The confidence database

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Abstract

Understanding how people rate their confidence is critical for characterizing a wide range of perceptual, memory, motor, and cognitive processes. However, progress has been slowed by the difficulty of collecting new data and the unavailability of existing data. To address this issue, we created a large database of confidence studies spanning a broad set of paradigms, participant populations, and fields of study. The data from each study are structured in a common, easy-to-use format that can be easily imported and analyzed in a variety of software packages. Each dataset is further accompanied by an explanation regarding the nature of the collected data. At the time of publication, the confidence database (available at osf.io/s46pr) contained 145 datasets with data from over 8,700 participants and almost 4 million trials. The database will remain open for new submissions indefinitely and is expected to continue to grow. This large collection of data will enable new discoveries and can serve as a blueprint for similar databases in related fields.

Introduction

Researchers from a wide range of fields use ratings of confidence to provide fundamental insights about the mind. Confidence ratings are subjective ratings regarding one's first-order task performance. For instance, participants may first make a decision regarding whether a probe stimulus belongs to a previously learned study list or not. A confidence rating, in this case, could involve the participants' second-order judgment regarding how sure they are about the accuracy of the decision made in that trial (i.e., accuracy of the first-order task performance). Such second-order judgments reflect people's ability to introspect and can be dissociated from the first-order judgment (Mamassian, 2016). Confidence ratings tend to correlate strongly with accuracy and response speed (Weidemann & Kahana, 2016) suggesting that they reflect relevant internal states.

The question of how humans (or other animals) evaluate their own decisions has always been an important topic in psychology, and the use of confidence ratings dates back to the early days of experimental psychology (Peirce & Jastrow, 1884). In addition, confidence has been used as a tool to, among many other things, determine the number of distinct memory retrieval processes (Ratcliff, Van Zandt, & McKoon, 1995), reveal distortions of visual awareness (Azzopardi & Cowey, 1997), understand the factors that guide learning (Robey, Dougherty, & Buttaccio, 2017), assess the reliability of eyewitness testimony (Wixted & Wells, 2017), test theories of sensory processing (Green & Swets, 1966) and decision-making (Balakrishnan & Ratcliff, 1996; Mueller & Weidemann, 2008), help estimate psychometric function fit parameters more efficiently (Yi & Merfeld, 2016) and characterize various psychiatric conditions (David, Bedford, Wiffen, & Gilleen, 2012). The wide application of confidence makes it a fundamental measure in psychological research.

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

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

Although data sharing can speed up scientific progress considerably, fields devoted to understanding human behavior, unfortunately, have cultures of not sharing data (Hardwicke & Ioannidis, 2018; Vines et al., 2014). For example, Wicherts et al. (2006) documented their painstaking and ultimately unsuccessful endeavor to obtain behavioral data for re-analysis. Nevertheless, recent efforts towards increased openness have started to shift the culture considerably and more and more authors post their data online (Munafò et al., 2017; Nelson, Simmons, & Simonsohn, 2018).

There are, however, several challenges involved in secondary analyses of data, even when such data have been made freely available. First, the file type may not be usable or clear for some researchers. For example, sharing files in proprietary formats may limit other researcher's ability to access them (e.g., if reading the file requires software that is not freely or easily obtainable). Second, even if the data can be readily imported and used, they may lack important information that the original researcher did not consider valuable. Third, researchers who need data from a large number of studies have to spend a considerable amount of time finding individual datasets, familiarizing themselves with how each dataset is organized, and bringing all datasets into a common format for analysis. Finally, given the size of the literature, it can be difficult to even determine what papers may have relevant data to test any new idea.

Here we report on a large-scale effort to create a database of confidence studies that addresses all of the problems above. The database uses an open standardized format (.csv files) that can easily be imported into any software program used for analysis. The individual datasets are formatted using the same general set of guidelines making missing data much less likely and ensuring that data re-use is much less time-consuming. Finally, creating a single collection of confidence datasets makes it much easier and faster to find datasets that could be re-used for the purposes of testing new ideas or models.

Details on the database

The confidence database is hosted on the Open Science Framework (OSF) website (osf.io/s46pr). Each dataset is represented by two files – a data file in .csv format and a readme file in .txt format.

The majority of data files contain the following fields: participant index, stimulus, response, confidence, response time of the decision, and response time of confidence rating. Depending on the specific design of each study, these fields can be slightly different (e.g., if there are two stimuli on each trial or confidence and decision are given with a single button press).

Further, many datasets include additional fields needed to fully describe the nature of the collected data.

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

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

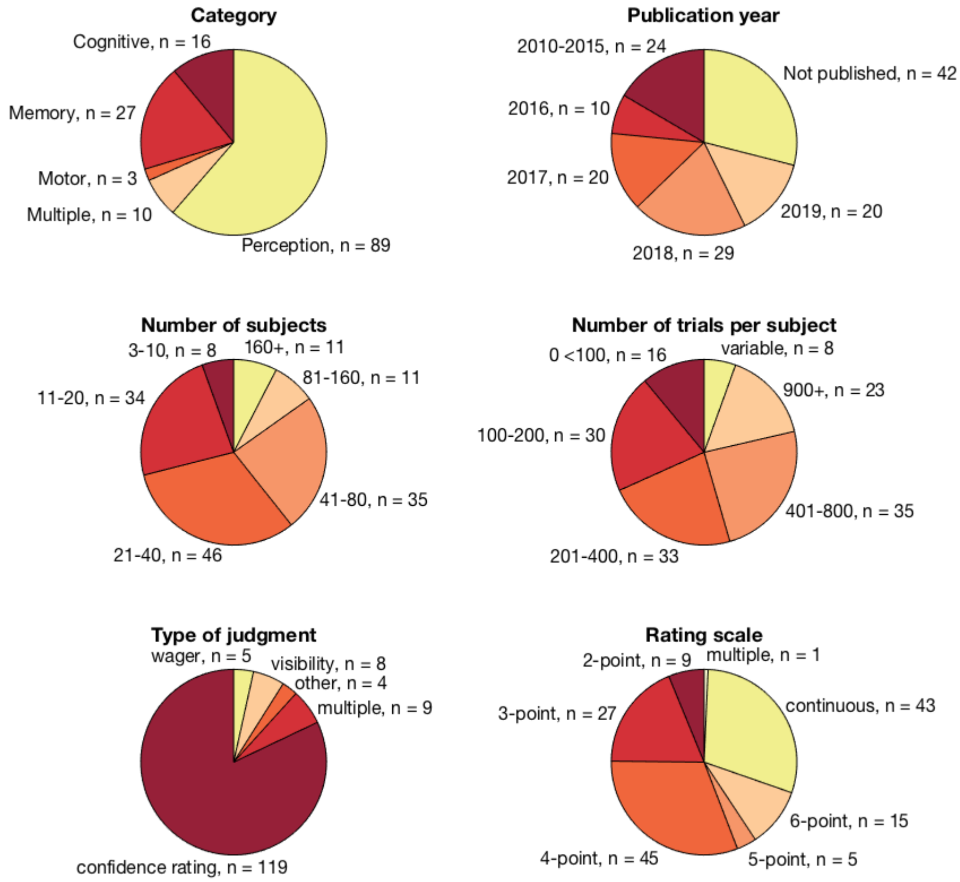

Figure 1. Datasets currently in the confidence database*. Pie charts showing the number of datasets split by category, publication year, number of participants, number of trials per participant, type of judgment, and rating scale. The label "Multiple" in the first pie chart indicates that the same participants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

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

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

At the time of publication, the confidence database contained 145 datasets, bringing together 8,787 participants, for a total of 3,955,802 individual trials. The data were collected mostly in laboratory experiments (from 18 different countries over five continents) but also in online experiments. Despite its already large size, the database still contains only a small fraction of the available data on confidence and is expected to continue to grow.

We encourage researchers who already make their data available to also submit their data to the confidence database. This would make their data easier to discover and re-use, and would multiply the impact of their research.

Data re-use

Anyone is encouraged to download and re-use the data from the database. The database is shared under the most permissive CC0 license thus placing the data in the public domain. As with the re-use of any other data, publications that result from such re-analysis should cite the current paper, as well as the listed citation for each of the datasets that were re-analyzed. We refer readers who wish to perform secondary data analyses to a useful discussion of this process, including the possibility of preregistering such analyses, by Weston et al. (2019).

We envision that the data from this database will be used for a variety of purposes such as developing and testing new models of confidence generation; comparing confidence across different subfields, rating scales, and populations; determining the nature of metacognitive deficits that accompany psychiatric disorders; characterizing the relationship between confidence, accuracy, and response times; and building theories of the response times associated with confidence ratings. Further, the database can also be used to test hypotheses unrelated to confidence due to the inclusion of choice, accuracy, and response time.

Data sharing in the behavioral sciences

It is a sad reality that "most of the data generated by humanity's previous scientific endeavors is now irrecoverably lost" (Hardwicke & Ioannidis, 2018). Data are lost due to outdated file formats; researchers changing universities, leaving academia, or becoming deceased; websites becoming defunct; and lack of interpretable metadata describing the raw data. It is unlikely that much of the data not already uploaded to websites dedicated to data preservation will remain available for future research several decades from now.

We hope that the current confidence database will contribute to substantially increased data preservation and could serve as an example for similar databases in other fields of behavioral science and beyond. Many subfields of psychology produce data that can be fully summarized in a single file using a common format and thus can be easily shared. The mere existence of such a database in a given field may encourage data sharing by facilitating the process of sharing data; indeed lack of easy options for data sharing is among the important factors preventing researchers from sharing their data (Houtkoop et al., 2018; King, 2007). A popular database can also provide the benefit of the extra visibility afforded to the studies in it. Databases could serve as invaluable tools for meta-analyses and as a means to minimize false positive rates that may originate from low-powered studies and publication bias (i.e., favoring significant findings) by simply including datasets that also show null effects. Importantly, it is critical that sharing data is done in an ethical fashion and that participant anonymity is not compromised (Alter & Gonzalez, 2018; Martone, Garcia-Castro, & VandenBos, 2018; Mello et al., 2013).

Facilitation of data sharing would benefit from determining the factors that prevent researchers from exercising this important practice as part of their dissemination efforts. One of these factors could be the notion that researchers who spent resources to collect the original dataset should have priority over others in re-using their own data (Houtkoop et al., 2018; Tenopir et al., 2011). We argue that sharing data can have positive consequences for individual researchers by increasing the visibility of their research, the citation rate (Colavizza, Hrynaszkiewicz, Staden, Whitaker, & McGillivray, 2019), and its accuracy by enabling meta-analysis. Another set of factors are those that deter researchers from using shared data in open repositories. One of those factors is the belief that utilizing shared data could limit the impact of the work. Milham et al. (2018) addressed such issues by demonstrating that manuscripts using shared data can, in fact, result in impactful papers in cognitive neuroscience and make a case for a more universal effort for data sharing.

Conclusion

The traditional unavailability of data in the behavioral sciences is beginning to change with different funding agencies requiring data sharing and individual researchers sometimes posting their data even without an official mandate to do so. The confidence database represents the first large-scale attempt to create a common database in a subfield of behavioral research. We believe that this effort will have a large and immediate effect on confidence research and will become the blueprint for many other field-specific databases.

Author contributions

The confidence database was conceived and organized by D.R. who also drafted the paper. All contributors at the time of publication are listed as authors in alphabetical order except for the first author D.R. All authors also edited and approved the final version of the manuscript.

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Competing interests

The authors declare no competing interests.

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