Experiment 2a

In experiment one, we argued that for the convergence of estimates to be a reliable cue to the accuracy of the estimates, even in the absence of priors about the competence of informants, the estimates have to be *independent*.

In experiment two, we test this independence assumption. We use the same setting as in experiment one, in which participants saw the fictional results of an estimation game involving several players. All participants will be presented with two scenarios: One in which three players make independent estimates, and one in which three players discuss before making their estimates. In both scenarios, estimates of players converge.

Based on the literature on information aggregation (e.g. Mercier & Morin, 2019), we form a first hypothesis:

> H1: *When making a guess based on convergent estimates of informants, participants will be more confident about their guess when informants were independent compared to when they weren't (i.e. they could discuss before).*

Our second, and main hypothesis is:

> H2: *Participants perceive informants whose estimates converge as more competent when they are independent, compared to when they weren't (i.e. they could discuss before).*

Materials

Introduction. "There is a series of games in which players have to estimate a quantity. Each game is played by three players. You have no idea how competent the players are: they might be completely at chance, or be very good at the task. It's also possible that some are really good while others are really bad.

You will see the results of two such games. Both are equally difficult and, as it so happens, for all games, the estimates have to be between 1000 and 2000.

Other than that, the games are completely unrelated: they have different solutions, involve different players and take place under different rules.

In each game, players are randomly drawn from the population and don't know each other."

[page break]

Introducing the first game as: "The first random sample of three players plays a game under the following rules: [condition]".

[page break]; stimulus + questions (see **Fig.1** below)

Introducing the second game(s) as: “Game number two is a new game with a different solution. Three new randomly drawn players play under different rules this time: [condition]”

Independence condition. “Players are asked to make completely independent decisions – they cannot see each other’s estimates, or talk with each other before giving their estimates.”

Dependence condition. “Players are asked to talk with each other about the game at length before giving their estimates.”

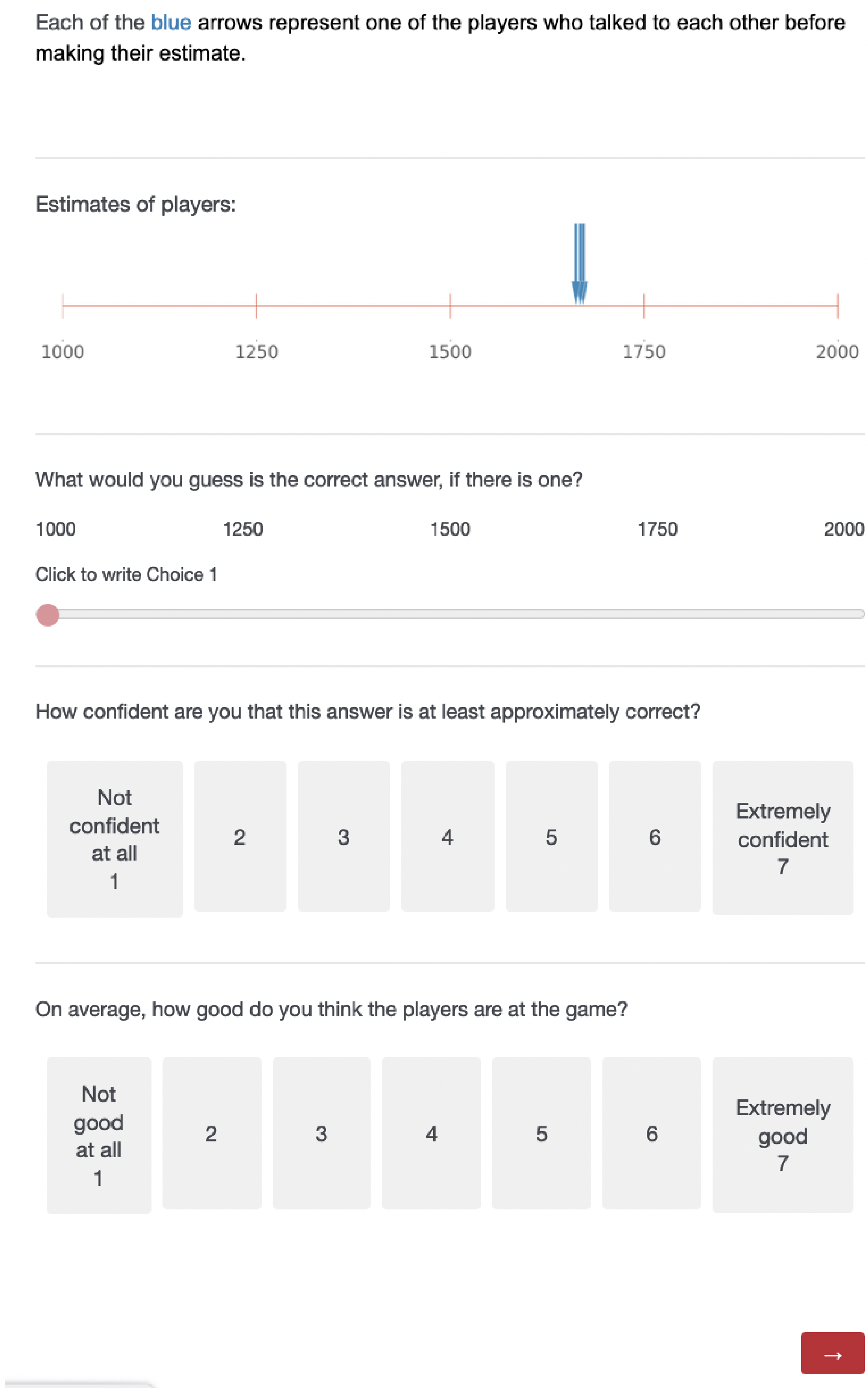


Fig.1: *Example for a stimulus in the dependence condition.*

Design and procedure

We manipulate the experimental factor *independence* with 2 levels, *dependent* and *independent*. We use a within-participant design, with each participant seeing all of the conditions. By contrast to experiment one, participants will see only one set of estimates (game result) per condition. The order in which individual participants see the two conditions will be randomized.

Stimuli. Our design requires that each participant sees 2 different sets of convergent estimates, one for each condition. Across all conditions, sets of estimates need to be equally convergent.

For experiment one, we had generated three series that included, respectively, two sets of estimates that were convergent and showed three estimates. We will use these sets of estimates here. They were generated with random draws from normal distributions with a standard deviation of 20. The means of the normal distributions that we drew our estimates from are distinct between sets of estimates and lie within the interquartile range of the scale (1250 to 1750; for more details see experiment one). Considering our within-participant design, this makes it more likely that participants understand each set of estimates as being the result of a different game, with a different solution.

Randomization. We have 3 series with two sets of estimates each. We will randomly assign individual participants to one of these series. Further, within the same series, we will randomly pair the sets of estimates with the conditions (*dependent* or *independent*) for each participant. Taken together, this strategy reduces the risk of confounding the effect of our manipulation with a potential effect of certain stimuli. Additionally, for each participant, we randomize the order of appearance of conditions.

Dependent variables. For each set of estimates participants respond to the following questions: First, we ask participants to make a guess about the correct answer based on the estimates they see (“What would you guess is the correct answer, if there is one?”). Participants indicate their numeric guess using a slider on a line identical with the one they see the estimates on. Participants are then asked about how confident they are regarding their own guess (“How confident are you that your answer is at least approximately correct?” on a 7-point Likert scale (“not confident at all” to “extremely confident”). Finally, participants are asked how they perceive the competence of the group of players whose estimates they saw in a game. Competence (“On average, how good do you think these players are at the game?”) is assessed on a 7-point Likert scale (from “not good at all” to “extremely good”).

Statistical analysis

All analyses will be conducted in R (v.4.1.1) using R Studio.

H1: We will perform a paired t-test to assess the effect of *independence* on participants’ *confidence* about their guesses. This test accounts for the dependency between the measures of confidence across conditions issued by our within-participant design. [R code: *t.test(confidence ~ independence, data = d, paired = TRUE))*]

As a robustness check, we will run a mixed model OLS regression in which we regress *confidence* ratings on independence. The model will include random intercepts and slopes for participants. [R code: *lmer(confidence ~ conditions (1 + conditions | participant), data)*]

H2: We will perform a paired t-test to assess the effect of *independence* on participants' *competence* ratings of the first player. [R code: *t.test(competence ~ independence, data = d, paired = TRUE)*]

For a robustness check, just as in H1, we will run a mixed model OLS regression with *independence* as predictor variable and with *competence* as dependent variable. [R code: *lmer(competence ~ conditions (1 + conditions | participant), data)*]

Exclusions. We will exclude participants failing (i.e. participants not answering the question or writing "yes" or "no" instead of "I pay attention") the following attention check:

Imagine you are playing video games with a friend and at some point your friend says:

"I don't want to play this game anymore! To make sure that you read the instructions, please write the three following words "I pay attention" in the box below. I really dislike this game, it's the most overrated game ever."

Do you agree with your friend?

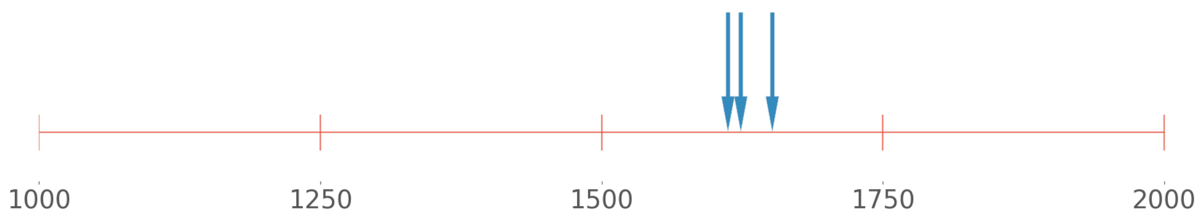
Power analysis. We performed an a priori power analysis with G*Power3. To compute the necessary number of participants, we decided that the minimal effect size of interest would correspond to a Cohen's d of 0.2 between two different experimental conditions, since this corresponds to what is generally seen as a small effect. We chose a t-test to detect the difference between two dependent means (matched pairs). This test is taking into account our within-participant design. In order to detect an effect size of Cohen's d = 0.2 with 80% power (alpha = .05, two-tailed), G*Power suggests we would need 199 participants in a paired samples t-test.

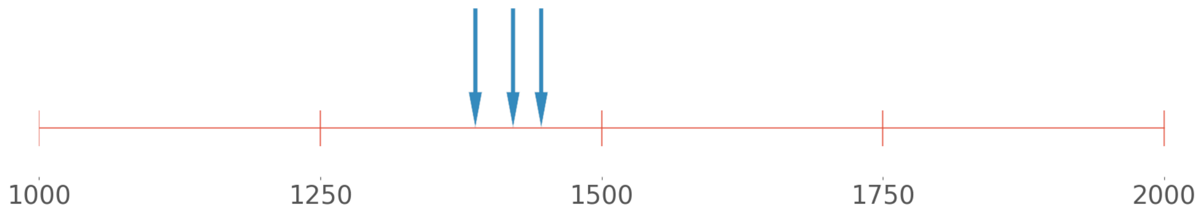
References

Mercier, H., & Morin, O. (2019). Majority rules: how good are we at aggregating convergent opinions?. Evolutionary Human Sciences

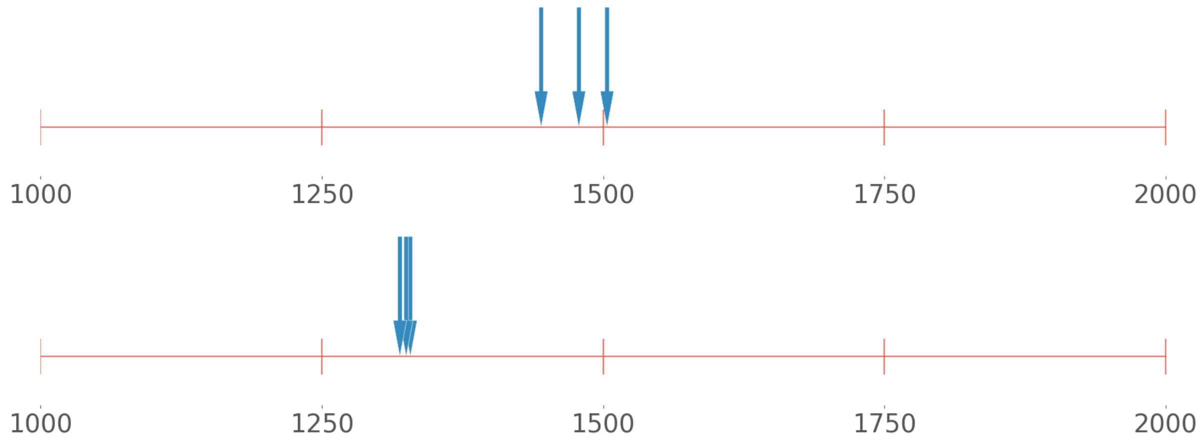
Appendix

a) Sets of estimates
   Series 1:





Series 2:



Series 3: