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Journal of Behavioral Decision Making

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Information on Judgment Invariance Influences Contributors' Opting-In Behavior in Sequential Collaboration

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Received: 24 June 2025 | **Revised:** 30 October 2025 | **Accepted:** 5 December 2025

Keywords: advice taking | anchoring | dependent judgments | online collaboration

ABSTRACT

Sequential collaboration describes an aggregation process intensively researched for numerical judgments which is characterized by a first contributor creating a judgment that is subsequently adjusted or maintained by following contributors. In previous research, participants performing sequential collaboration were only provided with information about the judgment of the person immediately preceding them in a sequential chain. However, in real-world collaborative projects (e.g., Wikipedia and Google Docs projects), more information about the past development of a sequential chain is often accessible or even directly displayed. As a concise piece of such information, we used judgment invariance, that is, the number of times a current judgment remained unchanged in the immediately preceding steps of a sequential chain. We hypothesized that increasing judgment invariance decreases both the probability and the magnitude of participants' judgment changes. Additionally, we hypothesized that the influence would be weakened with increasing expertise of participants. In three preregistered experiments, (G)LMM analyses suggested that increasing judgment invariance decreased the probability and magnitude of judgment changes confirming our hypothesized main effects. Concerning the interaction hypothesis of judgment invariance and expertise, a more ambiguous picture emerged. Experiment 1 was completely consistent with the interaction hypothesis. Experiment 2 supported it concerning the probability but not the magnitude of participants' judgment changes. In Experiment 3, a directionally reversed interaction effect was observed, possibly due to unconscientious participation. We conclude that the insight into the past development of a sequential chain, specifically information on judgment invariance, influences the judgment behavior of contributors in sequential collaborations. In summary, judgment invariance could be established as a substantial influence in sequential collaboration, which comes with practical implications for real-world collaborative projects.

1 | Theoretical Background

Past research revealed that collaborative projects such as Wikipedia or OpenStreetMap provide highly accurate information. In a literature review, Mesgari et al. (2015) concluded that Wikipedia featured high content quality and that, except for a few health-related topics, its articles were reliable. Similarly, contributions in OpenStreetMap are highly accurate to the degree that they are comparably accurate as commercial map services (Girres and Touya 2010; Zielstra and Zipf 2010). In addition, the quality of OpenStreetMap data is indirectly reflected in its extensive use by authorities and companies such as the French Police, the President's Office of the Italian Government, Amazon, Deutsche Bahn, and the New York Times.[1] Besides large-scale projects like Wikipedia or OpenStreetMap, collaboration practice takes place in everyday job projects and

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educational contexts. For instance, Web 2.0 software tools like Etherpad, Google Docs, or Microsoft Word open up the possibility to work together on a shared document that can be modified by each contributing person in real time. In fact, Google Docs alone has an estimated one billion users per month.[2] With this heavy use in mind, questions regarding the psychological functionality of this type of collaboration project become substantially relevant.

Indeed, in both large- and small-scale collaboration projects, people are allowed to change or maintain pieces of information one after another without needing further authorization. This cross-individual joint process is called *sequential collaboration* (Mayer and Heck 2024). The authors define it as a specific way of collaboration characterized by its dependent, sequential manner. Crucially, "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." (Mayer and Heck 2024, p. 213). Therefore, sequential collaboration can describe the underlying process of collaboration projects like Wikipedia, OpenStreetMap, as well as collaboration projects in EtherPad and Google Docs. Sequential collaboration has been tested empirically with numerical judgments (Mayer et al. 2023; Mayer and Heck 2024) and rank ordering tasks (Miller and Steyvers 2011). These studies demonstrated that sequential collaboration yields highly accurate judgments. This high accuracy of sequential judgments can be attributed to an *implicit* weighting mechanism, based on the opt-out possibility in sequential collaboration, that assigns greater weight to judgments based on contributors' expertise. The reason for this is that contributors with higher expertise are more likely to change a judgment (Mayer et al. 2023).

In previous studies about sequential collaboration, participants were only provided with information about the judgment of the participant immediately preceding them in the sequential chain (Mayer et al. 2023; Mayer and Heck 2024; Miller and Steyvers 2011). In practice, however, this might usually not be the case. The course of a sequential collaboration can be easily accessed (e.g., in Wikipedia or Google Docs) or is even directly displayed (e.g., in a shared Microsoft Word document). We expect that knowledge about the past development of a sequential chain has an influence on the probability of changing a judgment (opt-in/opt-out) and on the magnitude of judgment change. Consequently, this kind of knowledge should also have an influence on the implicit weighting mechanism proposed by Mayer et al. (2023). To close this research gap, the present paper investigates the effect of a certain piece of information about the change history of a sequential chain, namely, the number of times a current judgment has remained unchanged in the immediately preceding steps of a sequential collaboration. We term this special case of information about the past development of a sequential chain *judgment invariance*.

We begin by describing sequential collaboration and associated existing findings. As well, the hypothesized effects of judgment invariance in sequential collaboration are derived by outlining its parallels with evidence from the anchoring literature. Three experiments are described for which we employed both a city-location task as well as a task in which the dates of historical events were to be estimated. We both manipulated judgment invariance information and examined the effect of natural judgment invariances derived from real sequential collaborations.

1.1 | Sequential Collaboration

In a concise notation, sequential collaboration can be put the following way. Assume that there is a question on which a numerical judgment can be made. Let $P = \{p_1, \ldots, p_n\}$, $n \in \mathbb{N}$, be the set of persons who work on the question in a strict temporal sequence $p_1 < \ldots < p_n$. Sequential collaboration emerges if for $2 \leq i \leq n$,

1. the judgment of person p_{i-1} is shown to person p_i,
2. person p_i can decide to maintain or to change the judgment of person p_{i-1}.

After each person worked on the question, the judgment of person p_n forms the final estimate of the sequential collaboration process with regard to the question. By definition, there is no judgment presented to person p_1. It is important to realize that if the judgment of person p_{i-1} is maintained by person p_i, person p_{i+1} gets shown the judgment of person p_{i-1} as well. In the most extreme case, it could happen that person p_1 makes a judgment on the question, and this judgment is maintained until the last person p_n ends the sequential collaboration. Certainly, there is a large number of possible change-maintain-sequences in a sequential collaboration, at least if n is sufficiently large. As an example, let $P = \{\text{Peter, Tom, Lena, Kira, Henry}\}$ form a set of contributors. Suppose they make a judgment on the question "How long was the Titanic (in meters)?" in a fixed sequence. Two possible sequential collaboration situations are displayed in Figure 1. In the upper situation, the judgment is changed in all steps except the third one; in the lower situation, it is changed in the first step and maintained thereafter.

One could expect that sequential collaboration is an unstable process because each contributor is allowed to change the judgment presented to them completely. If Henry's judgment was far from the correct answer, the final estimate would be not right at all. Even if Kira's judgment was far from the correct judgment, there would be just Henry to possibly change it for the better. But the high information accuracy of large-scale sequential collaboration projects questions the instability expectation. Furthermore, empirical research provided evidence for the accuracy of final estimates in sequential collaboration.

Mayer and Heck (2024) conducted a series of three sequential collaboration experiments in which participants, one after another, answered general knowledge questions (Experiments 1 and 2) or located cities on maps (Experiment 3). Sequential chains of four or six participants were constructed. The finding that over the course of a sequential chain, individual contributions became significantly more accurate, was stable across all three experiments. Additionally, the probability of changing a judgment and the magnitude of changes decreased over the course of a sequential chain.

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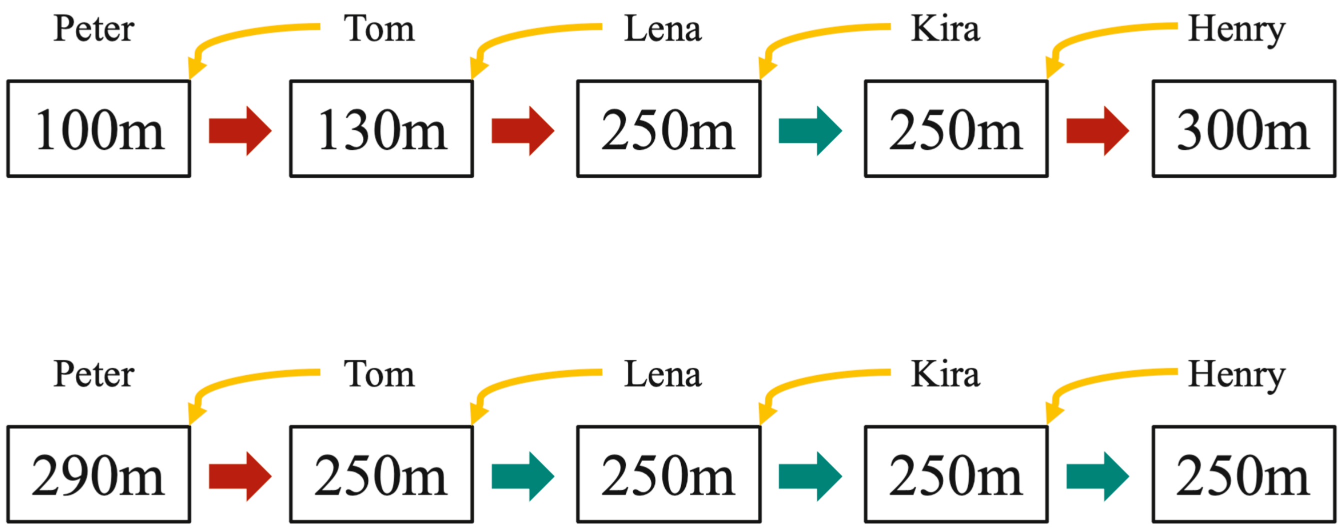

FIGURE 1 | Examples of a sequential collaboration - "How long was the Titanic (in meters)?" *Note.* Red arrows indicate that a judgment was changed, green arrows indicate that a judgment was maintained. The yellow arrows illustrate that only the judgment of person p_{i-1} was available to person p_i.

These effects were at least partially driven by contributors' expertise. Mayer et al. (2023) showed that participants' expertise influenced the frequency of judgment modification as well as of judgment accuracy. Specifically, experts made more frequent modifications and larger improvements in accuracy than nonexperts. Unlike Mayer et al. (2023), we included absolute accuracy instead of improvement in accuracy as dependent variable in our study, because it is easier to interpret. Therefore, we expect the following.

> **Hypothesis 1**: *With increasing expertise, participants change presented items (a) more frequently and (b) more accurately.*

Mayer et al. (2023) also found that a higher deviation between the judgment of person p_{i-1} and the correct judgment caused more frequent changes and larger improvements from person p_i. Although higher deviations were linked to larger improvements in accuracy, we still expect the absolute level of accuracy to decrease as deviation increases.

> **Hypothesis 2**: *With increasing deviation of the presented judgment from the correct answer, participants change presented items (a) more frequently and (b) less accurately.*

Both effects also interacted such that participants with higher expertise showed a steeper increase in the frequency of modifications and the size of improvements when the deviation increased. We incorporated these findings as supplementary hypotheses in our study, but note that the focus of this paper is not about the effect of deviation of the presented judgment. Therefore, we do not theoretically discuss its effect. Note again that we included absolute accuracy instead of improvement in accuracy as dependent variable in our study.

> **Hypothesis 3a**: *Expertise and item deviation interact such that the higher frequency of changes in the case of strongly deviating judgments is even higher for people who are high in expertise compared to participants who are low in expertise.*

> **Hypothesis 3b**: *Similarly, expertise and item deviation interact such that the low accuracy in the case of strongly deviating judgments is even lower for people who are low in expertise compared to participants who are high in expertise.*

Importantly, Mayer et al. (2023) attributed the increasing accuracy of judgments over the course of a sequential collaboration to an implicit weighting of judgments through the possibility of opting-out of a sequential chain. Opting-out means to choose to not modify the presented judgment, whereas contrarily, opting-in means choosing to modify the presented judgment. The weighting of judgments arises because participants with higher expertise choose to opt-in more frequently, which in turn leads to a higher frequency of expert judgments in the sequential chain (i.e., a larger weight of expert judgments). This implicit weighting mechanism was empirically supported by the finding that sequential collaboration without an opt-out possibility yielded less accurate judgments than sequential collaboration with an opt-out possibility (Mayer et al. 2025).

Interestingly, in the previously mentioned large-scale online collaborative projects, there is always the possibility of an insight into the history of the current judgment over the past course of the sequential chain. In other words, person p_i does not only see the judgment of person p_{i-1} but can instead (to a varying extent) take a look into the, if existent, judgments of persons p_{i-2}, p_{i-3} and so on. For example, in Wikipedia, there is a "page history" section for each article. This section represents an archive of all changes made to a particular article, including the order of changes and the differences between any two versions.[3] Thus, whereas previous experimental setups for sequential collaboration (Mayer et al. 2023, 2025; Mayer and Heck 2024) did

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not feature an option through which information on the chain history was accessible, the sequential collaboration implementations in the "real-world" offer such an opportunity. Therefore, it is important to extend the sequential collaboration paradigm and investigate the effects of providing information on the past development of sequential chains on an individual's judgment behavior.

1.2 | The Operationalization of Sequential Chain Information

To examine how chain histories can affect subsequent behavior in sequential collaboration, we implemented a manipulation of judgment invariance. It is defined as the number of times the judgment presented to person p_i has remained unchanged in the immediately preceding steps of a sequential collaboration. This judgment invariance is presented to person p_i together with the actual judgment of person p_{i-1} and forms a straightforward information on the past course of a sequential chain. High judgment invariances indicate that many directly preceding persons agreed about the item. In contrast, low judgment invariances reflect a disagreement among the directly preceding persons about the item. By definition, the judgment invariance presented to person p_i, $i > 1$, in a sequential collaboration is at most $i - 2$. For example, the sixth person in a sequential chain (p_6) gets displayed a judgment invariance of at most 4. This would mean that p_2, p_3, p_4, and p_5 did not change the judgment of p_1. Contrarily, a judgment invariance of 0, presented to a participant p_i, reflects that person p_{i-1} has made a change to the judgment of person p_{i-2}.

1.3 | Anchoring Effects and Sequential Collaboration

If people estimate a quantity under the impression of an initial value (referred to as an anchor), then the person's estimate of the quantity is influenced by the anchor, even if the anchor is completely arbitrary. This is how Tversky and Kahneman (1974) conceptualized anchoring effects as one of their famous cognitive heuristics. Anchoring effects were intensively studied and appeared to be robust over different contexts (see Furnham and Boo 2011, for a review).

In the last decade, authors employed models based on the general Bayesian framework of cognition (Griffiths et al. 2008) that proved advantageous in making predictions about anchoring effects. Lieder et al. (2012) concluded in a study that anchoring effects align with a Bayesian cognitive framework. Furthermore, Turner and Schley (2016) proposed the *Anchor Integration Model* (AIM), which enables the quantitative prediction of anchoring effects. Because each presented judgment in a sequential chain constitutes an anchor, the AIM is also suitable to descriptively explain and predict effects in sequential collaboration.

In the AIM, expertise corresponds to *prior* beliefs, the anchor to *evidence*, and the final judgment to the *posterior* distribution of judgments. The posterior is the result of combining prior beliefs and evidence. Therefore, the final judgment of a person is the result of a combination of expertise and the anchor. A higher level of expertise is reflected in a more informative prior (e.g., a distribution with smaller variance). Similarly, a higher level of informativeness of the anchor is reflected in more informative evidence (e.g., a distribution with smaller variance). A highly informative prior is challenging to overcome by evidence. Conversely, highly informative evidence is challenging to overcome by the prior.

This first statement implies that persons with higher expertise should be less influenced by an anchor. The prediction is supported by the work of several authors who provided empirical evidence that people with higher expertise about the target question were less susceptible to anchoring effects than people with lower expertise (Smith et al. 2013; Smith and Windschitl 2015; Wilson et al. 1996). Translated to sequential collaboration, higher expertise of person p_i should decrease the influence of the judgment of person p_{i-1} on the judgment of p_i. As stated above, this was already found by Mayer et al. (2023) who observed that higher expertise was related to higher change probabilities and higher improvements in sequential collaboration.

The second statement implies that persons should be more influenced by a highly informative anchor. Wegener et al. (2010) referred to numerical anchoring data that supported this hypothesis arguing that a higher source credibility of an anchor increased the anchoring effect compared to a lower source credibility of an anchor. Accordingly, Dowd et al. (2014) found a positive main effect of high versus low source credibility on the weight that was placed on an externally provided anchor. Further, recent meta-analyses that, among other variables, compared the anchoring effect elicited by informative versus uninformative anchors concluded that informative anchors induce a higher anchoring effect (Bystranowski et al. 2021; Ioannidis 2023; Röseler and Schütz 2022; Schley and Weingarten 2023). Put together, both the Bayesian framework of anchoring and the empirical evidence support the notion that the informativeness of an anchor influences the anchoring effect. On this basis, we argue that in a sequential collaboration, a higher judgment invariance makes the judgment of a person p_{i-1} appear more informative to the subsequent person p_i. Therefore, the influence of the judgment of person p_{i-1} on the judgment of person p_i should increase in that case. This leads directly to Hypotheses 4a and 4b.

> **Hypothesis 4a**: *The more frequently the current judgment has remained unchanged in the immediately preceding steps of the sequential collaboration, the less frequently a participant changes the presented judgment (change probability).*

> **Hypothesis 4b**: *The more frequently the current judgment has remained unchanged in the immediately preceding steps of the sequential collaboration, the smaller the distance between the presented judgment and the provided judgment (change magnitude).*

The obvious question seems to be whether judgment invariance and participants' expertise are expected to interact in a sequential collaboration. This question can be answered by tracing it

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back to the AIM. Assume that a nonexpert makes judgments about a quantity and an uninformative versus an informative anchor is presented. The influence of the anchor should increase strongly with its increasing informativeness. In contrast, assume that an expert makes judgments about a quantity and an uninformative versus an informative anchor is presented. Now, the influence of the anchor should increase less strongly with increasing informativeness relative to the case of the nonexpert. Therefore, we assume an interaction effect between individuals' expertise and judgment invariance.

> **Hypothesis 5a**: *The more expertise a participant has, the less susceptible this participant is to the influence of judgment invariance with regard to the frequency of change of presented judgments.*

> **Hypothesis 5b**: *The more expertise a participant has, the less susceptible this participant is to the influence of judgment invariance with regard to the magnitude of change of presented judgments.*

Three experiments were conducted to test our hypotheses. Experiments 1 and 2 manipulated both the information about judgment invariance and the degree to which the judgment deviated from the correct judgment. Expertise was measured. In contrast, Experiment 3 employed a natural development of a sequential collaboration, including naturally occurring information on judgment invariance and deviation of a judgment from the correct judgment. Again, expertise was measured. The overarching goal of all experiments was to test if information on judgment invariance exerts an influence on participants' judgments and thereby on the development of a sequential collaboration.

2 | Experiment 1

2.1 | Methods

In Experiment 1, participants performed a city-location task that was based on the original paradigm of Experiment 3 from Mayer and Heck (2024). Participants had to locate 56 European cities on maps that pictured parts of Europe. As in Mayer et al. (2023), the first set of items formed the expertise measure, whereas the second set of items formed the sequential collaboration phase. Experiment 1 was not preregistered.

2.1.1 | Participants

Participants were recruited via email at the University of Tübingen and took part in the online experiment in exchange for participating in a gift card lottery. We collected complete data from 442 participants. Following our exclusion criteria, participants who exceeded a 15 % proportion of timeouts or judgments out of areas of interest were planned to be excluded. Also, it was planned to exclude participants who repeatedly clicked the same position in trials where they submitted their *own* judgment or who changed their browser window more than five times throughout the experiment. Because we had no such instances, no participants were excluded based on these criteria. According to the exclusion criterion of suspected cheating in the independent judgment phase, five participants were excluded. After the exclusion on the participant level, 126 single data points (i.e., trials) characterized as a *timeout* (i.e., a trial response time ≥ 40s) and 677 characterized as a *judgment out of bounds* (i.e., a trial judgment outside the designated white areas) were excluded.

This resulted in a final sample of 437 participants, of which 211 were female, 214 were male, and 12 were nonbinary. Participants had a mean age of 31.18 (SD = 13.45) and a generally high level of education with 52.17 % holding a college degree, 40.50 % holding a high school diploma, 0.23 % holding a vocational training diploma, 1.37 % holding a secondary school diploma, 0.23 % still attending school, and 5.49 % indicating "something else".

2.1.2 | Materials and Procedure

The experimental task was built on seven maps of parts of Europe, namely, (1) Austria and Switzerland with eight city-location items, (2) France with five city-location items, (3) Italy with five city-location items, (4) Spain and Portugal with five city-location items, (5) United Kingdom and Ireland with five city-location items, (6) Germany with twenty-five city-location items, and (7) Poland, Czech Republic, Hungary, and Slovakia with four city-location items. Neighboring countries to the respective target countries on a specific map were displayed in dark gray, whereas target countries themselves were displayed in white. Importantly, geographical characteristics (e.g., rivers, lakes, cities, and federal states) were shown neither in target nor in neighboring countries. The only exceptions would be the sea that was depicted in light blue and the country borders that were represented by solid black lines. Each map's resolution was 800 x 500 pixels and was scaled to 1:5,000,000.

After providing informed consent, as well as finishing a practice phase with three items, participants independently indicated the position of 17 cities which served as a measure for participants' expertise. Following another practice phase with three items, the sequential collaboration part consisting of 39 items[4] began. Then, participants were informed about the red dot on the map indicating the city-location judgment of a former participant in the experiment. Additionally, the information on judgment invariance was presented. Participants then decided to either maintain the presented position as was or to change it by clicking on the map. After completing the task, participants provided demographic information and were debriefed and thanked. In Figure 2, one exemplary item from the sequential-collaboration phase is depicted.

Importantly, we did not present participants with actual location judgments of former participants and therefore no actual judgment invariances were used. The presented positions and the judgment invariances were preselected and randomly assigned. Deviations of the presented position to a correct city-location were 0, 40, 80, or 120 pixels; judgment invariances of 0, 1, 2, 4, and 6 were chosen. Each combination of city, deviation and judgment invariance could occur. In both tasks, expertise measurement and sequential collaboration, items were

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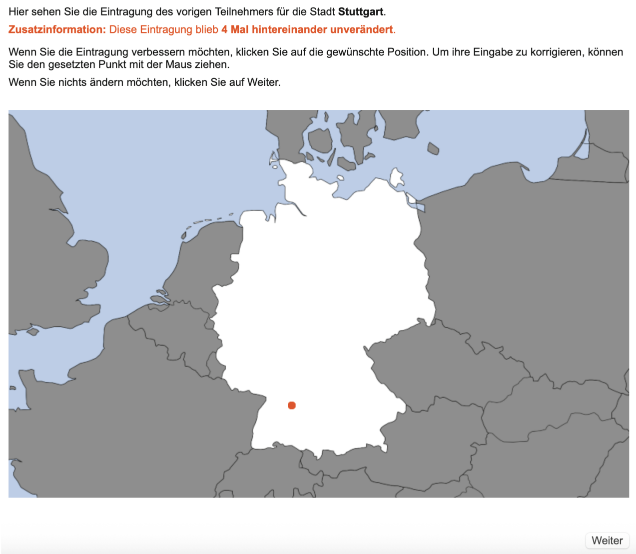

FIGURE 2 | Exemplary item from the sequential-collaboration phase in Experiment 1. *Note.* Translation of the instruction: "Here you can see the entry of the previous participant for the city of Stuttgart. Additional information: This entry has remained unchanged for four consecutive times. If you want to improve the entry, click on the desired position. To correct your entry, you can drag the point with the mouse. If you do not want to change anything, click on Next."

randomized block-wise such that the order in which the maps were presented were randomized as well as the order of cities within maps.

2.1.3 | Design

A within-subject design with the independent variables expertise, deviation, and judgment invariance was established. This resulted in 20 (4 presented deviations x 5 presented invariances) factor level combinations fused with a continuous variable (expertise). All hypotheses were tested using (generalized) linear mixed models.

2.2 | Results

The analyzed data contained 23,696 judgments. Of these 6807 were provided in the expertise measurement phase, whereas 16,889 were provided in the sequential collaboration phase. We tested the fixed effects of participants' expertise, deviation, and judgment invariance, as well as the interactions between participants' expertise and deviation and between participants' expertise and judgment invariance on change probability, change magnitude, and accuracy by the means of (generalized) linear mixed models. The logit function served as the link function to predict the participants' dichotomous decision to change (coded as 1) or to maintain (coded as 0) the presented judgment. Importantly, the same predictors were included in each of the models. We included random intercepts for items and participants in all models to account for the nested structure of our data.

Orthonormal linear contrasts for both presented deviation and presented judgment invariance were deployed. The expertise of individual participants was calculated as the z-standardized negative mean deviation in their judgments to the correct city positions in the independent phase. Consequently, it formed a continuous predictor with higher values reflecting higher expertise and lower values reflecting lower expertise. Change magnitude was operationalized as the distance between the presented judgment and the provided judgment. To obtain the accuracy score, we calculated the negative distance of a given judgment to the corresponding correct position.

First, we examined the variable *change probability*. The relationship between expertise and change probability was positive and significant ($\hat{\beta} = 0.42$, 95% CI $[0.27, 0.56]$, $z = 5.66$, $p < 0.001$), supporting Hypothesis 1a and suggesting that higher expertise went along with a higher probability to change presented judgments. As predicted by Hypothesis 2a, the linear contrast of deviation was also positive and significant ($\hat{\beta} = 1.16$, 95% CI $[1.08, 1.24]$, $z = 28.35$, $p < 0.001$) indicating that participants changed presented judgments more frequently, the more inaccurate the presented judgment was. Additionally, with $\hat{\beta} = -0.17$, 95% CI $[-0.26, -0.09]$, $z = -4.00$, $p < 0.001$, the linear contrast of judgment invariance was negative and significant, which corroborated Hypothesis 4a. This provides evidence that changes occurred less frequently when more of the directly preceding (fictitious) participants in the sequential chain had maintained their judgment. For the interaction of expertise and deviation and the interaction of expertise and judgment invariance, we obtained positive and significant effects ($\hat{\beta} = 0.49$, 95% CI $[0.41, 0.57]$, $z = 11.95$, $p < 0.001$ and $\hat{\beta} = 0.21$, 95% CI $[0.12, 0.29]$, $z = 4.64$, $p < 0.001$, respectively.) This suggested that higher expertise pronounced the positive main effect of deviation but made the negative main effect of judgment invariance less pronounced, which aligned with Hypotheses 3a and 5a, respectively.

Second, we investigated the variable *change magnitude*. Even though we stated no hypotheses about the main effects of expertise and deviation on change magnitude, we report the results for the sake of completeness. The relationship between expertise and change magnitude was positive and significant ($\hat{\beta} = 4.87$, 95% CI $[3.92, 5.82]$, $t(434.31) = 10.03$, $p < 0.001$), indicating larger changes made by participants with higher expertise. Additionally, the linear contrast of deviation was positive and significant ($\hat{\beta} = 13.44$, 95% CI $[12.06, 14.82]$, $t(16202.70) = 19.08$, $p < 0.001$), indicating larger changes made to more inaccurate presented judgments. Corroborating Hypothesis 4b, the linear contrast of judgment invariance was negative and significant with $\hat{\beta} = -1.62$, 95% CI $[-3.17, -0.08]$, $t(16201.15) = -2.06$, $p = 0.039$. One step further, the interaction between expertise and judgment invariance ($\hat{\beta} = 4.15$, 95% CI $[2.60, 5.69]$, $t(16201.69) = 5.26$, $p < 0.001$) was significant as well. This effect had been stated in Hypothesis 5b and pointed to an attenuated judgment invariance effect going along with higher expertise.

The effects described are depicted in Figure 3. The figure indicates that change probability and change magnitude increase with increasing expertise. Additionally, it shows that change probability and change magnitude decrease with increasing judgment invariance (main effect) but primarily for nonexperts (interaction effect).

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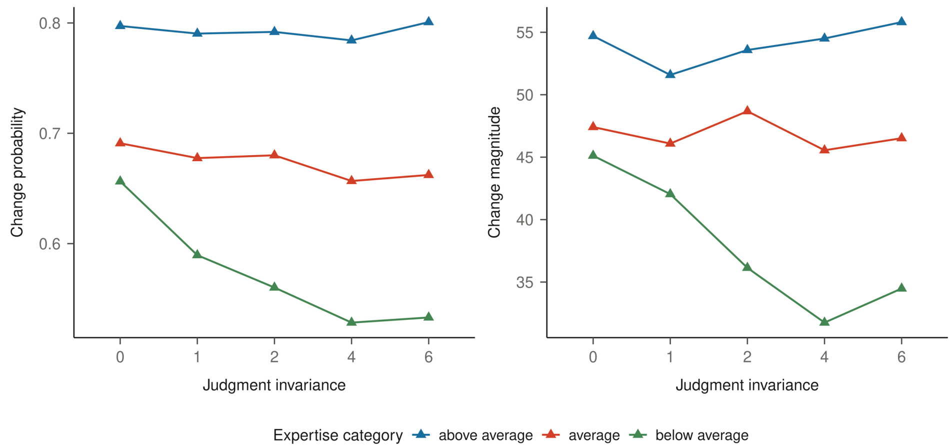

FIGURE 3 | Empirical means for change probability and change magnitude as a function of judgment invariance and expertise in Experiment 1. *Note.* Below average were participants who held a standardized expertise score below −1, above average were participants who held a standardized expertise score above 1.

Third, to test Hypotheses 1b, 2b, and 3b, we tested the *accuracy* of judgments. The relationship between expertise and accuracy was positive and significant ($\widehat{\beta} = 9.80$, 95% CI $[9.04, 10.56]$, $t(434.25) = 25.27$, $p < 0.001$), which supported Hypothesis 1b and therefore the notion of higher expertise going along with higher accuracy. As anticipated in Hypothesis 2b, there was a negative and significant relationship between the contrast of deviation and accuracy $\widehat{\beta} = -16.08$, 95% CI $[-17.05, \ -15.11]$, $t(16421.01) = -32.55$, $p < 0.001$). The interaction of expertise and deviation on accuracy was positive and significant ($\widehat{\beta} = 3.51$, 95% CI $[2.54, 4.48]$, $t(16420.72) = 7.11$, $p < 0.001$) which was in line with Hypothesis 3b. Thus, the latter indicated that the negative relationship of deviation and accuracy was attenuated with higher expertise.

2.3 | Discussion

The results of Experiment 1 supported all our hypotheses. Most importantly, the manipulation of judgment invariance induced an effect on judgment change probability. This effect was less pronounced for experts. Furthermore, an effect of judgment invariance on change magnitude emerged. In addition, an interaction effect of expertise and judgment invariance on change magnitude was found. It is important to note that more focus should be placed on the effects on change probability, because these effects drove the effects on change magnitude. This is due to the change magnitude values of zero of those respondents who did not change the presented judgment. Nevertheless, it is reasonable to include the unchanged judgments because, if one were to exclude them, parts of the judgment invariance effect would be artificially eliminated. Crucially, Experiment 1 supports the claim that information about the past development of a sequential chain influences its participants' judgments and, consequently, the course of the sequential chain itself.

However, the surveyed convenience sample included mostly highly educated students and university employees, who were likely to possess high levels of geographic expertise. Two issues arose from this sample. First, the expertise variance might have been limited, possibly causing limited effects of judgment invariance due to the hypothesized lower susceptibility of experts to judgment invariance. Moreover, in real-world online collaborations, not only students with high expertise are involved but also individuals from different backgrounds. Therefore, it is presumably profitable to test the same hypotheses as in Experiment 1 with a sample that exhibits a higher expertise variance to (a) increase the judgment invariance effect and (b) increase the comparability of the experiment with real-world situations.

3 | Experiment 2

With the suspected limited variance in the expertise variable in Experiment 1 in mind, a more diverse sample was targeted in Experiment 2. Beyond that, having the aim of magnifying the effect of the judgment invariance manipulation, it was sought to increase the salience of the judgment invariance information. As another anticipated driver of effect size, the maximum value of judgment invariance was raised to 10, but the number of judgment invariance levels was kept the same. Therefore, the factor levels of judgment invariance were pulled apart. The aim of the modifications in the experimental paradigm and the intended change in the sample composition was to increase the variance in the expertise variable and to increase the effect size of judgment invariance. Together, this should contribute to increased statistical power. All hypotheses, conditions, and data analyses were preregistered online (https://aspredicted.org/qgp6-dy42.pdf).

3.1 | Methods

3.1.1 | Participants

For Experiment 2, participants were recruited via an online panel provider and were rewarded for their participation in the experiment according to the panel reward standards. We collected complete data from 561 participants. The exact same exclusion criteria as in Experiment 1 were applied. The procedure led to an exclusion of 13 participants, of which all 13 were due to too many *judgments out of areas of interest*. Subsequently, another 419 critical single data points were excluded due to being

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timeouts or *judgments out of bounds*. This resulted in a final sample of 548 participants of which 250 were female, 297 were male, and 1 was nonbinary. Participants had a mean age of 46.87 (SD = 15.74) and a diverse educational background with 29.20 % holding a college degree, 21.17 % holding a high school diploma, 25.18 % holding a vocational training diploma, 15.69 % holding a secondary school diploma, 0.36 % still attending school, and 0.55 % indicating "something else".

3.1.2 | Material, Procedure, and Design

Two modifications compared to the material, procedure, and design used in Experiment 1 were established. First, the judgment invariance levels were changed to 0, 1, 2, 6, and 10. Second, the judgment invariance information was *additionally* put on an extra questionnaire page right before the page displaying the item itself. Besides these modifications, the same methods as in Experiment 1 were employed.

3.1.3 | Power Analysis

We performed an a priori simulation-based power analysis for the investigated fixed effects by the means of the R packages *simr* (Green and MacLeod 2016) and *mixedpower* (Kumle et al. 2021). The results indicated that a sample size of 475 should ensure a statistical power of at least 75% for all fixed effects specified in the models. We planned with a sample size of 500 to build in a buffer for potential exclusions. Unfortunately, the a priori power analysis was based on two models that were specified slightly different than the models preregistered and used in our studies. Therefore, we decided to conduct additional post hoc power analyses for the fixed effects of expertise, judgment invariance, and their interaction for the change probability and change magnitude models using the package *simr*. The analyses resulted in post hoc power estimates of 0.94 for the main effect of the contrast of judgment invariance on change probability, 0.61 for the main effect of the contrast of judgment invariance on change magnitude, 0.85 for the interaction of the contrast of judgment invariance and expertise on change probability, and 0.26 for the interaction of the contrast of judgment invariance and expertise on change magnitude.

3.2 | Results

The analyzed data held 30,379 judgments, of which 8661 belonged to the expertise measurement phase, whereas 21,718 belonged to the sequential collaboration phase. As intended, the variance in expertise was higher in the sample of Experiment 2 than in the sample of Experiment 1 (SD_{Exp2} = 34.1, SD_{Exp1} = 22.1). Levene's test for the homogeneity of variance was significant with $F(1, 983)$ =85.64, $p < 0.001$. Again, we started by examining the variable *change probability* using a generalized linear mixed model specified in the same way as in Experiment 1 including a linear contrast for presented judgment invariance. The relationship between expertise and change probability turned out to be not significant ($\hat{\beta} = 0.22$, 95% CI $[-0.03, 0.47]$, $z = 1.75$, $p = 0.080$), which was not consistent with Experiment 1 and Hypothesis 1a. The linear contrast of deviation was positive and significant ($\hat{\beta} = 0.57$, 95% CI $[0.49, 0.64]$, $z = 14.79$, $p < 0.001$) indicating that more deviating presented judgments led to a higher frequency of judgment change and therefore supporting Hypothesis 2a. Additionally, with $\hat{\beta} = -0.17$, 95% CI $[-0.25, -0.08]$, $z = -3.96$, $p < 0.001$, the linear contrast of judgment invariance was negative and significant. This reflected a decrease in the frequency of judgment changes with increasing judgment invariance, hence supporting Hypothesis 4a. The interaction of expertise and deviation and the interaction of expertise and judgment invariance showed positive and significant effects ($\hat{\beta} = 0.50$, 95% CI $[0.42, 0.58]$, $z = 12.46$, $p < 0.001$ and $\hat{\beta} = 0.13$, 95% CI $[0.05, 0.22]$, $z = 3.04$, $p = 0.002$, respectively). The former effect displayed the steeper relationship of experts to change a judgment when deviation was increasing thereby confirming our Hypothesis 3a. The latter showed the less negative relationship of experts to change a judgment when judgment invariance was increasing, and it therefore supported Hypothesis 5a.

Thereafter, we analyzed the variable *change magnitude* with the same linear mixed model as in Experiment 1. In line with Experiment 1, the relationship between expertise and change magnitude was positive and significant ($\hat{\beta} = 4.01$, 95% CI $[2.31, 5.71]$, $t(545.00) = 4.63$, $p < 0.001$) as was the linear contrast of deviation ($\hat{\beta} = 3.80$, 95% CI $[2.65, 4.95]$, $t(20810.17) = 6.48$, $p < 0.001$). Again, this reflected that participants changed judgments more heavily with increasing expertise and deviation, which underpinned Hypotheses 1b and 2b. The linear contrast of judgment invariance was negative and significant with $\hat{\beta} = -1.39$, 95% CI $[-2.67, -0.10]$, $t(20810.72) = -2.11$, $p = 0.035$, which stood in accordance with Experiment 1 and Hypothesis 4b. Hence, participants changed judgments less heavily when judgment invariance was higher. Further analysis revealed a positive and significant interaction between expertise and deviation ($\hat{\beta} = 6.01$, 95% CI $[4.86, 7.16]$, $t(20810.46) = 10.24$, $p < 0.001$), which confirmed Hypothesis 3b. Contrary to Hypothesis 5b, the interaction between expertise and judgment invariance was not significant ($\hat{\beta} = 0.98$, 95% CI $[-0.31, 2.27]$, $t(20811.96) = 1.49$, $p = 0.136$). Thus, experts did not show less susceptibility to judgment invariance in their change magnitude of judgments than nonexperts.

Figure 4 shows the descriptive means of change probability and change magnitude of Experiment 2. It generally indicates a decrease in change probability and magnitude with increasing judgment invariance (over all expertise levels). However, for participants in the above average expertise category (i.e., more than one standard deviation above the mean), the decreases in change probability and magnitude seem to be achieved only with the highest judgment invariance category. Note also that participants in the two lower expertise categories hardly differ in terms of change probability and magnitude.

Each of the three replication Hypotheses 1b, 2b, and 3b concerning the variable *accuracy* was supported by our analyses. The relationship between expertise and accuracy was significantly positive ($\hat{\beta} = 13.06$, 95% CI $[11.99, 14.13]$, $t(545.08) = 23.97$, $p < 0.001$), whereas the relationship between deviation and accuracy was significantly negative ($\hat{\beta} = -18.19$, 95% CI $[-19.23, -17.14]$, $t(21128.80)$

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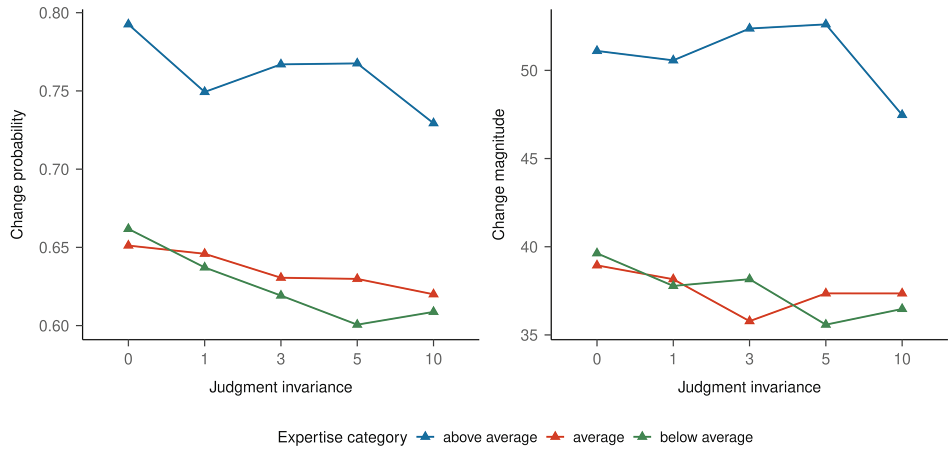

FIGURE 4 | Empirical means for change probability and change magnitude as a function of judgment invariance and expertise in Experiment 2. *Note.* Below average were participants who held a standardized expertise score below − 1, above average were participants who held a standardized expertise score above 1.

$= -34.24$, $p < 0.001$). Moreover, the interaction of expertise and deviation turned out to be positive and significant ($\hat{\beta} = 2.53$, 95% CI [1.49, 3.57], $t(21129.80) = 4.76$, $p < 0.001$).

3.3 | Discussion

Experiment 2 successfully replicated the effects found in Experiment 1. All hypotheses were supported except for Hypothesis H1a, the effect of expertise on judgment change probability, and Hypothesis 5b, the interaction of expertise and judgment invariance on judgment change magnitude. For the first, one explanation would be that experts indeed changed strongly deviating judgments more often than nonexperts but in addition changed little deviating judgments less often than nonexperts. In fact, this interaction of expertise and deviation was found in Experiment 2 and may have masked the main effect of expertise on change probability. A similar finding was reported recently by Mayer and Kimmerle (2025). However, the main effect of expertise on the dependent variable change magnitude could be found; thus, the main effect was not masked by the interaction of expertise and deviation for this dependent variable. Another explanation for the nonemergence of the main effect of expertise on change probability grounds on Figure 4. Only participants with above average expertise seemed to differ in change probability and magnitude from participants with average and below average expertise. The mass of datapoints stemmed from participants of the latter two categories which could have masked a main effect. One could argue that the same holds for the variable change magnitude, for which the main effect of expertise was significant despite this. However, it is plausible that in the latter case, the data stemming from participants with higher expertise just sufficed, while in the former case they did not.

For the nonemergence of the interaction of expertise and judgment invariance on change magnitude, a possible explanation would be that the general expertise in the sample for Experiment 2 was lower than in Experiment 1. A lower general expertise in the sample could have increased the overall sample susceptibility to the information on judgment invariance. Thus, experts and nonexperts (relative to the sample) could have been similarly influenced by the judgment invariance information, which means nothing other than the absence of an interaction. The low power for the detection of the interaction effect of expertise and judgment invariance must also be taken into account. Low power of tests of interaction hypotheses is a general problem (Aguinis et al. 2005; Mathieu et al. 2012).

Importantly, even if not all hypothesized effects were supported, Experiment 2 could again show effects of the information on judgment invariance in sequential collaboration. Nonetheless, we only examined sets of single fictitious and highly controlled sequential steps in the reported Experiments 1 and 2. This comes with plausibility issues in two ways: First, an issue is that participants might find the presented deviations and judgment invariances implausible and consequently they might show unwanted reactions. Second, because the (fixed) values of deviation and judgment invariance might be unrealistic compared to real-world sequential chains, the transfer to the latter ones is problematic. Therefore, in Experiment 3, we investigated the hypotheses regarding judgment invariance effects by employing *naturally developed* sequential chains instead of looking at single, fictitious sequential steps. Additionally, to achieve a higher degree of generalizability, we changed the experimental task type from the previously used city-location task to a new history knowledge task.

4 | Experiment 3

Two goals motivated Experiment 3. First, we aimed at enhancing the generalizability of our results with changes in the experimental setting. To achieve this, we made use of general knowledge questions about historical events. Second, and more importantly, real sequential chains were generated. This means that no preselected judgments and, respectively, judgment invariances were presented. In contrast, the participants' genuine judgments and the resulting genuine number of consecutive invariant judgments at a specific chain position (i.e., judgment invariance) were utilized.[5] The same predictors as in Experiment 1 and 2 were used for the (G)LMM analysis, but for the sake of clarity, we only interpreted the effects that included judgment

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invariance. Separately, we tested the effect of chain position (i.e., the position of a judgment inside a sequential chain) on judgment accuracy as an additional replication hypothesis of Mayer and Heck (2024). Again, hypotheses, conditions, and data analyses were preregistered online (https://aspredicted.org/c77b-4d2q.pdf).

4.1 | Methods

4.1.1 | Participants

Participants were recruited using an online panel provider and were rewarded for their participation according to the panel reward standards. A sample size of 800 was targeted to ensure enough fully occupied sequential chains. The ultimately analyzed sample in Experiment 3 comprised 875 participants. Nine participants had to be excluded because either they had only one observation in the sequential collaboration phase, which made it impossible to estimate a random person intercept, or they provided no valid responses in the independent judgment phase, preventing the calculation of an expertise score. A total of 450 of our participants were male, whereas 422 were female. Participants had a mean age of 45.15 (SD = 13.65) and again a diverse educational background with 27.87 % holding a college degree, 14.79 % holding a high school diploma, 32.11 % holding a secondary school diploma, 24.66 % holding a lower secondary school diploma, and 0.57 % having no school diploma.

4.1.2 | Material and Procedure

A total of 60 items were generated asking for the year a historical event happened. We aimed at covering various areas with those items, including science, politics, art and sport. Of the 60 items, 42 items (7 for each century from 15th to 20th) were considered suitable based on a pilot test with 205 valid cases and were selected for Experiment 3. One exemplary item that was used, asked "In which year did Martin Luther put the 95 theses on the castle church in Wittenberg?" Two items per century (i.e., 12 items) were randomly chosen and assigned to the expertise measurement phase. The remaining 30 items formed the sequential phase. The exact items, their correct solution, as well as data of the pilot study can be found in Appendix A.

After providing informed consent, participants independently indicated the year in which a historical event in question took place for 12 items. As in the former experiments, in each of the 30 items in the sequential phase of the experiment, participants were presented with a judgment of a former participant as well as the associated information on judgment invariance. However, this time, the judgment and the associated judgment invariance stemmed from a real sequential chain formed of responses of previous participants of the experiment. To prevent the presentation of absurd judgments to participants, the range of deliverable judgments spanned 1–2024. We randomly selected 120 judgments per item from the independent individual judgments that were collected in the pilot study to start the sequential chains. By definition, these chain-starting judgments had a judgment invariance value of 0. By randomly drawing chains for each item, we made sure that participants were provided with judgments from various previous contributors. Sequential chains were constructed up to a length of twelve judgments, that is, one person from the pilot study and eleven from Experiment 3 itself. Consequently, the highest value of judgment invariance that could theoretically be presented was 10. This could happen if the first 10 members performing sequential collaboration did not change the initial judgment in succession and the 12th member of this sequential chain got to the turn. After completing the task, participants were debriefed and thanked.

4.1.3 | Data Analysis

According to our preregistration, we planned no data exclusions. This was due to our intention to create sequential collaboration naturally. Unfortunately, a considerable number of participants did not participate conscientiously in the experiment. In our opinion, however, this would not happen in real-life applications of sequential collaboration because people exhibit a strong self-selection to online collaborative projects. Therefore, we decided to cautiously and transparently deviate from the preregistration in terms of data exclusions.

First, if a chain position in a sequential chain was assigned to two participants, we excluded both judgments and the subsequent judgments in the chain. The double assignment could happen due to extremely long response times from participants, for example, when participants left their device while participating and returned later. When a participant was assigned to a sequential chain, that chain remained blocked for 30 min, meaning it could not be assigned to another participant during that time. However, even if the first participant had not yet completed the study, the chain was still unlocked after the blocking period ended and could be assigned to a new participant. As a result, this new participant occupied the same chain position as the first participant. Secondly, we defined a lower (year 400, i.e., around 1000 years before the earliest event in the task) and an upper bound (year 2024) beyond which responses were considered implausible to prevent these judgments from exerting strong leverage on our regression results. We excluded all implausible responses as well as the *subsequent* responses in a sequential chain following these implausible responses. These judgments were most likely typing errors where participants failed to enter one of the intended numbers and therefore entered very low values. Thirdly, apart from unconscious participation, due to a small glitch in the programming, in few cases, judgment invariances "jumped" in steps greater than 1 within directly consecutive judgments. The affected judgments and the subsequent judgments in the respective chains were excluded as well.

4.2 | Results

The described exclusions reduced the number of datapoints in our analysis from 37,128 to 34,542. A total of 297 judgments had to be excluded due to double allocations and invariance "jumps". Further 2108 exclusions were due to implausible values; 181 exclusions resulted from the nine participants either having no judgments in the independent phase or just one judgment in the sequential collaboration phase. Of the resulting 34,542

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datapoints, 24,331 stemmed from the sequential collaboration phase. The other 10,211 datapoints formed the independent judgments used to estimate participants' expertise. Importantly, we observed 3247 sequential chains. Most of the chains consisted of twelve judgments, that is, one independent starting judgment and eleven sequential judgments. In Appendix B, histograms of the frequencies of chain lengths as well as of the frequencies of maximum judgment invariances are presented. Note that even though most of the chains had a length of 12, only in far fewer cases was a judgment invariance of 10 achieved. Nevertheless, a substantial variance of judgment invariances and full coverage of the possible judgment invariance range was achieved.

Again, in each mixed model that we present in this section, we included persons and items as random intercept effects. As a conceptual replication hypothesis, we first analyzed the relationship of chain position and judgment *accuracy* with an LMM. There was no increase in accuracy with increasing contrast of chain position ($\hat{\beta} = -2.02$, 95% CI $[-7.80, 3.75]$, $t(14533.42) = -0.69$, $p = 0.492$), which did not confirm our replication hypothesis.

Then, we analyzed the variable *change probability* using the same GLMM specification as in Experiments 1 and 2. Hypothesis 4a was supported with a significant negative main effect of the contrast of judgment invariance ($\hat{\beta} = -0.88$, 95% CI $[-1.09, -0.66]$, $z = -8.05$, $p < 0.001$) indicating a decreasing change probability with increasing judgment invariance. Additionally, there was a significant interaction between the contrast of judgment invariance and expertise ($\hat{\beta} = -0.35$, 95% CI $[-0.61, -0.09]$, $z = -2.64$, $p = 0.008$), although the direction of the effect was not as anticipated in Hypothesis 5a. Instead of the expected weaker effect of judgment invariance on experts, a stronger (i.e., more negative) effect with increasing expertise became apparent.

For the outcome variable *change magnitude*, the same pattern emerged. A significant negative main effect of the contrast of judgment invariance ($\hat{\beta} = -13.70$, 95% CI $[-18.81, -8.58]$, $t(23909.89) = -5.25$, $p < 0.001$) indicated a decreasing change magnitude with increasing judgment invariance. Yet again, the interaction of the contrast of judgment invariance and expertise was significant but directionally reversed compared to the anticipated interaction ($\hat{\beta} = -9.32$, 95% CI $[-14.27, -4.36]$, $t(24037.65) = -3.69$, $p < 0.001$), indicating a stronger (i.e., more negative) effect of judgment invariance on change magnitude with increasing expertise. This stood in contrast to our Hypothesis 5b. As can be seen in Figure 5, participants with an expertise score below average showed a rather unsystematic change magnitude behavior as a function of judgment invariance. Although this should not be overly interpreted, because the expertise category groups differed in size and therefore in the stability of the mean estimate, it could point to careless participation. Importantly, change probability and change magnitude descriptively decrease with increasing judgment invariance in the judgments of participants in the average expertise group, which contributed the most data to the analysis.

4.2.1 | Exploratory Results

A considerable number of participants in Experiment 3 scored conspicuously low on the expertise measure. Such a particularly low expertise score could indicate careless participation in the experiment. We decided to conduct an additional exploratory analysis of the interaction hypotheses but only with those participants who scored well on the expertise measure. Therefore, we excluded the judgments of participants who held a raw expertise score below –200 (i.e., an average absolute judgment error of 200 years) and the judgments of participants who followed them in a sequential chain. We determined the exclusion criterion based on grounds related to content. We considered an average deviation of 200 years to be substantial, because the historical events only took place in a range of 600 years. Data from 206 participants were fully excluded; data from 669 participants remained. For both change probability and change magnitude, the interaction of the contrast of judgment invariance with expertise was not significant but positive ($\hat{\beta} = 0.29$, 95% CI $[-0.17, 0.76]$, $z = 1.25$, $p = 0.212$, respectively $\hat{\beta} = 4.42$, 95% CI $[-4.80, 13.64]$, $t(8110.06) = 0.94$, $p = 0.347$). In contrast to the main analysis of Experiment 3,

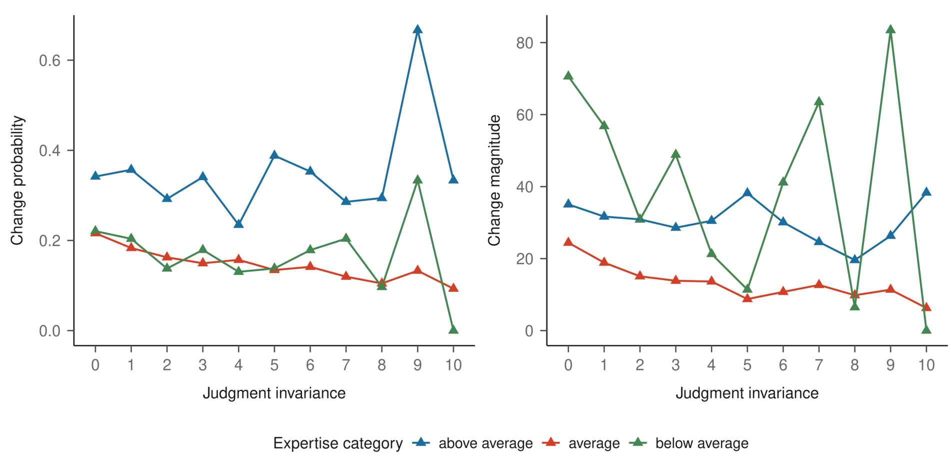

FIGURE 5 | Empirical mean change probability and change magnitude as a function of judgment invariance and expertise in Experiment 3. *Note.* Below average were participants who held a standardized expertise score below -1, above average were participants who held a standardized expertise score above 1.

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for participants with a higher expertise score and at least on a descriptive level, the expected interactions emerged—that is, the negative effects of judgment invariance became less negative with increasing expertise.

4.3 | Discussion

For both dependent variables, that is, change probability and change magnitude, Experiment 3 showed a main effect of judgment invariance. More generally, for naturally evolving sequential chains, information on the past of a sequential chain had an influence on the development of the respective chain. Somewhat curious, the hypothesized interaction effects between expertise and judgment invariance on both dependent variables were directionally reversed. One possible explanation might be that the expertise measure was not optimal. As operationalized in this experiment, low expertise could have also reflected a low conscientiousness in working on the experimental tasks, whereas high expertise could have reflected a high conscientiousness in working on the experimental tasks. Consequently, judgment invariance would have had no effect on "nonexperts" (i.e., participants who did not care about the tasks) but some effect on "experts" (i.e., participants who did care about the tasks). This could have led to the observed, unexpectedly negative interaction effect of expertise and judgment invariance.

5 | General Discussion

In three experiments, we investigated the effect of information on judgment invariance in sequential collaboration. More specifically, we investigated its effect on the probability of changing a presented judgment and on the magnitude of change of the presented judgment in a sequential collaboration. Experiments 1 and 2 manipulated the information on judgment invariance and the deviation of the presented judgment in a city-location task; participants' expertise was measured. In these experiments, we found that with higher judgment invariance, the change probability and change magnitude for a presented judgment decreased. Moreover, for participants with higher expertise these relationships were weaker than for participants with lower expertise. Note again that in contrast to Experiment 1, we could not find the interaction of judgment invariance and expertise on change magnitude in Experiment 2. In Experiment 3, we observed the mechanics of naturally developing sequential collaborations including judgment invariance information. The sequential collaboration was embedded in a general knowledge task about historical events. Here, participants changed presented judgments less frequently and less strongly when the judgment invariance was higher. However, with increasing expertise, we found a more pronounced effect of judgment invariance on the frequency to change a presented judgment and on the magnitude of judgment change. This was not hypothesized and may be due to careless responding as the exploratory analysis indicated.

Note also that the replication hypotheses concerning the main and interaction effects of the variables expertise and deviation on judgment change probability and judgment accuracy were supported, besides the nonsignificant main effect of expertise on judgment change probability in Experiment 2. Thereby, our results strengthen the findings of Mayer et al. (2023). and Mayer and Heck (2024).

Notably, in each experiment, the main effects of judgment invariance on both the probability and the magnitude of judgment change were demonstrated. Next to the influence of contributors' expertise and the accuracy of the presented judgment, judgment invariance could be established as a new influence in sequential collaboration. This means that the insight in the past development of a sequential chain has an influence on the judgment decision of an individual in a sequential chain and thereby on the development of the sequential collaboration as a whole. Besides influences due to the contributor and the presented content, also information about the sequential chain itself affects judgments in sequential collaboration.

With respect to the anchoring literature, our results support the hypothesis that more informative anchors induce a greater anchoring effect on judgments. Because more informative anchors are incorporated as more informative evidence into the Bayesian framework of anchoring, and more informative evidence exhibits a stronger influence on the posterior, our results generally support this framework as well.

It is worth mentioning that, in addition to the Bayesian framework of anchoring (e.g., AIM), the scale distortion theory (Frederick and Mochon 2012) offers another influential account of anchoring effects. It proposes that an anchor does not affect people's internal representation of a quantity—as the AIM does—but that it distorts the scale on which the internal representation of the quantity is placed. Therefore, when explaining the mechanisms of sequential collaboration using anchoring, scale distortion instead of Bayesian updating could be the underlying principle. However, it is more straightforward to predict the effects of information on judgment invariance in sequential collaboration under the Bayesian updating account than under the scale distortion account, because the informativeness of an anchor is a natural component in the former but not in the latter theory.

5.1 | Social Conformity as an Alternative Explanation

The effect of information on judgment invariance exhibits parallels to the well-known phenomenon of social conformity. Social conformity is defined as "the act of changing one's behavior to match the responses of others" (Cialdini and Goldstein 2004, p. 606). Furthermore, social conformity is usually distinguished into normative and informational conformity (Deutsch and Gerard 1955). Whereas normative conformity results from the goal to be accepted by others, informational conformity results from the goal to behave correctly in ambiguous situations by using the behavior of others as a piece of information. Classical experiments of normative and informational conformity originate from Asch (1956) and Sherif (1935), respectively.

Information on judgment invariance presumably induces normative and, in particular, informational social conformity effects. Consequently, the social conformity perspective offers

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an alternative explanation of the effects of judgment invariance in sequential collaboration. In fact, the three experiments presented here are not capable of determining which of the two perspectives—anchoring versus social conformity—is more adequate for explaining the effects of judgment invariance. Both perspectives predict the same results in our experiments. Therefore, the effect of judgment invariance in sequential collaboration can also be situated within the social conformity context.

Moreover, even without the inclusion of judgment invariance information, sequential collaboration itself can be regarded as a sequence of social conformity scenarios. Each contributor may exhibit social conformity with respect to their predecessor, who likewise may have exhibited social conformity to the one before, and so on. Although the sequential collaboration paradigm was designed to minimize social influences (e.g., no direct social contact, anonymous judgments), they will never be eliminated completely, since collaboration by definition involves social touchpoints. Yet, a numerical judgment in a sequential chain always constitutes an anchor as well. Consequently, anchoring influences will never be entirely eliminated either. Sequential collaboration is presumably shaped by both aspects—social conformity and anchoring. Future research should examine which influence plays the dominant role or whether the theoretical overlap of both influences is inextricable. Possibly, just as anchoring can be explained by a Bayesian cognitive framework (e.g., Griffiths et al. 2008; Turner and Schley 2016), social conformity might be subsumed under a Bayesian framework of social influence (e.g., Ciranka and van den Bos 2020). The Bayesian view might constitute a theoretical overlap of anchoring and social conformity, explaining their joint influence in sequential collaboration. However, additional targeted research is needed to make informed statements.

From a more practical standpoint, distinguishing between the underlying influences of (information on judgment invariance in) sequential collaboration is of subordinate priority. Insight into the past development of sequential chains is often available in real-world scenarios of sequential collaboration such as Wikipedia, OpenStreetMap, or shared online documents. Transferring the results of our studies to these real-world scenarios suggests that insight possibilities have an influence on the development of sequential collaborations. For example, the insight of a person into the version history of a collaboratively edited online document is presumed to shape the development of the document. Whether this influence is positive or negative with regard to the outcome of the sequential collaboration depends on whether or not the contributor is able to improve the overall product. Regarding the specific insight of judgment invariance, a higher level of invariance should be beneficial when associated with good judgment but detrimental when associated with poor judgment. In a naturally developing sequential chain, there should be a tendency that higher judgment invariances are associated with good judgments, because poor judgments are changed more often (cf. the effect of judgment deviation). However, there might be some point where the effect of judgment invariance (or the effect of other pieces of information about the past of a sequential chain) overwhelms the effect of poor judgments.

In our experiments, the effect of judgment deviation was stronger than the effect of judgment invariance, but this holds only for our specific experimental design choice. In other scenarios, the existence of a tipping point where the effect of judgment invariance (or the effect of other pieces of information about the past of a sequential chain) overwhelms the effect of poor judgments is plausible. Future research may examine such a tipping point in judgment invariance and whether it is associated with the quality of the presented judgment.

Thus, online collaborative projects may profit from selectively making the change history salient to users. New and inexperienced users who are more likely to worsen already long existing entries should be made aware of long periods of invariance or the change history. This measure may prevent careless adjustments to otherwise highly accurate information.

5.2 | Limitations and Future Research Directions

Even though results are promising and extend the scope of known influences to sequential collaboration, the described experiments have nonetheless some limitations.

In our study, only numerical judgments were investigated. Contrarily, in real-world sequential collaborations, written text is oftentimes the object of engagement. Therefore, it is important to extend the sequential collaboration literature with studies that use real written text instead of numerical judgments. However, this was not the goal of the present study.

Additionally, in Experiment 3, judgment invariance was not manipulated but only observed. In a strict sense, Experiment 3 cannot be termed an experiment. This may pose a limitation with respect to the validity of causal inference. Nonetheless, our hypothesis about the main effect of judgment invariance was still confirmed and overall results aligned with previous findings. Moreover, the naturalistic setting of Experiment 3 increases the external validity of our conclusions, while the manipulations of Experiments 1 and 2 ensure their internal validity.

6 | Conclusion

Our findings extend the sequential collaboration literature by adding a variable of practical relevance. Based on our experiments, we conclude that the insight into the past development of a sequential chain, specifically information on judgment invariance, influences the judgments of contributors in sequential collaborations. Therefore, in real-world applications such as online collaborative projects, participants' insights into the past development of sequential chains are expected to shape the outcomes of the collaborative processes.

Author Contributions

Vincent Eric Fischer: conceptualization, methodology, investigation, formal analysis, writing – original draft preparation, writing – review and editing. **Maren Mayer:** conceptualization, methodology, writing – review and editing, supervision. **Joachim Kimmerle:** writing – review and editing, supervision.

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Acknowledgements

Open Access funding enabled and organized by Projekt DEAL.

Data Availability Statement

Data and R scripts for the analyses are available at the Open Science Framework (https://osf.io/m8e6q/).

Endnotes

[1] https://welcome.openstreetmap.org/about-osm-community/consumers/ (accessed May 27, 2025).

[2] https://explodingtopics.com/blog/google-workspace-stats (accessed May 27, 2025).

[3] See https://en.wikipedia.org/wiki/Help:Page_history (accessed May 30, 2025).

[4] The original material consisted of 40 items for the sequential collaboration phase. However, due to technical issues judgments for Geneva on the map of Austria and Switzerland were not captured correctly. Therefore, we excluded this item from the analysis.

[5] We improperly use the term “experiment” although no independent variable was manipulated. This is to ensure consistency.

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Appendix A

General Knowledge Questions Used in Experiment 3 with Descriptive Statistics from the Pilot Study

Item	Correct answer	Mean	SD	Median	Phase
In which year was the structure of deoxyribonucleic acid (DNA) decoded?	1953	1941.18	36.76	1952	IN
In which year was Heisenberg's uncertainty principle discovered?	1927	1901.20	91.06	1923	IN
In which year did Vincent van Gogh paint "The Starry Night"	1889	1837.15	84.76	1870	IN
In which year did 17 nations sign the first International Metre Convention in Paris?	1875	1839.75	83.26	1850	IN
In which year was the first targeted medical vaccination given?	1796	1861.87	57.22	1880	IN
In which year did Thomas Newcomen invent the first version of the steam engine?	1712	1792.03	56.19	1790	IN
In which year did William Shakespeare die?	1616	1663.57	122.66	1646	IN
In which year did Rembrandt complete the painting "The Night Watch"	1642	1732.05	110.84	1740	IN
In which year did Martin Luther put the 95 theses on the castle church in Wittenberg?	1517	1534.69	69.50	1517	IN
In which year did Galileo Galilei formulate the "Golden Rule of Mechanics"	1594	1547.20	199.42	1572	IN
In which year was Jeanne d'Arc executed?	1431	1519.60	247.37	1480	IN
In which year did the first European ship reach India via the sea route around Africa?	1498	1501.80	201.36	1500	IN
In which year did Martin Luther King give his "I have a dream" speech?	1963	1960.76	13.20	1963	SE
In which year did the first manned space mission take place?	1961	1959.52	9.62	1960	SE
In which year was women's suffrage introduced in Switzerland?	1971	1959.62	31.91	1970	SE
In which year was the first human heart transplant performed?	1967	1956.81	32.36	1963	SE
In which year did the Brazilian men's national soccer team win the World Cup for the first time?	1958	1955.77	18.77	1958	SE
In which year did the first Boston Marathon take place?	1897	1925.36	37.44	1920	SE
In which year did the first Olympic Games of the modern era take place?	1896	1840.78	266.40	1898	SE
In which year was slavery officially ended in the United States?	1865	1869.28	42.50	1865	SE
In which year did Jane Austen publish her novel "Pride and Prejudice"	1813	1872.47	62.22	1870	SE
In which year was the Statue of Liberty in New York City inaugurated?	1886	1862.30	45.38	1876	SE

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Item	Correct answer	Mean	SD	Median	Phase
In which year was Goethe's “The Sorrows of Young Werther” published?	1774	1804.77	48.99	1797	SE
In which year was Mozart's “The Magic Flute” premiered?	1791	1776.35	57.16	1780	SE
In which year was Uranus discovered by William Herschel?	1781	1794.03	134.09	1820	SE
In which year did Scotland and England unite (Act of Union)?	1707	1692.74	205.17	1707	SE
In which year was Carl Friedrich Gauss born?	1777	1789.79	85.52	1800	SE
In which year did the Pilgrim Fathers reach America with their ship Mayflower?	1620	1636.58	91.53	1622	SE
In which year did the Great Fire of London occur?	1666	1679.69	143.96	1666	SE
In which year was Isaac Newton's work “Philosophiae Naturalis Principia Mathematica” published?	1687	1733.27	105.14	1750	SE
In which year did the construction of the Taj Mahal begin?	1632	1492.94	378.33	1600	SE
In which year did the Salem witch trials take place?	1692	1622.67	159.75	1650	SE
In which year did Titian complete the painting “Venus of Urbino”	1538	1487.51	349.50	1550	SE
In which year did Nicolaus Copernicus publish his magnum opus, which contained a heliocentric model of the cosmos?	1543	1556.17	156.78	1560	SE
In which year was Michelangelo commissioned to make the statue of David?	1501	1561.35	147.49	1546	SE
In which year did Ferdinand Magellan's fleet of ships set sail, the first to successfully circumnavigate the globe?	1519	1583.59	167.43	1566	SE
In which year was the work “La Dafne” by Jacopo Peri premiered, which is considered the first opera in history?	1598	1564.17	240.39	1600	SE
In which year did the Battle of Azincourt take place during the Hundred Years' War?	1415	1506.28	256.06	1470	SE
In which year was Leonardo da Vinci born?	1452	1504.85	164.60	1489	SE
In which year did the Spanish Inquisition begin?	1478	1522.20	161.62	1515	SE
In which year was the Sistine Chapel in Rome inaugurated?	1483	1422.09	336.36	1520	SE
In which year did the Western Schism end and with it the period in which three competing popes existed simultaneously?	1417	1369.99	280.27	1415	SE

Note: IN is short for independent judgments used to measure expertise; SE is short for sequential collaboration.

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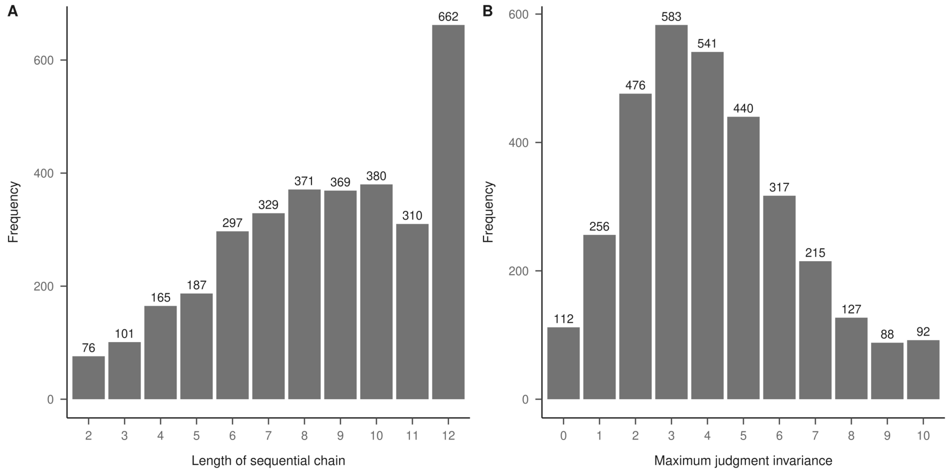
Appendix B

Histograms of the Sequential Chain Length and the Maximum Invariance in Experiment 3



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