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Sequential Collaboration: The Accuracy of Dependent, Incremental Judgments

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Abstract

Online collaborative projects in which users contribute to extensive knowledge bases such as Wikipedia or OpenStreetMap have become increasingly popular while yielding highly accurate information. Collaboration in such projects is organized sequentially with one contributor creating an entry and the following contributors deciding whether to adjust or to maintain the presented information. We refer to this process as *sequential collaboration* since individual judgments directly depend on the previous judgment. As sequential collaboration has not yet been examined systematically, we investigate whether dependent, sequential judgments become increasingly more accurate. Moreover, we test whether final sequential judgments are more accurate than the unweighted average of independent judgments from equally large groups. We conducted three studies with groups of four to six contributors who either answered general knowledge questions (Experiments 1 and 2) or located cities on maps (Experiment 3). As expected, individual judgments became more accurate across the course of sequential chains and final estimates were similarly accurate as unweighted averaging of independent judgments. These results show that sequential collaboration profits from dependent, incremental judgments, thereby shedding light on the contribution process underlying large-scale online collaborative projects.

Keywords: wisdom of crowds, teamwork, mass collaboration, group decision making

Sequential Collaboration: The Accuracy of Dependent, Incremental Judgments

Collaborative online projects have become a popular source for information gathering over the last twenty years. The most prominent example is Wikipedia, an online encyclopedia that allows users to contribute semantic information to various topics in the form of structured articles (Wikipedia Contributors, 2021). Giles (2005) showed that information on Wikipedia is very accurate in general. Moreover, certain topics such as information on cancer or certain drugs are similarly accurate as official health information or text books (Kräenbring et al., 2014; Leithner et al., 2010). Another example of online collaboration is OpenStreetMap, a collaborative project that aims at generating a comprehensive, open, and free-to-use map of the world (OpenStreetMap Contributors, 2021). OpenStreetMap does not only comprise geographical numeric information about the locations of objects such as coordinates but also semantic information such as names of streets, areas, buildings, and other useful information (e.g., addresses or websites of shops and restaurants). Comparing the accuracy of OpenStreetMap with commercial map providers or governmental sources also revealed a comparable accuracy (e.g., Girres & Touya, 2010; Zielstra & Zipf, 2010).

The high accuracy of Wikipedia and other online collaborative projects has often been attributed to the wisdom of crowds (e.g., Arazy et al., 2006; Kittur & Kraut, 2008; Niederer & Dijck, 2010), which refers to the aggregation of judgments from different informants (Galton, 1907; Surowiecki, 2004). The term “wisdom of crowds” is a broad concept encompassing various methods of eliciting and aggregating judgments. As a measure for crowd wisdom, prior work often examined the unweighted mean or median of independent individual judgments (e.g., Budescu & Chen, 2014; Davis-Stober et al., 2014; Galton, 1907; Hueffer et al., 2013; Larrick & Soll, 2006; Merkle et al., 2020). The high accuracy of these judgments is due to the central limit theorem which ensures that errors in independent, individual judgments cancel out (Hogarth, 1978) and has been demonstrated for various tasks and in various contexts (e.g., Hueffer et al., 2013; Steyvers et al., 2009). The accuracy of unweighted averaging of independent individual

judgments increases when judgments bracket the true answer (Larrick & Soll, 2006; Simmons et al., 2011) and are negatively correlated and unbiased (Davis-Stober et al., 2014; Keck & Tang, 2020).

The collection and aggregation of judgments in online collaborative projects can be regarded as a certain type of wisdom of crowds. However, in online collaboration, judgments are usually not collected independently and then aggregated mechanically, but rather elicited in a dependent and sequential manner. Instead of providing independent judgments, contributors encounter already existing entries and decide whether to change the presented information reflecting the latest version of an entry or whether to maintain the presented version. We refer to this way of collaborating as sequential collaboration. Because unweighted averaging is known to result in highly accurate estimates for various tasks and contexts, we will use it as a benchmark for assessing the accuracy of sequential collaboration.

In the following, we first define sequential collaboration and distinguish it from other forms of collaboration and aggregating judgments. Next, we discuss prior research on dependent judgments which has shown both positive and detrimental effects of dependency. Our main goal is to compare sequential collaboration to unweighted averaging. We investigate why and under which conditions the elicitation of incremental, dependent judgments can benefit accuracy compared to taking the unweighted average of independent individual judgments. In three studies, we used general knowledge questions and maps on which cities should be positioned to test whether sequential collaboration within small groups of four to six contributors yields improved judgments. Moreover, we tested whether the final judgments of a sequential chain are more accurate than estimates obtained by aggregating independent individual judgments. In line with our hypotheses, we found that judgment accuracy increased over the course of sequential chain and that sequential collaboration yielded similarly accurate results as unweighted averaging.

Sequential collaboration

As outlined above, collaboration in online projects is often organized sequentially by making incremental changes to the latest available information. Sequential collaboration starts with one contributor creating an initial, independent entry. The next contributors encountering this entry then decide whether to adjust or maintain the presented information. Whenever the entry is changed, the information is updated such that only the latest version of the entry is presented to the next contributor. For example, the first contributor might respond to the question “How tall is the Eiffel Tower?” with 420 meters. The second contributor encountering this judgment could simply maintain it while the third contributor might adjust the height to 290 meters. After several contributors have adjusted and maintained the judgment, the correct height of 300 meters may be entered. The sequence of decisions of whether to maintain or adjust entries made by a previous contributor forms a sequential chain. Figure 1 displays how group estimates are generated with unweighted averaging and in sequential collaboration. In the former, the aggregated estimate is obtained by averaging independent individual judgments; in the latter, the estimate is the last judgment in a sequential chain generated by adjusting and maintaining previous judgments.

Even though sequential collaboration is performed by a group of individuals and shares some aspects with other forms of group decision making, it also has some unique features distinguishing it from other forms of collaboration. In research on group decision making, group work usually takes place simultaneously (Kerr & Tindale, 2004; Lu et al., 2012; Stasser & Titus, 1985) even though interactions do not necessarily take place in person (Dennis, 1996; Dennis et al., 1998; Lu et al., 2012). In a paradigm organized like this, all members of the group have the opportunity to listen to all judgments and opinions, to ask questions to other group members, and to share justifications and other information. In sequential collaboration, however, information is shared only by adding or correcting the judgment of a previous contributor which implies that the dependency between judgments is limited to the displayed information.

Figure 1

Illustration of group estimates in unweighted averaging and sequential collaboration.

Furthermore, direct interactions with other contributors are neither necessary nor possible in sequential collaboration, and additional information such as the number of adjustments already made to this information or reasons why information was adjusted are initially not available.

A form of collaboration similar to sequential collaboration is the Delphi method (Dalkey & Helmer, 1963; Geist, 2010; Jeste et al., 2010). The Delphi method was designed to obtain judgments on a given topic from a group of experts who do not interact directly. First, experts provide independent judgments and justifications for these judgments, which are then combined in a report by a moderator. This report is sent to all experts who can then revise their judgments based on the judgments and information included in the report. When experts have reached a sufficient consensus, the individual judgments are aggregated to a final result. The Delphi method is similar to sequential collaboration in that individuals do not directly interact with each other.

However, in sequential collaboration, contributors do neither receive judgments of several other contributors nor justifications of these judgments. Moreover, contributors are not necessarily required to provide a judgment, and even if they do, they may not notice if their judgment is in turn adjusted by others. Finally, the Delphi method focuses on eliciting judgments by a group of experts, whereas in sequential collaboration, neither the specific contributors nor the number of contributors has to be predefined.

Possible issues and benefits of sequential collaboration

Even though sequential collaboration seems to be a successful way of integrating judgments of various individuals, the process of sequentially deciding whether to adjust or maintain a previous judgment has not been systematically examined yet. Nonetheless, research on related phenomena allows us to derive testable predictions.

Possible issues for the accuracy of sequential collaboration may arise from the anchoring effect (Tversky & Kahneman, 1974). Anchoring describes the robust phenomenon that a presented numerical value influences subsequent, often unrelated numerical judgments (Mussweiler et al., 2004). This effect may undermine the accuracy of sequential collaboration such that adjustments made to a previous judgment are systematically biased toward the previous judgment. Especially, when the previous judgment heavily over- or underestimates the correct value, anchoring might affect later judgments such that arriving at accurate, unbiased estimates is prolonged or hindered.

The conditions under which information provided by others is considered in forming a judgment has been extensively studied in the advice-taking literature (Bonaccio & Dalal, 2006). Egocentric discounting describes the phenomenon that advice is generally underweighted relative to one's own initial judgment, in turn resulting in less accurate judgments compared to equally weighing the advice and one's own judgment (Yaniv & Kleinberger, 2000). In sequential collaboration, egocentric discounting could lead contributors to adjust the presented previous judgment mainly according to their prior beliefs, which in turn could be detrimental to accuracy as the chain may not converge to the correct answer. However, advice taking improves when

no initial individual judgment is formed before receiving advice (Koehler & Beauregard, 2006). This resembles the situation in sequential collaboration more closely since contributors are directly confronted with the previous judgment and do not have to form an initial, independent judgment. Hence, compared to the standard advice-taking paradigms, contributors in sequential collaboration may be more likely to accept a presented judgment.

Prior research also provides preliminary evidence in favor of the accuracy of sequential collaboration. Providing participants with a frame of reference improves subsequent judgments, especially because it prevents extreme judgments (Bonner et al., 2007; Laughlin et al., 1999). Previous judgments in a sequential chain may serve as a frame of reference that prevents extreme judgments and fosters to reach an accurate estimate earlier. However, especially at the beginning of a sequential chain, judgments by previous contributors may not provide an accurate frame of reference.

Providing judgments of other individuals can also improve the accuracy of aggregation methods based on unweighted averaging. Imitating successful individuals leads to more accurate judgments (King et al., 2012), and discussions in dyads also improve judgments, but only when initial independent judgments are formed (Minson et al., 2017). Moreover, Becker et al. (2017) showed that information about others' judgments is beneficial when this information equally weighs all other judgments (as opposed to overweighing judgments of a single, highly influential individual). Given that individual judgments can be improved by providing judgments of others, sequential collaboration may lead to more accurate judgments. Especially the finding that imitating successful individuals improves accuracy (King et al., 2012) is relevant for sequential collaboration as contributors may often be presented with the currently best judgment in the sequential chain which can easily be imitated by not making a change. However, while King et al. (2012) selected the currently most accurate judgment from a large pool of independent judgments, the judgments presented in a sequential chain are not necessarily very accurate, especially if only a few contributors have encountered and edited it.

Sequential collaboration may also benefit from the fact that in group work, not all group members contribute to a given task equally and some do not contribute at all (free-rider effect, Bray et al., 1978) and that group members often contribute less the more they feel that their contribution is dispensable (Kerr & Bruun, 1983). Such effects may also be observed in sequential collaboration since contributors can maintain a previous judgment when thinking that they cannot substantially improve it. This opt-out mechanism could in turn improve accuracy since giving respondents the possibility to select the questions to be answered improves accuracy of unweighted averaged judgments (Bennett et al., 2018). The fact that contributors can self-select which judgments to adjust may thus lead to a higher accuracy of the resulting judgments. However, this requires that contributors can accurately distinguish which judgments to maintain (assuming they cannot substantially contribute to it) and which judgments to adjust (assuming they can improve the present state of an entry).

Miller and Steyvers (2011) performed a study closely resembling sequential collaboration in a rank-ordering task. Participants were presented either with judgments of previous participants (resulting in a sequential chain of judgments) or with randomly generated rank orders (resulting in independent judgments). They could opt out from answering by accepting the presented rank order, which was the order made by the previous participant. Miller and Steyvers (2011) found that both the group aggregate and the average subject’s performance increased for sequential compared to independent judgments. Moreover, the last judgment in such a sequential chain was more accurate than the group aggregate of independent judgments. Forming sequential chains may, thus, lead to improved judgment accuracy and even outperform the aggregation of independent judgments. Moreover, these results suggest that providing an opportunity to opt out can be beneficial both for individual and for group accuracy.

Hypotheses

Based on prior research, we expect that sequential collaboration is an effective method of eliciting and aggregating individual judgments. Our first two hypotheses

233 concern basic assumptions about sequential collaboration:

234 *Hypothesis 1:* Over the course of a sequential chain, (1a) the probability of
235 changing a judgment and (1b) the magnitude of change decrease.

236 *Hypothesis 2:* Over the course of a sequential chain, the accuracy of the
237 most recent judgment increases.

238 Given its high accuracy, unweighted averaging can be used as a benchmark for
239 other forms of collaboration. As discussed above, sequential collaboration may profit
240 from the possibility that contributors are not required to adjust the presented
241 information (Bennett et al., 2018), but rather can decide to maintain the presented
242 judgment if they perceive their own judgments to be dispensable (Kerr & Bruun, 1983).
243 Since providing information about judgments from others can improve accuracy (Becker
244 et al., 2017; King et al., 2012; Minson et al., 2017), especially when such information is
245 organized in a sequential chain (Miller & Steyvers, 2011), accuracy of sequential
246 collaboration may exceed that of unweighted averaging:

247 *Hypothesis 3:* Sequential collaboration yields more accurate group estimates
248 than unweighted averaging.

249 Since unweighted averaging is known to yield highly accurate estimates, it is also
250 plausible that sequential collaboration does not yield better but merely similarly
251 accurate estimates. This would already be an important and relevant finding because
252 sequential collaboration may not profit from the central limit theorem for means of
253 independent random variables the same way as unweighted averaging does (Hogarth,
254 1978). Sequential collaboration does not involve the computation of a mean of
255 individual judgments, and thus, the central limit theorem is not directly applicable
256 (Zhang et al., 2022). However, contributors may integrate the presented information
257 when forming their own judgment (Bonaccio & Dalal, 2006). Such an implicit averaging

of the presented and the internally generated judgment could result in increased accuracy due to error cancellation.

To test our hypotheses, we conducted three online experiments (two of which were preregistered) using chains of four to six contributors in sequential collaboration and corresponding group sizes for unweighted averaging.¹ The materials comprised general knowledge questions with numerical judgments in the first two experiments and geographic maps on which participants had to position cities in the third experiment.

Experiment 1

Method

Materials. We presented 65 difficult general knowledge questions such as “How tall is the Eiffel Tower?” or “When was Leonardo da Vinci born?” to the participants. The questions were taken from an item pool on general knowledge questions (Pohl, 1998) and updated with contemporary information whenever necessary. The median of correctly answered questions was 0.53% ($MAD = 0.78\%$) indicating that the questions were indeed difficult to answer correctly for participants. All items, their correct numerical answers, and the unit in which the answer had to be given are provided in Table A1 in the Appendix.

Participants. For this online study, 310 German college students participated via a German panel provider. The compensation ranged between 0.60EUR and 1EUR according to the time for participation. To control data quality already during data collection, participants who changed their browser window or switched to other programs more than five times were excluded during participation. Based on the results of the pilot study, we suspected participants to look up answers when more than 10% of the questions were answered correctly. This was the case for three participants who were not considered for building sequences and whose data were excluded for the analysis. Two participants were excluded due to irregular answer patterns in more than

¹ Prior to conducting the three experiments reported in the present manuscript, we also conducted a pilot study to pretest and improve the experimental paradigm.

10% of the questions (i.e., answering with number series such as “23456” or answering “0”). Lastly, two participants were excluded since the same position in a sequential chain was assigned to two participants due to a technical issue. We kept the data of the participant whose data was used throughout the rest of this sequential chain. Our final sample comprised 303 participants, of whom 76.6% were female, 22.8% were male, and 0.7% did identify as diverse. The mean age of the sample was 23.8 years ($SD = 3.2$).

Design and procedure. Participants were randomly assigned to the independent-judgments questionnaire (192 participants) or the sequential-collaboration questionnaire (111 participants). After consenting to the study, they were introduced to the corresponding tasks illustrated in Figure 2. In the independent-judgments questionnaire, one general knowledge question per trial was presented to participants who had to type their judgment into a text box before proceeding to the next question. In the sequential-collaboration questionnaire, participants also saw one general knowledge question per trial, but additionally, the answer of a previous participant was shown below the question. Participants decided whether to adjust or maintain the presented judgment. Only in the former case, the text box appeared in which the new judgment could be entered before proceeding to the next question. Participants were informed that the presented judgments are from one or more of the previous participants and did not know their position in the sequential chain.

General knowledge questions were presented in random order and the unit in which the judgment had to be given was provided directly after the text box. To prevent looking up answers, we implemented a time limit of 30 seconds for entering a judgment in both conditions. Additionally, we implemented a minimum waiting time of two seconds in the sequential-collaboration condition to prevent clicking through the study. After answering all questions, participants provided demographic information, were thanked for participation, and debriefed.

In the unweighted-averaging condition, 155 participants completed the independent-judgments questionnaire and their judgments were then averaged. In the

Figure 2

Questionnaires used in Experiments 1 and 2.

a) Independent judgments

How large is the Eiffel Tower?

Please answer this question. If you do not know the correct answer, please give a judgment that is as accurate as possible.

225 meters

b) Sequential Collaboration

The previous participant answered the question:

How large is the Eiffel Tower?

with:

225 meters

Would you like to change the judgment of the person who answered this question previously?

☒ yes

☐ no

Please enter your judgment here.

270 meters

sequential-collaboration condition, independent initial judgments are required to start sequential chains. Hence, we initialized sequential chains by 37 participants who answered the independent-judgments questionnaire. We used a sequence length of four, meaning that each sequential chain consists of one participant completing the independent-judgments questionnaire followed by three participants completing the sequential-collaboration questionnaire consecutively. For each participant, only the latest judgment in the sequential chain was presented. This procedure resulted in a sample size of 148 participants in the sequential-collaboration condition.

Results

Before analyzing the data, we excluded 314 judgments that were timed out after 30 seconds. Since sequential chains containing such a judgment were excluded

completely, this resulted in the exclusion of 809 judgments in total. Hence, 18,886 judgments remained for analysis.

Since judgments are given on vastly different scales (e.g., from single digits for the length of a soccer goal up to millions for the number of students enrolled in German universities), a standardization of raw judgments is necessary. To this end, we subtracted the correct answer for each question from the raw judgments before dividing the result by the standard deviation of all judgments obtained with the independent-judgments questionnaire. The resulting *standardized errors* are equal to zero for correct judgments while being negative and positive in case of under- and overestimation, respectively. Moreover, we used *absolute standardized errors* for testing hypotheses concerning the accuracy of judgments and estimates.

After standardizing the judgments, we removed the 1% most extreme values from the data as these judgments may distort the results. Excluding outliers across conditions is also recommended by André (2021) who demonstrated that excluding outliers separately within each condition can increase false-positive rates. We identified 189 extreme judgments with this procedure. Again, we excluded both these judgments and the corresponding sequences, resulting in a final sample of 18,626 judgments.

Confirmatory analyses.

Hypothesis 1a states that change probability decreases over the course of a sequential chain. To test this prediction, we only considered data of participants completing the sequential-collaboration questionnaire who could decide whether to change or maintain a presented judgment (position 2, 3, or 4 in a sequential chain). We modeled the decision whether to adjust or maintain a judgment as a function of the chain position in the sequence by fitting a generalized linear mixed model with the R packages lme4 (Bates et al., 2015) and lmerTest (Kuznetsova et al., 2017). Since the dichotomous dependent variable can only be 1 (adjust) or 0 (maintain), we used a logit link function. As every participant answered the same 65 items, and we added random intercepts for items and participants to account for the nested structure of our data

(Pinheiro & Bates, 2000). We added crossed random effects of items and participants to all hierarchical models reported since all reported studies have a data structure in which individual judgments are nested in items and participants. Lastly, we set polynomial contrasts to test for a decline in change probability with increasing chain position.²

Figure 3 shows the mean change probability for each chain position with corresponding between-subjects error bars and violin and box plots indicating the distribution of change probabilities for participants (aggregated across items). Even though descriptively in line with Hypothesis 1a, the linear trend of the effect of chain position on change probability was not significant ($\beta = -0.311$, $CI = [-0.685, 0.063]$, $z = -1.629$, $p = .103$).

Hypothesis 1b states that change magnitude decreases over the course of a sequential chain. Again, we only used judgments from the sequential-collaboration questionnaire (chain positions 2, 3, and 4) and excluded all trials in which participants did not change the presented judgment of a previous participant. Change magnitude was computed as the absolute difference between the standardized error of a judgment and the standardized error of the previous judgment. We fitted a linear mixed model with change magnitude as a continuous dependent variable and chain position as independent variable, and included polynomial contrasts for the factor chain position. In line with Hypothesis 1b, the model revealed a significant negative linear trend of chain position ($\beta = -0.042$, $CI = [-0.074, -0.011]$, $t(82.093) = -2.633$, $p = .010$). Figure 4 shows the empirical means of change magnitude for each chain position with between-subjects error bars as well as violin and box plots of the distribution of change magnitudes for participants (aggregated across items).

Hypothesis 2 states that judgments become more accurate over the course of a

² Whenever testing polynomial contrasts, we only report results for the linear trend since we are interested in a decrease in change probability (Hypothesis 1a), in change magnitude (Hypothesis 1b), and in absolute error (Hypothesis 2). Other trends are only reported when being statistically significant.

Figure 3

Change probability within a sequential chain.

Note. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of change probabilities for the participants (aggregated across items).

sequential chain. To test this prediction, we only considered data from the
 sequential-collaboration condition. We fitted a linear mixed model with absolute
 standardized errors as dependent variable and chain position as independent variable.
 Since fixed-effect coefficients in linear mixed models have been shown to be robust when
 residuals are not normally distributed (LeBeau et al., 2018; Schielzeth et al., 2020), we
 did not transform the dependent variable accordingly. Furthermore, we set polynomial
 contrasts for the factor chain position.

Figure 5 shows the mean absolute standardized errors for each chain position
 with corresponding violin and box plots. In line with Hypothesis 2, judgments became
 more accurate as the distance to the correct answer declines over the course of a

Figure 4

Change magnitude within a sequential chain.

Note. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of change magnitude for the participants (aggregated across items).

sequential chain. This pattern was also confirmed by the linear mixed model showing a significant negative linear trend ($\beta = -0.024$, $CI = [-0.036, -0.011]$, $t(143.55) = -3.800$, $p < .001$).

Hypothesis 3 states that sequential-collaboration estimates are more accurate than estimates obtained with unweighted averaging. Before testing this hypothesis, we checked whether the randomization worked as intended, meaning that participants completing the independent-judgments questionnaire had the same judgment accuracy irrespective whether they were included in the unweighted-averaging condition or served as starters for sequential chains (position 1) in the sequential-collaboration condition. We only considered data obtained with the independent-judgments questionnaire and

Figure 5

Accuracy of judgments within a sequential chain.

Note. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of errors for the participants (aggregated across items).

fitted a linear mixed model with the absolute standardized error as dependent and condition as independent variable. We did not find a significant effect of condition on the absolute standardized error ($\beta = 0.005$, $CI = [-0.012, 0.023]$, $t(198.37) = 0.598$, $p = .550$) indicating that the randomization worked as intended.

Next, we computed the accuracy of the group estimates for each condition. For sequential collaboration, the estimate for each chain is the judgment at the last chain position (position 4). Accuracy of these estimates is defined as the absolute standardized error of the last judgment in a sequential chain. For unweighted averaging, the group estimate is the mean of judgments for groups of four participants. We computed the absolute standardized errors of these estimates by (1) randomly assigning

participants to virtual groups of four, (2) averaging the four standardized errors for each question, and (3) computing the absolute value of the average.³ Since the number of participants in the unweighted-averaging condition (i.e., 155 participants) is not a multiple of four, we randomly selected one participant whose data was duplicated before generating the virtual groups. This procedure resulted in absolute standardized errors of estimates of the 65 items presented in the study for 39 groups of participants in the unweighted-averaging condition and 37 sequences of participants in the sequential-collaboration condition.

To test Hypothesis 3, we fitted a linear mixed model with absolute standardized errors as dependent variable and condition as independent variable. Figure 6 displays the mean absolute standardized error and corresponding 95% between-subjects confidence intervals with violin and box plots referring to the distribution of group accuracy (aggregated across items). Contrary to Hypothesis 3, estimates in the sequential-collaboration showed a slightly higher mean absolute error of estimates meaning that these judgments were descriptively less accurate. However, the linear mixed model did not show a significant effect of condition ($\beta = 0.008$, $CI = [-0.005, 0.022]$, $t(72.15) = 1.237$, $p = .220$).

To explore the robustness of our results, we conducted additional analyses examining the influence of outlier exclusions and transformations of judgments on the accuracy of unweighted averaging and sequential collaboration. We also performed non-parametric, descriptive assessments of the hypotheses using the common-language effect size and observation-oriented modeling. The additional analyses led to similar conclusions as those reported in the main text and can be found in the supplementary material at <https://osf.io/96nsk/>.

³ To check the robustness of the grouping, we computed the mean difference in absolute standardized errors of estimates between conditions and the corresponding linear mixed model for 100 different random groupings in the unweighted-averaging condition. The mean difference in absolute estimates was 0.007 ($SD = 0.001$) for Experiment 1 and 0.01 ($SD = 0.001$) for Experiment 2. The results of the linear mixed model remained the same for all 100 comparisons in both experiments.

Figure 6

Accuracy of unweighted averaging and sequential collaboration.

Note. Estimates for sequential collaboration pertain to the last judgment in a sequential chain. Black points display the empirical means for each condition, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the corresponding distribution of participants (aggregated across items).

Exploratory comparison of different aggregation methods.

We additionally assessed the effect of various aggregation methods for obtaining group estimates. For independent judgments, we computed the mean and the median of the four judgments within each group. For sequential collaboration, we did not only consider the last value in a chain but also aggregated the four individual judgments in a chain using the mean and the median. Furthermore, we computed a weighted mean with the weights $1/10$, $2/10$, $3/10$, and $4/10$ for judgments at chain positions 1, 2, 3, and 4, respectively.

Table 1

Comparison of different aggregation methods for independent judgments and sequential collaboration.

Experiment	Method	Aggregation	Absolute Error	<i>SE</i>	Squared Error	<i>SE</i>
Experiment 1	Sequential collaboration	Last Value	0.16	0.01	0.11	0.01
		Mean	0.16	0.01	0.11	0.01
		Median	0.17	0.01	0.12	0.01
		Weighted Mean	0.16	0.01	0.11	0.01
	Independent judgments	Mean	0.16	< 0.01	0.08	< 0.01
		Median	0.14	< 0.01	0.07	< 0.01
Experiment 2	Sequential collaboration	Last Value	0.12	< 0.01	0.07	0.01
		Mean	0.13	< 0.01	0.08	0.01
		Median	0.13	< 0.01	0.08	0.01
		Weighted Mean	0.13	< 0.01	0.08	0.01
	Independent judgments	Mean	0.13	< 0.01	0.07	< 0.01
		Median	0.13	< 0.01	0.08	< 0.01
Experiment 3	Sequential collaboration	Last Value	46.17	1.01	4120.77	208.22
		Mean	46.00	0.86	3615.98	152.01
		Median	44.90	0.95	3820.80	184.06
		Weighted Mean	43.33	0.85	3338.07	151.41
	Independent judgments	Mean	53.74	0.71	4205.06	114.84
		Median	47.95	0.74	3723.38	131.24

For all aggregation methods and both conditions, Table 1 shows the mean absolute error and the mean squared error of the group estimates. The most accurate estimates were obtained when using median aggregation for independent judgments. Similar to the confirmatory analysis of Hypothesis 3, estimates obtained with unweighted averaging were descriptively more accurate than those of sequential collaboration irrespective of the aggregation method for both absolute and squared

errors. For sequential collaboration, all aggregation methods yielded similar accurate results which were overall less accurate than aggregating independent individual judgments.

Discussion

Overall, Experiment 1 yielded mixed results. The results indicate that a basic assumption about sequential collaboration holds, namely, that contributors can improve the accuracy of previous judgments by correcting each other sequentially. There was, however, no evidence for Hypothesis 3 as unweighted averaging and sequential collaboration yielded similarly accurate group estimates. Furthermore, the exploratory moderator analyses showed that the accuracy of sequential collaboration was not much influenced by different aggregation methods while independent judgments showed more accurate estimates when taking the median rather than the mean. This may be due to reducing the effect of extreme judgments which may distort the mean.

While Experiment 1 provides first insights into sequential collaboration, it has some limitations which restrict the generalizability of our results. First, the sample was restricted to college students who typically have a similar age and educational background. The limited diversity in individuals' expertise might have reduced the chances of improving previous judgments in sequential collaboration since the distribution of knowledge might have been too homogeneous. Second, we implemented a rather short chain length of four individuals. Results might differ when using longer chains since additional contributors might improve the sequential-collaboration estimate substantially.

Experiment 2

To address the limitations of Experiment 1, we conducted a second experiment using the same general knowledge questions while increasing the chain length from four to six and collecting an adult sample with no restrictions in age or education. Thereby, we test the robustness of our findings, especially the improvement of judgments within a sequential chain, and apply the paradigm to a more diverse sample and a longer

sequential chain. The design and confirmatory analyses were again preregistered.⁴ Note that we did not preregister Hypotheses 1a and 1b concerning the change probability and change magnitude within a sequential chain. Moreover, we improved the exclusion criteria for extreme judgments as already applied in Experiment 1 and added an exploratory analysis comparing different aggregation methods for independent judgments and sequential collaboration. All analyses concerning the accuracy of estimates (Hypotheses 2 and 3) are again based on absolute standardized errors similar as in Experiment 1.

Method

Materials, design, and procedure. Experiment 2 used the same design and questions as Experiment 1 (see Figure 2 and Table A1, respectively) with some minor adjustments. Since the sample was not restricted in age, we extended the time limit for answering a question from 30 to 40 seconds. Moreover, we implemented a chain length of six meaning that the first participant in a sequential chain answered the independent-judgments questionnaire and was then followed by five participants answering the sequential-collaboration questionnaire.

Participants. A German panel provider sampled 686 participants for this study. Participants were compensated between 0.75EUR and 1EUR depending on the time for study completion. During data collection, 21 participants were suspected to look up answers as they entered more than 10% correct answers, and were thus excluded both for building sequential chains and for the analysis. Moreover, 8 participants had irregular answer patterns and were excluded. One participant was excluded since the position in the sequential chain was allocated to two different participants. After excluding these participants and, if necessary, participants in the corresponding sequential chains, the final sample comprised 646 participants. Half of the participants were female (49.9%), the mean age was 48.1 years ($SD = 19.5$). Most participants had a college degree (27.2%), followed by a high-school diploma (25.5%), and vocational

⁴ The preregistration form is available at <https://aspredicted.org/8vn9m.pdf>.

education (23.1%) while 24.2% of the participants had a lesser education attainment.

Results

As preregistered, we first excluded judgments (and corresponding chains) that were timed out after 40 seconds. After this exclusion, 40,324 out of 41,990 judgments remained. The judgments were then standardized item-wise similarly as in Experiment 1 by subtracting the correct answer and dividing by the standard deviation of all independent judgments. Finally, the 1% most extreme judgments (and corresponding chains) were excluded from the data resulting in 39,699 judgments for the analysis. We conducted the same confirmatory and exploratory analyses as for Experiment 1.

Confirmatory analyses.

To test whether change probability decreases over the course of a sequential chain (Hypothesis 1a), we fitted a generalized linear mixed model with the decision whether to adjust or maintain a judgment as dependent variable. Figure 3 displays the distribution of change probabilities for each chain position. As hypothesized, the change probability decreased over the course of a sequential chain as indicated by a significant negative linear trend ($\beta = -0.581$, $CI = [-0.982, -0.181]$, $z = -2.843$, $p = .004$).

Next, we fitted a linear mixed model to test whether change magnitude decreases over the course of a sequential chain (Hypothesis 1b). Figure 4 shows that change magnitude slightly decreased over the course of a sequential chain. However, we did not find a significant negative linear trend ($\beta = -0.016$, $CI = [-0.040, 0.009]$, $t(174.228) = -1.249$, $p = .214$).

To test whether accuracy of judgments increases over the course of a sequential chain (Hypothesis 2), we estimated a linear mixed model with absolute standardized errors as dependent variable. As predicted, the model revealed a significant negative linear trend of chain position ($\beta = -0.045$, $CI = [-0.054, -0.036]$, $t(290.96) = -9.528$, $p < .001$). Accordingly, Figure 5 shows a decrease of absolute standardized errors over the course of a sequential chain.

Before testing whether sequential collaboration yielded more accurate estimates

than unweighted averaging (Hypothesis 3), we checked whether the randomized assignment to conditions was successful. We analyzed only data obtained with the independent-judgments questionnaire and fitted a linear mixed model with absolute standardized error of individual judgments as dependent variable and condition as independent variable. The model did not show a significant effect of condition on accuracy ($\beta = 0.003$, $CI = [-0.011, 0.017]$, $t(390.99) = 0.385$, $p = .701$). This indicates that no condition had an a priori advantage in judgment accuracy.

The error of group estimates in both conditions was computed as already established in Experiment 1. Since sequential chains had six participants, virtual groups for unweighted averaging were also composed of six participants.⁵ We then fitted a linear mixed model with the absolute standardized error of the group estimate as dependent variable. Figure 6 shows that sequential-collaboration estimates were slightly more accurate than those obtained with unweighted averaging. This impression was confirmed by a linear mixed model showing a significant difference of the absolute standardized error across conditions ($\beta = 0.014$, $CI = [0.005, 0.023]$, $t(100.71) = 3.067$, $p = .003$).

Exploratory comparison of different aggregation methods.

Table 1 shows a comparison of different aggregation methods for sequential collaboration and independent judgments. In contrast to Experiment 1, for absolute errors, sequential collaboration provided the most successful aggregation of individual judgments when using the last judgment in a sequence. However, when focusing on squared instead of absolute errors, taking the mean in unweighted averaging was similarly accurate as the last value of a sequential chain. Overall, the differences between conditions and aggregation methods are small and there seems to be no clear

⁵ To check the robustness of the grouping, we computed the mean difference in absolute standardized errors of estimates between conditions and the corresponding linear mixed model for 100 different random groupings in the unweighted-averaging condition. The mean difference in absolute estimates was 0.007 ($SD = 0.001$) for Experiment 1 and 0.01 ($SD = 0.001$) for Experiment 2. The results of the linear mixed model remained the same for all 100 comparisons in both experiments.

advantage in the accuracy of estimates between unweighted averaging and sequential collaboration. Further robustness analyses can be found in the supplementary material.

Discussion

Experiment 2 also showed that a basic assumption of sequential collaboration holds, namely, that the accuracy of judgments increases through incremental changes. Moreover, sequential-collaboration estimates were more accurate than estimates obtained with unweighted averaging in the confirmatory analysis. However, the comparison of different aggregation methods across conditions revealed that there are only small differences in accuracy between sequential collaboration and unweighted averaging.

Experiments 1 and 2 investigated the accuracy of sequential collaboration when eliciting quantitative judgments. However, both experiments used general knowledge questions which limits the generalizability of the results and may pose some issues. First, the questions are prone to extreme judgments. For instance, one participant answered 120,000,000,000,000,000 kilometers to the question “How long is the mean distance between Earth and Moon?” for which the correct answer is 384,400 kilometers. Having extreme judgments in the data might especially hurt the performance of unweighted averaging. Furthermore, general knowledge questions occur rather seldom in online collaboration projects, thus limiting the ecological validity of the conclusions. Thus, we conducted a conceptual replication using different materials which are less prone to extreme judgments and more closely resemble actual online collaboration projects.

Experiment 3

Experiment 3 is a conceptual replication of Experiment 1. Both studies used a similar design with some minor changes due to the different material. Instead of general knowledge questions, participants were presented with geographic maps on which they had to locate the positions of different cities. We thus focus on two-dimensional location judgments (i.e., x- and y-coordinates) rather than one-dimensional numerical

judgments. In contrast to general knowledge questions, two-dimensional location judgments on geographical maps are naturally constrained by the size of the map (more precisely, by the maximum distance between the correct location and all possible judgments) which limits the maximum range of extreme judgments. We preregistered Experiment 3 at aspredicted.org.⁶ Going beyond the preregistration, we also tested whether change probability (Hypothesis 1a) and change magnitude (Hypothesis 1b) decrease over the course of a sequential chain. Furthermore, we adjusted the outlier analysis as described in Experiments 1 and 2, and added an exploratory analysis comparing different aggregation methods.

Method

Participants. We recruited 417 adult participants via a commercial German panel provider which compensated participants according to the time for completing the study. Since participants were presented with maps, they were supposed to only participate using a computer. Due to issues in the recruitment of participants by the panel provider, 39 participants were nonetheless able to access and complete the study using mobile devices. We excluded all participants using mobile devices and all sequences including these participants, thus excluding 70 participants in total. Additionally, four participants were able to access and complete the study a second time. Therefore, we excluded the data collected at the second participation. Since two of these participants were assigned to the sequential-collaboration condition for their second participation and sequences were built based on their judgments, we excluded another 10 participants in total. We also checked whether participants looked up the correct answers or whether participants clicked at a similar position for all items and identified one participant who was suspected to look up answers who was thus excluded. The final sample comprised 333 participants of whom 46.0% were female. The mean age was 45.5 years ($SD = 15.2$). Participants had a diverse educational background with 35.4% holding a college degree, 24.9% having a high school diploma, 24.0% having

⁶ The preregistration form is available at <https://aspredicted.org/9j9de.pdf>.

vocational education, and 18.3% having a lesser educational attainment.

Materials. As stimulus material, we selected seven maps displaying different European countries: (1) Italy, (2) France, (3) Germany, (4) United Kingdom and Ireland, (5) Austria and Switzerland, (6) Spain and Portugal, and (7) Poland, Czech, Hungary, and Slovenia. All maps were on a scale of 1:5,000,000 with an image resolution of 800 x 500 pixels. Regarding the available geographic information, the maps only showed land mass, oceans, and country borders. The countries of interest were colored white while all other countries were colored gray; oceans were colored blue and country borders were represented as black lines. Overall, we selected 57 cities across all seven maps. For each map, we selected between 4 and 17 cities while considering the expected geographic knowledge of German participants. Table B1 provides a comprehensive overview of the materials, and all maps are also available in the supplementary material (<https://osf.io/96nsk/>).

Design and procedure. We randomly assigned participants to either the sequential-collaboration questionnaire (112 participants) or the independent-judgments questionnaire (221 participants). As in Experiment 1, we formed sequences of four participants meaning that one participant who answered the independent-judgments questionnaire started a sequential chain followed by three participants who completed the sequential-collaboration questionnaire. This resulted in 183 participants in the unweighted-averaging condition and 150 participants in the sequential-collaboration condition.

After being informed about the aim of the study and providing informed consent, participants were instructed about the task. In the independent-judgments questionnaire, participants had to indicate the position of the given cities on the presented map as accurately as possible. In the sequential-collaboration questionnaire, participants were provided with the location judgment of a city given by a previous participant. Subsequently, they could choose either to modify the given position by indicating a new position or to directly continue to the next city without changing the presented location judgment. The order in which the seven maps were presented was

randomized as was the order of the presented city within each map. Furthermore, each trial asked about the position of only one city such that participants provided only a single location judgment before continuing to the next city. Participants were given 40 seconds to indicate the city's position or to decide to not change the presented position. Additionally, participants completing the sequential-collaboration questionnaire had a waiting period of 2 seconds before they could continue to the next city. Finally, participants provided demographic information, were debriefed, and thanked for participation.

Results

As dependent variable for Hypotheses 2 and 3, we computed the Euclidean distance to the correct answer for each judgment.⁷ Next, we excluded 225 judgments (and corresponding sequential chains) that were timed out after 40 seconds, meaning that 18,433 out of 18,981 judgments remained for analysis. We again excluded the 1% most extreme judgments (i.e., 184 judgments) as defined by the distance to the correct answer. After the exclusion of sequential chains that contained outliers, 18,161 judgments remained for analysis.

Confirmatory analyses.

To test whether change probability decreases over the course of a sequential chain (Hypothesis 1a), we fitted a generalized linear mixed model with the decision whether a judgment was adjusted or maintained as dependent variable. Figure 7 displays the change probability for each chain position with error bars as well as violin and box plots illustrating the distribution of change probabilities for participants (aggregated across items). In line with Hypothesis 1a, the plot shows a decreasing change probability with increasing chain position. This visual impression was confirmed by the model which revealed a significant negative linear trend of chain position ($\beta = -0.937$, $CI = [-1.845, -0.028]$, $z = -2.021$, $p = .043$).

⁷ All hypotheses were also analyzed using the x- and y-coordinate separately as dependent variables. These analyses yielded the same results as the analysis using Euclidean distances as dependent variable.

Figure 7

Change probability within a sequential chain in Experiment 3.

Note. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of change probabilities for the participants (aggregated across items).

To test whether the magnitude of changes decreases over the course of a sequential chain (Hypothesis 1b), we fitted a linear mixed model with change magnitude as dependent variable. Figure 8 shows the empirical mean and distribution of the change magnitude across chain positions. In line with our hypothesis, we found a significant negative linear trend of chain position ($\beta = -14.952$, $CI = [-24.139, -5.765]$, $t(108.971) = -3.190$, $p = .002$). Furthermore, we also found a significant positive quadratic trend ($\beta = 9.507$, $CI = [0.279, 18.736]$, $t(108.984) = 2.019$, $p = .046$) which indicates a larger difference between positions 2 and 3 than between positions 3 and 4 (cf. Figure 8).

To test whether judgments become more accurate over the course of a sequential

Figure 8

Change magnitude within a sequential chain in Experiment 3.

Note. Distances were converted from pixels to kilometers for this figure. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of change magnitude for the participants (aggregated across items).

chain (Hypothesis 2), we fitted a linear mixed model with chain position as independent variable and Euclidean distance of each judgment to the true position of a city as dependent variable. The model revealed a significant linear trend between chain position and distance ($\beta = -17.610$, $CI = [-24.801, -10.419]$, $t(145.17) = -4.777$, $p < .001$). Furthermore, the quadratic trend was also significant ($\beta = 8.316$, $CI = [1.125, 15.507]$, $t(145.17) = 2.256$, $p = .026$). In combination with the negative linear trend, the positive quadratic trend, indicates that accuracy improved more between positions 2 and 3 compared to positions 3 and 4, a pattern also displayed in Figure 9. An overview of the judgments given by the participants for each city can be

found in the supplementary material.

Figure 9

Accuracy of judgments within a sequential chain in Experiment 3.

Note. Distances were converted from pixels to kilometers for this figure. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of distances to the correct answers for the participants (aggregated across items).

Before comparing the accuracy of sequential collaboration and unweighted averaging (Hypothesis 3), we again performed a randomization check. To compare judgment accuracy in the independent-judgments questionnaire across conditions, we estimated a linear mixed model with the Euclidean distance to the true position as dependent variable. We did not find a significant difference in accuracy between judgments in the unweighted-averaging condition and judgments that were used to start sequential chains in the sequential-collaboration condition ($\beta = -0.768$, $CI = [-10.691, 9.160]$, $t(220.25) = -0.152$, $p = .879$), thus indicating that the

randomization was successful.

Figure 10

Accuracy of estimates obtained with unweighted averaging and sequential collaboration in Experiment 3.

Note. Distances were converted from pixels to kilometers for this figure. Estimates for sequential collaboration pertain to the last judgment in a sequential chain. Points display the empirical means for each chain position, error bars show the corresponding 95% between-subjects confidence intervals. Violin and box plots illustrate the distribution of distances to the correct answers for the participants (aggregated across items).

We computed group estimates for each condition similar as in Experiments 1 and 2. Estimates obtained with independent judgments were based on random groups of four participants. We averaged the four location judgments separately for each coordinate, thereby computing the geometric center. For sequential-collaboration, estimates pertain the last judgment in each chain. As a dependent variable, we computed the Euclidean distance between the resulting mean estimate and the true

695 position of each city.

Figure 11

Estimated and actual locations of five cities on the map of Italy.

Note. All maps presented in this experiment were generated using QGIS 3 (<https://www.qgis.org/en/site/index.html>) licensed under Creative Commons CC BY-SA. To illustrate the material, this map of Italy resembles the one presented in the experiment.

696 Figure 10 displays the mean distance to the true position with corresponding
 697 error bars and violin and box plots indicating the distribution of mean distances for
 698 different the two experimental groups (aggregated across items). In line with
 699 Hypothesis 3, sequential-collaboration estimates resulted in a smaller distance to the
 700 true position than estimates obtained with unweighted averaging. This impression was
 701 supported by a linear mixed model with the Euclidean distance as dependent variable,
 702 showing that sequential collaboration yielded more accurate estimates than unweighted
 703 averaging ($\beta = -7.411$, $CI = [-14.532, -0.301]$, $t(80.70) = -2.049$, $p = .044$).

704 Figure 11 illustrates the high accuracy of sequential collaboration for five cities

on the map of Italy. The figure shows the mean estimates of the two methods as well as the actual positions of the five cities. For Florence, Milan, Rome, and Venice, sequential collaboration yielded more accurate estimates than unweighted averaging, while both methods yielded similarly accurate estimates for Naples. Across all maps and cities, sequential collaboration resulted in location estimates that were 16.03 kilometers closer to the actual position than those obtained via unweighted averaging (see Figure 10). In Figure 11, this value resembles the difference of the average distance of the two estimates for the location of Rome (13.55 kilometers). Similar plots for the other six maps are available in the supplemental material.

Exploratory comparison of different aggregation methods.

Similarly as in Experiments 1 and 2, we compared different aggregation methods for sequential collaboration and unweighted averaging. Table 1 shows that sequential collaboration generally yielded more accurate estimates than unweighted averaging when focusing on the Euclidean distance. However, sequential-collaboration estimates yielded similar accurate estimates when using the mean, median, or the weighted mean. When measuring accuracy in terms of squared Euclidean distance, median aggregation of independent judgments was more accurate than the last judgment in sequential collaboration but all other aggregation for sequential collaboration remained more accurate.

Discussion

Experiment 3 replicated the results of Experiments 1 and 2 using geographic maps instead of general knowledge questions. Sequential collaboration yielded more accurate estimates over the course of a sequential chain while change probability and change magnitude of judgments decreased. Additionally, sequential collaboration yielded more accurate results than unweighted averaging in the confirmatory analysis. However, the exploratory analysis revealed that various methods of aggregating judgments into estimates for sequential collaboration yielded similar accurate estimates.

General discussion

Sequential collaboration describes a collaboration method in which contributors form a sequential chain of judgments by deciding whether to adjust or maintain the latest judgment provided by a previous contributor. In three online studies using general knowledge questions and geographic maps, we examined whether change probability and change magnitude decrease over the course of a sequential chain (Hypotheses 1a and 1b, respectively) whereas judgment accuracy increases (Hypothesis 2). As a benchmark, we compared the accuracy of estimates obtained with sequential collaboration to estimates obtained with unweighted averaging (Hypothesis 3). All three experiments provided evidence that accuracy increased within sequential chains of judgments, whereas a decrease in change probability was observed only in Experiments 2 and 3, and a decrease in change magnitude only occurred in Experiments 1 and 3. Sequential collaboration outperformed unweighted averaging only in Experiments 2 and 3 while showing a similar level of accuracy in Experiment 1. While this pattern did not remain as clear in the exploratory analysis showing mixed patterns for the comparison with different aggregation measures, it is noteworthy that sequential collaboration and unweighted averaging overall performed similarly well in terms of accuracy.

The present work contributes to research on how judgments are influenced when providing information about the judgments of others. Several studies already hinted towards dependent judgments being beneficial for individual judgments in certain situations (Becker et al., 2017; King et al., 2012; Koehler & Beaugard, 2006; Minson et al., 2017) with Miller and Steyvers (2011) implementing a design quite similar to sequential collaboration. We extend this line of research by showing that even a very high level of dependency of judgments can yield accurate estimates. The observed improvement in accuracy within chains of judgments indicates that sequential collaboration was neither obstructed by anchoring effects (Mussweiler et al., 2004; Tversky & Kahneman, 1974) nor by high rates of inaccurate changes, for instance, due to egocentric discounting (Bonaccio & Dalal, 2006). Our results show that sequential collaboration provides accurate estimates in controlled online studies involving

quantitative knowledge and location judgments. This is in line with prior research showing that large-scale online collaboration projects which rely on this basic mechanism provide high-quality information (e.g., Leithner et al., 2010; Zielstra & Zipf, 2010).

Moderators across and within experiments

The mixed results across experiments may be due to several factors relevant for the performance of sequential collaboration and unweighted averaging. First, while Experiment 1 used a homogeneous sample of university students, Experiments 2 and 3 used more diverse samples (i.e., German adults with a wide range in age and educational background). Limited diversity can not only reduce the performance of unweighted averaging (Davis-Stober et al., 2014; Oliveira & Nisbett, 2018). Sequential collaboration may also generally benefit from diverse samples, since heterogeneity in knowledge increases the chances that a few experts provide accurate corrections to the judgments of the remaining, less knowledgeable contributors. Hence, participants may had fewer chances of correcting each other in Experiment 1 compared to the more diverse samples in Experiments 2 and 3.

Second, the inconsistent pattern of results may be due to the difficulty of the different tasks. Whereas the general knowledge questions in Experiments 1 and 2 were very difficult, locating cities on geographical maps (Experiment 3) was easier because participants likely had some basic geographic knowledge (e.g., from school, the media, or by visiting some of the cities). The difficulty of the tasks can explain the substantial difference in change probabilities (approximately 20% in Experiments 1 and 2 compared to 60% in Experiment 3). Higher change probabilities indicate that participants in the sequential-collaboration condition were more likely to improve judgments within a sequential chain.

Third, the experiments differed in the length of the sequential chains (i.e., the group size varied between 4 and 6). Sequential collaboration may require longer chains especially for more difficult items because substantial improvements in judgments occur

less frequently. In Experiment 1, the high item difficulty combined with the shorter sequential chains of only four contributors may have reduced the performance of sequential collaboration.

Fourth, certain tasks and materials may be better suited either for unweighted averaging or for sequential collaboration. Unweighted averaging has often shown to be highly accurate when aggregating numerical point judgments as in Experiments 1 and 2 (Galton, 1907; Hueffer et al., 2013; Surowiecki, 2004) and is also quite robust against biases in such scenarios (Davis-Stober et al., 2014). In contrast, sequential collaboration may be more suitable for more complex tasks, such as positioning cities on maps as in Experiment 3 or generating rank orders (Miller & Steyvers, 2011; Steyvers et al., 2009). In more complex tasks, it is easier for contributors to integrate partial knowledge into the judgment. For instance, one may know that Berlin is located close to the Polish border, and in turn correct the latitude of a presented judgment to the East without modifying any other aspect of the judgment (e.g., longitude). The contribution of partial knowledge is also likely in online collaborative projects such as Wikipedia where contributors usually edit only small parts of an article while rarely (re-)writing complete articles. In complex tasks, mechanical aggregation methods may even lead to unreasonable estimates. For instance, unweighted averaging of two-dimensional location judgments can result in estimates for a city that are located in a lake or an ocean. In contrast, contributors in sequential collaboration usually do not provide such unreasonable judgments.

Fifth, we also compared different aggregation methods. For unweighted averaging, we computed the mean and the median. For sequential collaboration, we used the last value of a sequential chain as well as the mean, the median, and the weighted mean across chain positions. We found that all aggregation methods yielded similar results for absolute errors in Experiment 1, and for absolute as well as squared errors in Experiment 2. However, in Experiment 1, unweighted averaging resulted in smaller squared errors than sequential collaboration. In Experiment 3, sequential collaboration generally yielded smaller absolute errors than unweighted averaging for all

aggregation methods. However, with respect to squared errors, sequential collaboration showed a similar accuracy as unweighted averaging. Overall, different aggregation methods can affect the accuracy of estimates. This may be especially relevant in small groups of only four or six contributors in which extreme judgments have a large influence on the resulting estimates.

Possible mechanisms

Our results provide first insights into sequential collaboration, but the three experiments do not provide explanations *why* sequential collaboration yields accurate results. Prior research points to different mechanisms that could lead to improved judgments over the course of a sequential chain. Sequential collaboration may yield accurate results because individual judgments are implicitly weighted by expertise. Both the weighting of judgments by expertise (Budescu & Chen, 2014; Merkle et al., 2020) and the selection of experts based on prior performance (Mannes et al., 2014) improve accuracy when aggregating independent judgments. However, sequential collaboration does neither implement an explicit weighting mechanism nor a selection of individuals based on expertise. Instead, the task structure allows contributors to maintain a judgment if they do not feel they can substantially contribute to the presented judgment. In fact, subjective confidence can be a valid indicator of expertise (Mannes et al., 2014), leading participants to not contribute to group work when they feel their judgment is dispensable (Kerr & Bruun, 1983). Judgments in sequential collaboration are implicitly weighted since experts are more likely to make adjustments, thus adding a larger contribution to the final outcome. In contrast, contributors without expertise are more likely to maintain the presented judgment. In an ideal case, sequential collaboration may lead to improvements in judgments until a correct judgment is no longer changed.

The high accuracy of sequential collaboration may merely be due to the opportunity of contributors to opt out of answering and not due to the dependent nature of sequential judgments. In fact, allowing participants to self-select the subset of

questions to be answered improves judgment accuracy and group estimates (Bennett et al., 2018; Galton, 1907). However, typical designs building on unweighted averaging do not allow individuals to select whether to answer a question or not but rather requires them to answer all questions irrespective of their expertise or meta-cognitive knowledge (Larrick & Soll, 2006). In our three studies, we compared this typical paradigm to sequential collaboration, meaning that the two experimental conditions did not only differ in the level of dependency but also in the possibility of opting-out of providing a judgment. Future research should further examine the role of the opt-out mechanism in sequential collaboration.

In general, allowing participants to self-select whether to answer a question when applying unweighted averaging to the resulting judgments may lead to quite varying numbers of judgments per question. Bennett et al. (2018) observed that some of the easiest questions were answered by almost all participants while other, more difficult questions were answered not even by a single participant or only very few participants. This can render independent individual judgments with an opt-out option rather uneconomical and inefficient. In contrast, the opt-out mechanism in sequential collaboration ensures a higher efficiency because the decision whether to opt out is made in context of the perceived quality of the presented judgment. Hence, opting-out of adjusting a judgment is informative with respect to the accuracy of the current estimate.

Limitations and future research

Our experiments on sequential collaboration have some limitations. First, we only studied a very simple type of sequential collaboration where contributors could only change or maintain a previous judgment. However, Wikipedia and OpenStreetMap offer several additional functions such as discussion sites, a board of moderators checking on the contributors' activities, and a history of all changes ever made to an entry. These additional functions are likely to influence contributors' behavior in online collaborative projects even though they are less prominent than the information itself which is directly available in an article or on a map.

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Appendix A

General Knowledge Questions

Table A1

Table of items for Experiment 1 and Experiment 2 using general knowledge questions.

Item	Question	Correct answer
1	How large is the Eiffel Tower?	300 meters
2	How many sovereign countries are located in Africa?	54 countries
3	How long is the Nile?	6650 kilometers
4	How old was Johann Wolfgang von Goethe?	82 years old
5	How many bones does a human have?	214 bones
6	What is earth's mean radius?	6371 kilometers
7	How old was Martin Luther King Jr.?	39 years old
8	How tall is the Brandenburg Gate?	26 meters
9	How high was the highest temperature ever measured on earth?	57 °C
10	At what temperature does lead melt?	328 °C
11	In which year did the first manned space flight take place?	1961
12	How high is Mount Everest?	8848 meters
13	How much does a tennis ball weigh?	57 grams
14	How many keys does a typical piano have?	88 keys
15	How fast can a cheetah run?	112 kilometers per hour
16	How long can a blue whale become?	33 meters
17	How much do ten liters of oxygen weigh?	14 grams
18	When was UNICEF founded?	1946
19	How many prime numbers are in the interval between 1 and 1000?	168 prime numbers
20	How many star constellations are officially recognized?	88 constellations
21	How many kilocalories do ten gummy bears have (i.e. 30 grams)?	98 kilocalories
22	How long is a soccer goal?	7 meters
23	When was the last capital punishment enforced in France?	1977
24	How many plays of Shakespeare are preserved?	33 plays
25	How long is the kidney of a full-grown person?	12 centimeters
26	How many species of the hawaiian honeycreeper exist?	21 species
27	When was the lightning rod invented?	1752
28	When did the first modern Olympic Games take place?	1896
29	How fast can a raindrop fall?	9 meters per second
30	When was Leonardo da Vinci born?	1452
31	What is the maximum time that a total solar eclipse can take?	7 minutes
32	How many strings does a concert harp have?	47 strings
33	What is mean life expectancy for women in Germany?	81 years

Table A1

*Table of items for Experiment 1 and Experiment 2 using general knowledge questions.
(continued)*

Item	Question	Correct answer
34	How wide is Lake Constance at its widest point?	14 kilometers
35	How long is the distance between earth and sun in million kilometers?	150 million kilometers
36	When was women's suffrage adapted in Switzerland?	1971
37	How many chapters does the Quran have?	114 chapters
38	How many times larger is the diameter of Jupiter compared to the diameter of Earth?	11 times
39	How large is the island of Borkum?	31 square-kilometers
40	How many singles did the Beatles officially release?	22 singles
41	How old was Alexander the Great when he waged his first campaign?	18 years old
42	How many species of insects live in Antarctica?	52 species
43	How many federal states does Austria have?	9 federal states
44	When was the first human heart transplant performed?	1967
45	How many marriages were there in Germany in 2018?	449,466 marriages
46	How many students were enrolled in German university in the winter term of 2019 / 2020?	2,897,336 students
47	How many floors does Burj Khalifa have?	163 floors
48	How far is Frankfurt (Main) from Berlin (linear distance)?	424 kilometers
49	When was the first color film available in Germany?	1936
50	When was the numerus clausus first applied in German universities?	1968
51	How far is Paris from London (linear distance)?	343 kilometers
52	How far is Dortmund from Hamburg (linear distance)?	284 kilometers
53	How far is Munich from Athens (linear distance)?	1,496 kilometers
54	How tall is the Statue of Liberty including its pedestal?	93 meters
55	When was slavery officially ended in the United States?	1865
56	When was the first Autobahn inaugurated?	1921
57	When did Albert Schweitzer receive the Nobel Peace Prize?	1952
58	How long is the mean distance between Earth and Moon?	384,400 kilometers
59	In which year was Uranus discovered by William Herschel?	1781
60	How many letters does the Arabic script have?	28 letters
61	How deep is the Pacific at the deepest point?	10,094 meters
62	When was Astrid Lindgren born?	1907
63	How much does the heart of a full-grown person weigh?	300 grams
64	How long can a Green Anaconda become?	8 meters
65	After how many days has a person's top layer of skin completely renewed?	28 days

Appendix B

Cities selected for different maps

Table B1

Table of items for Experiment 3 using map material.

Item	Map	Cities
1	Austria and Switzerland	Zurich, Geneva, Basel, Bern, Vienna, Graz, Linz, Salzburg
2	France	Paris, Marseille, Lyon, Toulouse, Nice
3	Italy	Rome, Milan, Naples, Florence, Venice
4	Spain and Portugal	Madrid, Barcelona, Seville, Lisbon, Porto
5	United Kingdom and Ireland	London, Birmingham, Glasgow, Liverpool, Dublin
6	Poland, Czech, Hungary and Slovenia	Warsaw, Prague, Bratislava, Budapest
7	Germany	Berlin, Hamburg, Cologne, Frankfurt, Stuttgart, Düsseldorf, Leipzig, Dortmund, Essen, Bremen, Dresden, Hannover, Nuremberg, Duisburg, Wuppertal, Bielefeld, Bonn, Münster, Karlsruhe, Mannheim, Augsburg, Wiesbaden, Braunschweig, Kiel, Munich