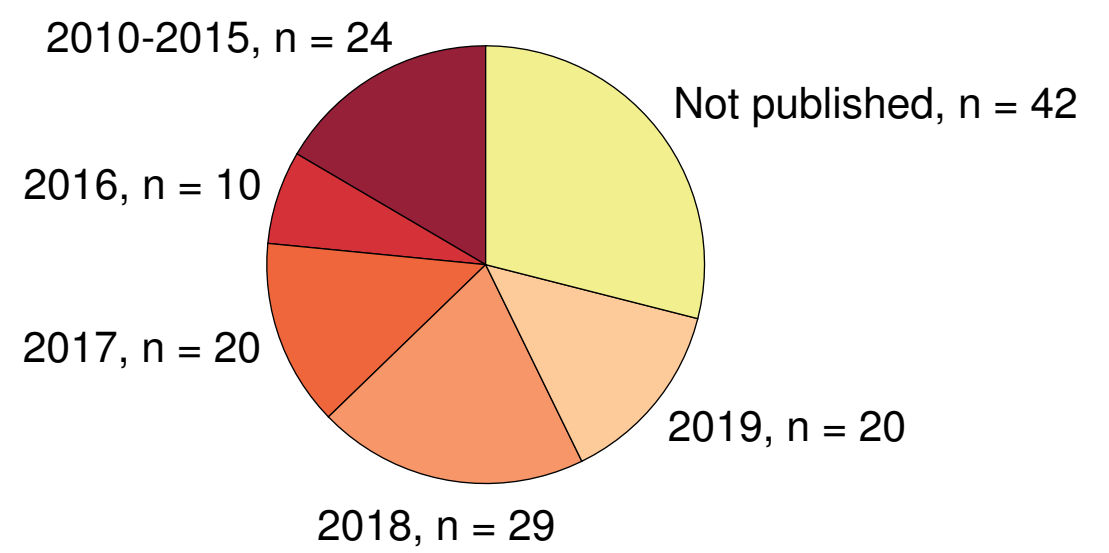
670 **Figure 5. Confidence scale use for perception and memory studies.** The percent of 2-point, 3-point,
671 4-point, 5-point, 6-point, 7-to-11-point, and continuous confidence scales were plotted separately for

672 perception and memory datasets. We combined the 7- to 11-point scales because of the low number
673 of datasets with such scales. The two domains differed in how often they employed 3-point and
674 continuous scales.

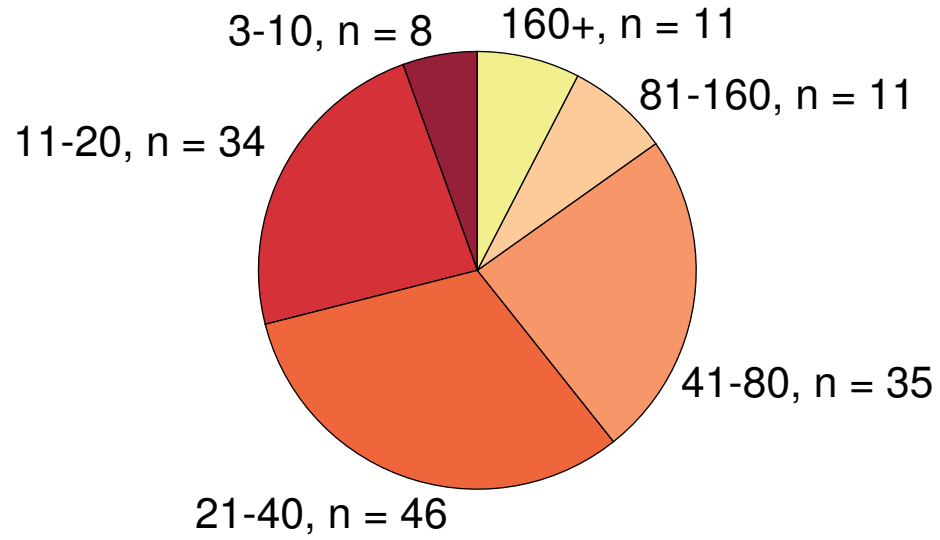
Category



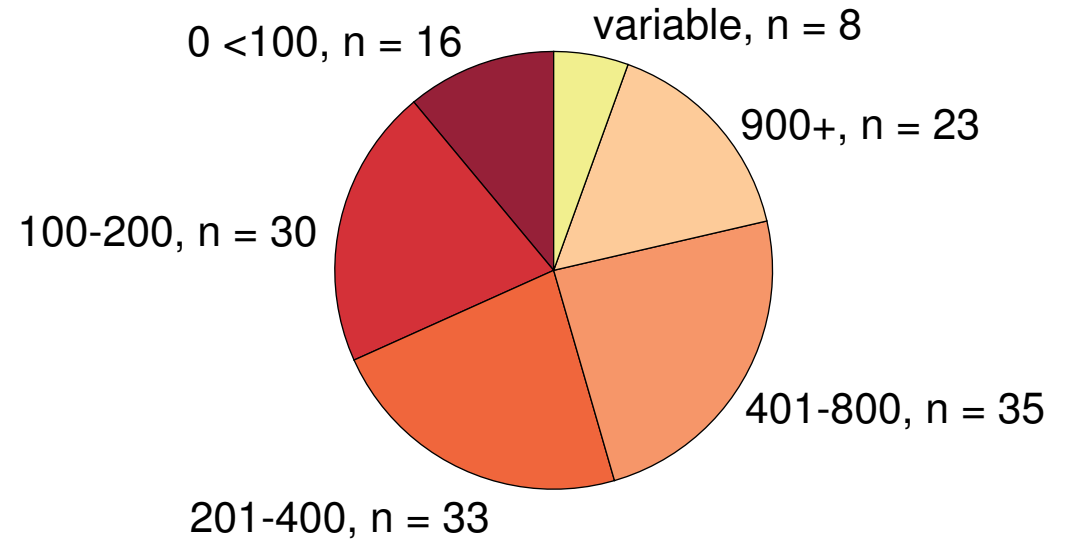
Publication year



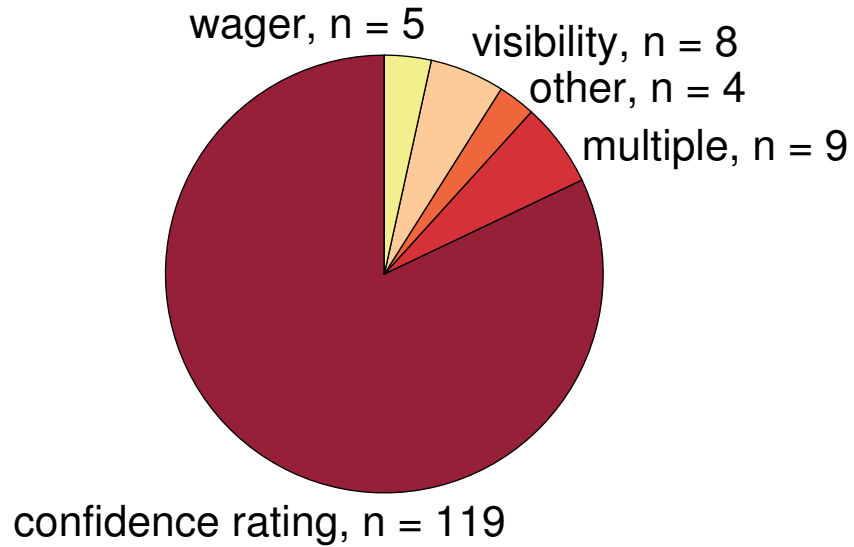
Number of subjects



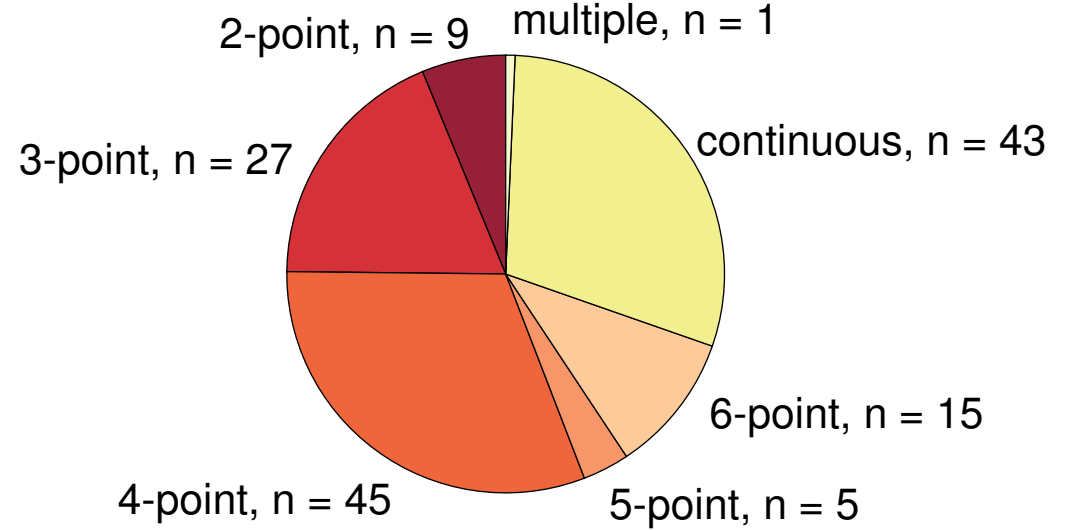
Number of trials per subject



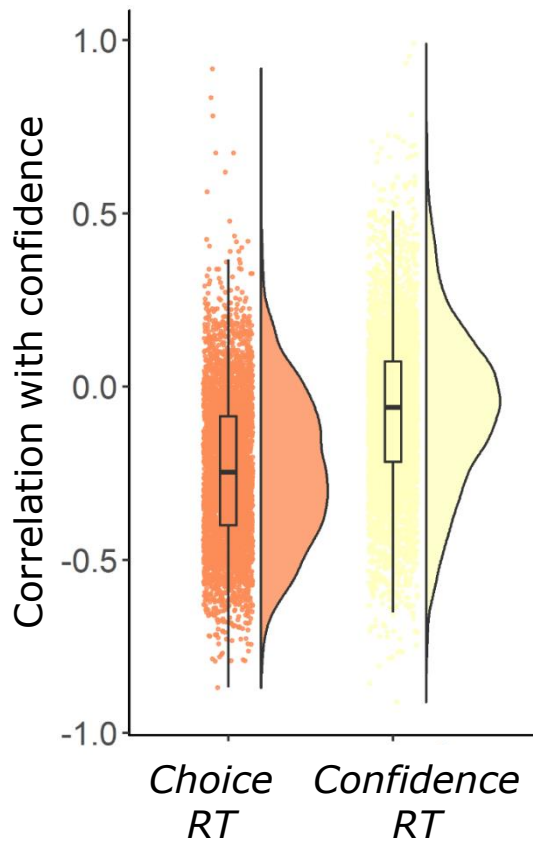
Type of judgment



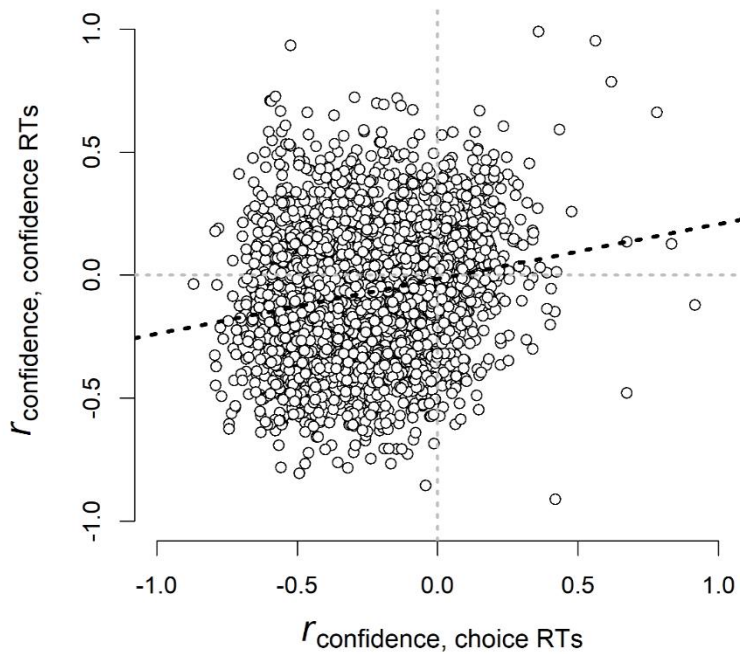
Rating scale



A.



B.



Beta value

0.150
0.100
0.05
0.00

lag-1

lag-2

lag-3

lag-4

lag-5

lag-6

lag-7

History of confidence RTs

