Formalization of Social Influences on Estimation Tasks

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Author Note

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Objective

This report aims to formalize theoretical assumptions regarding the effects of social influence on group accuracy and wisdom of crowds potency within the Judge-Advisor System (JAS) paradigm. Additionally, we will examine how varying degrees of the Dunning-Kruger effect (where individuals with low expertise overestimate their abilities while those with high expertise underestimate theirs) might impact these dynamics.

Verbal Introduction

The wisdom of crowds effect, first observed by Galton in 1907, refers to the phenomenon where the aggregation of independent individual judgments can produce estimates that are more accurate than most individual judgments (Jayles et al., 2017). This effect has been widely documented across various domains, including prediction markets, political forecasting, and general knowledge estimation tasks (Surowiecki, 2004). Central to the effect is the notion that cognitive diversity among individuals leads to error cancellation when estimates are aggregated (Rader, Larrick, & Soll, 2017).

The judge-advisor system (JAS) paradigm offers a structured approach to studying how individuals incorporate advice into their decision-making (Sniezek & Buckley, 1995). In this paradigm, participants (judges) provide an initial estimate, receive advice (typically in the form of estimates from others), and then have the opportunity to revise their original estimate. This experimental design allows researchers to quantify the extent to which people incorporate others' input. This process is fundamental to many real-world scenarios, from professional consultations to everyday social interactions (Bailey, Leon, Ebner, Moustafa, & Weidemann, 2023).

While traditional wisdom of crowds theory emphasizes the importance of fully independent judgments for maximizing collective accuracy (Lorenz, Rauhut, Schweitzer, & Helbing, 2011), recent evidence suggests that under certain conditions, social influence may actually improve group estimation accuracy (Jayles et al., 2017). It is hypothesized that this is the case, because subjects can use the power of the Wisdom of Crowds by adjusting 50% towards whatever advice they receive (Bailey et al., 2023). In practice, they adjust by only 0.39, thereby weighing their own opinion more highly (egocentric discounting) (Bailey et al., 2023).

Relevant Phenomena

Studies have found that within the JAS paradigm, the accuracy of individual estimates and aggregated group estimates is higher after subjects have received advice, than for their first, fully independent guesses. Subjects tend to integrate the estimate received as advice into their second guess, moving toward it.

The analysis of strength of evidence as well as generalizability for this phenomenon heavily depend on which studies we include during our limited search. Most importantly, it depends on whether we regard the meta-analysis of Baileys et al. as representative of our phenomenon. In their work, they find the robust effect, that people move towards the advice they receive in their second estimates, but they also state that they did not include whether this move resulted in increased or decreased accuracy, due to concerns of having to exclude too many studies from their dataset. Because of this lack of accuracy measurements, we exclude their paper from our evaluation.

Strength of Evidence

The phenomenon of improved estimation accuracy after receiving advice shows moderate evidence across multiple studies. The evidence strength is supported by methodologically sound experimental designs with standardized protocols, controlled variables, and adequate sample sizes (for example 520 participants in Becker, 279 in Gürçay). All studies except for (Lorenz et al., 2011) demonstrate statistical significance for the basic effect of accuracy improvements. In a re-analysis of their data, Gürçay et al. later do find an effect with different outcome measurements. According to Becker, Brackbill, and Centola (2017), decentralized networks lead accuracy improvements, while results for centralized networks are mixed.

UTOS

For Units, evidence comes primarily from university students in WEIRD countries, limiting generalizability. Treatment variations show consistency across different forms of social information (statistical feedback, peer estimates, network influence, and confidence information), with effects persisting across these variations. Even group discussions yielded a positive effect (Gürçay, Mellers, & Baron, 2015). Based on this sample of studies, Treatments seem to be relatively generalizable.

Outcome measurements vary (mean absolute error, percentage deviation, log-transformed differences), yet capture improvement in accuracy post-advice, except in the case of (Lorenz et al., 2011). The fact that (Gürçay et al., 2015) can simply identify an effect in the data of Lorenz et al. (2011) due to different measurements and analyses indicates limited generalizability across outcomes.

Settings have been tested across different countries (France, Japan) (Jayles et al., 2017) and modalities (digital platforms, laboratory environments), though primarily in controlled experimental contexts rather than naturalistic settings. In general, we conclude a low generalizability across settings.

The phenomenon can be considered low to moderately robust. It demonstrates consistency across different operationalizations of treatments in controlled settings, however, its robustness is limited by homogeneous sampling, artificial interaction paradigms, and lack of evidence from naturalistic environments where more complex social dynamics might influence the effect.

Core Constructs

The theory explains how individuals incorporate social information into their estimates. The key paradigm (JAS) involves individuals making an initial estimate (First Estimate), receiving social information from others, and then producing a revised estimate (Second Estimate).

- Prior Knowledge (PK) represents an individual's expertise regarding the estimation task, ranging from 0 (no knowledge) to 1 (expert) [PK1, PK2]. The distribution of this knowledge across a group (GPK) follows a truncated normal distribution [PK1, PK2, PK3].
- Confidence (CONF) reflects an individual's trust in their own estimate and is directly determined by their prior knowledge [CONF1, CONF2, CONF3]. It is on a scale of 0 to 1, where 0 means they don't believe in their estimate at all and 1 means they are fully confident in its accuracy. We used a simplification and set CONF = PK in our base model, because they closely related (Jayles et al., 2017).
- First Estimates (IFE) follow a lognormal distribution where the variance decreases with higher prior knowledge [FE1, FE2]. More knowledgeable individuals produce less variable estimates closer to the true value [PK3].
- Social Information (SI) is calculated as the mean of other group members' first estimates [SINFO1].
- Weight on Advice (WOA) is the central mechanism determining how individuals combine their first estimate with social information [WOA1, WOA2, WOA3, WOA4]. WOA is influenced by:

  - An individual's confidence in their first estimate [CONF1, CONF2]
  - The perceived distance between their estimate and the social information [D1, D2, D4, D5]

- Second Estimates (ISE) are calculated as a weighted average of an individual's first estimate and the social information [WOA1-WOA7].

- Collective Accuracy (ACC) measures how close the group's estimates are to the true value, calculated as the mean absolute deviation from the true value.

Even though not explicitly mentioned in our VAST Model, we also aim to investigate the Wisdom of Crowds effect, as well as the tendency for egocentric discounting, meaning the phenomenon that individuals tend to have a WOA < 0.5, meaning they value their own estimate more highly than the social information of the group [EGO1, EGO2]. We aim to test in our simulations, whether and under what circumstances WOC and Egocentric Discounting can be shown to exist.

For our extension, we incorporate the Dunning-Kruger effect into our confidence calculation, based on the initial paper from 1999. We interpret the Dunning-Kruger Effect to mean novices being significantly more confident in their knowledge than would be reasonable for them, while experts are less confident than would be reasonable for them [DK1, DK2]. Dunning & Kruger posit, that this happens, because low-knowledge subjects also lack the metacognitive skills to realize their lack of skill [DK3].

VAST Display

In our VAST display we tried to separate between the overall paradigm and the theoretical model according to which changes in accuracy occur.

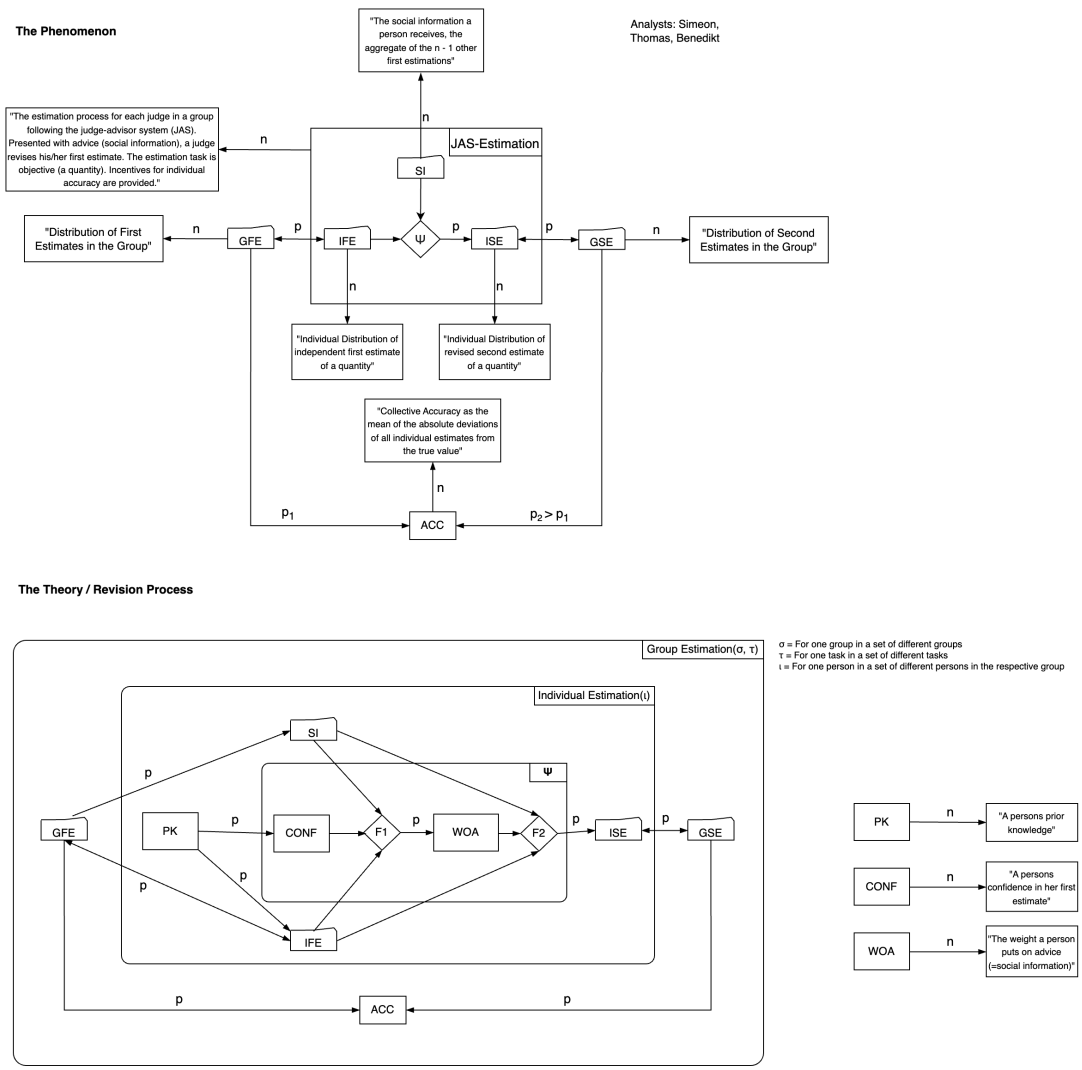


Figure 1

Theory Formulation

Our model starts with a group of subjects, who each have a different prior knowledge with regards to the estimation task [PK2]. Those with higher prior knowledge have more accurate first estimates and will be more confident in them, whereas those with lower prior knowledge will have less accurate ones, while being less confident. The core of our theory lies within the revision coefficient (Becker et al., 2017). Confidence and prior knowledge should be highly correlated (without the Dunning-Kruger effect), so accurate individuals will not be moved much by potentially inaccurate social information, while less knowledgeable individuals shift more toward advice. As long as this is the case, we should find improvements in group accuracy.

This mechanism is modeled via our calculation of Weight of Advice, which determines by what percentage subjects move towards the advice they received from their initial estimate. Highly confident individuals will generally stay close to their initial estimate, whereas those with low confidence will weight advice more highly. A second factor is distance between what people's first estimate was and what advice they are receiving. Low distance leads to a decreased weight of advice (Rader et al., 2017), whereas high distance makes people doubt their first estimate more.

We then calculate the accuracy for both first estimates and second estimates in order to determine 1. whether the groups second estimates are more accurate (closer to the true value) than their first estimates and 2. how strong a potential Wisdom of Crowds effect is.

Because individuals do move toward social information, their estimation diversity decreases (Lorenz et al., 2011). This should in theory also diminish the potency of the Wisdom of Crowds effect for second estimates, i.e. aggregating will lead to less pronounced improvements in comparison to the first estimates.

By including the Dunning-Kruger effect, we effectively water down the strong correlation between prior knowledge and confidence. Those with lower prior knowledge have too much confidence given how little knowledge they have, whereas experts are less confident in their judgements than they should be (Kruger & Dunning, 1999). We predict that for extreme overconfidence of novices and extreme underconfidence of experts, social influence will be detrimental to group accuracy.

Formal Model Development

All code and materials have been uploaded to the Social Influence Formalization repository.

In developing our formal model we made multiple simplifications and also deviated from the theory. The model uses a deterministic function combining confidence and distance between estimates, whereas actual human weight assignment includes additional factors like advisor characteristics [WOA3, WOA4] and social dynamics not captured here [WOA7].

Furthermore, some authors report a reactance effect when individuals notice a high distance between their estimate and received advice [D6]. We limited ourselves to not modeling this and assumed that the higher the distance between our initial estimate and the social information, the more people will move towards the advice, due to fear of being totally wrong [D2, D4].

Prior Knowledge to Confidence

In our basic modeling of confidence, we assumed that CONF = PK [CONF3]. In reality CONF would most likely also follow a distribution across intra-individual "samplings" of it, while also being influenced by different personality tendencies [WOA7]. Additionally, in our Dunning-Kruger extension, we pegged the mapping to trace the percentile over- and underestimations found in the initial Dunning-Kruger paper [DK1, DK2, DK3], based on truncated normal distribution of prior knowledge, with mean=0.5 and SD=0.15. We made sure to identify which percentiles correspond to which levels of prior knowledge (for example percentile=0.12 <-> PK=0.324), but we did not make it dynamically adapt to different kinds of prior knowledge distributions.

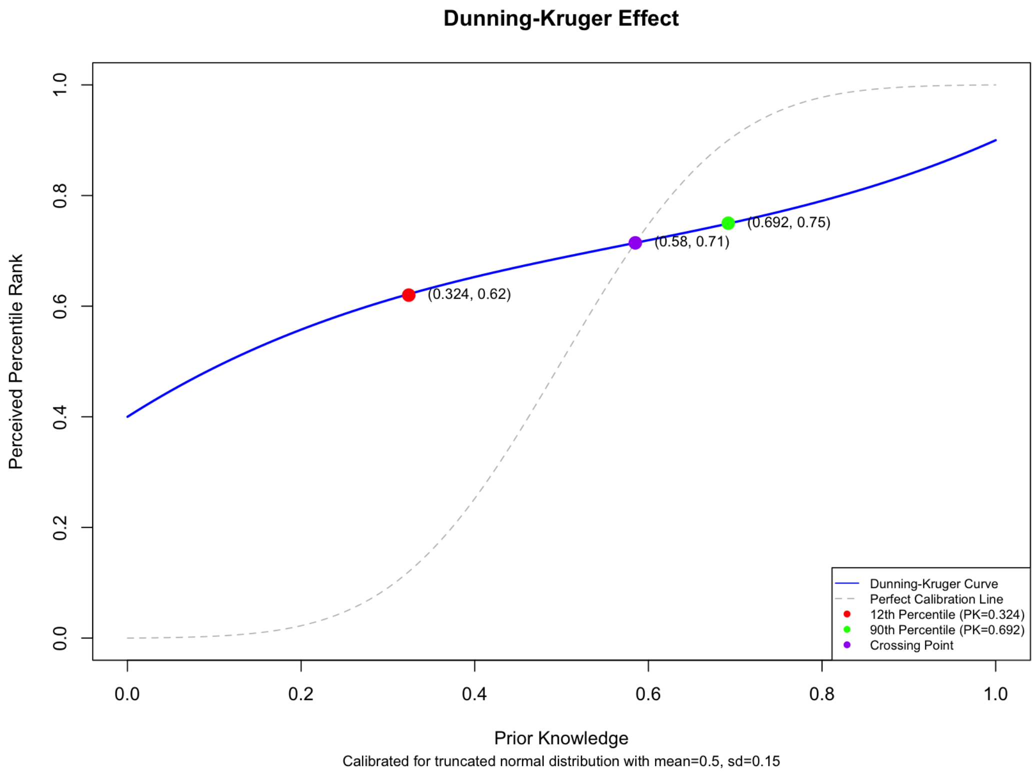


Figure 2

Weight of Advice

This function determines how much individuals are influenced by advice based on their confidence and the distance between their first estimate and social information [WOA1, WOA2]. It calculates a log-based distance measure, then adjusts the weight using confidence values [CONF1, CONF2] and a tanh transformation. Higher confidence decreases the weight given to advice [REV4, REV5], while larger distances (with tanh transformation) can increase it [D2, D4]. The result is constrained between 0 and 1.

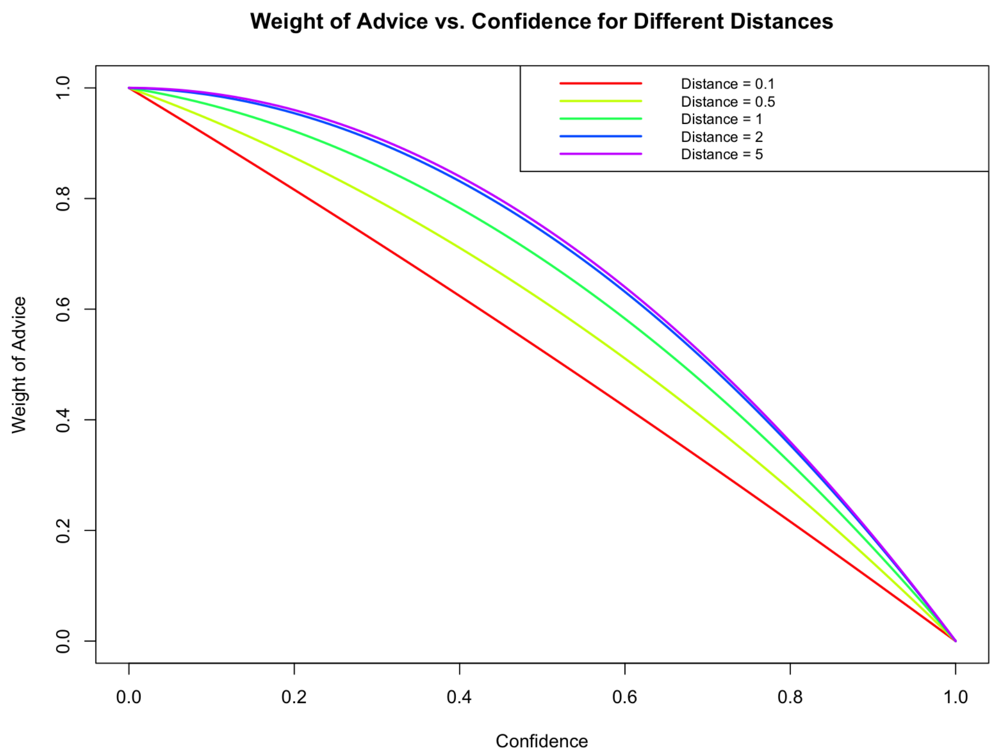


Figure 3

Psi

Psi integrates social information with an individual's first estimate to determine the expected second estimate. It uses the Weight of Advice to calculate how much an individual relies on social information versus their own initial judgment. The expected second estimate is a weighted average.

Prior Knowledge to First Estimate

The relationship is logarithmic - higher prior knowledge leads to more accurate estimates with less variance [PK3, FE1, FE2]. Specifically, estimation error standard deviation decreases linearly with prior knowledge. Estimates are drawn from a lognormal distribution centered around the true value, with the spread determined by the individual's prior knowledge.

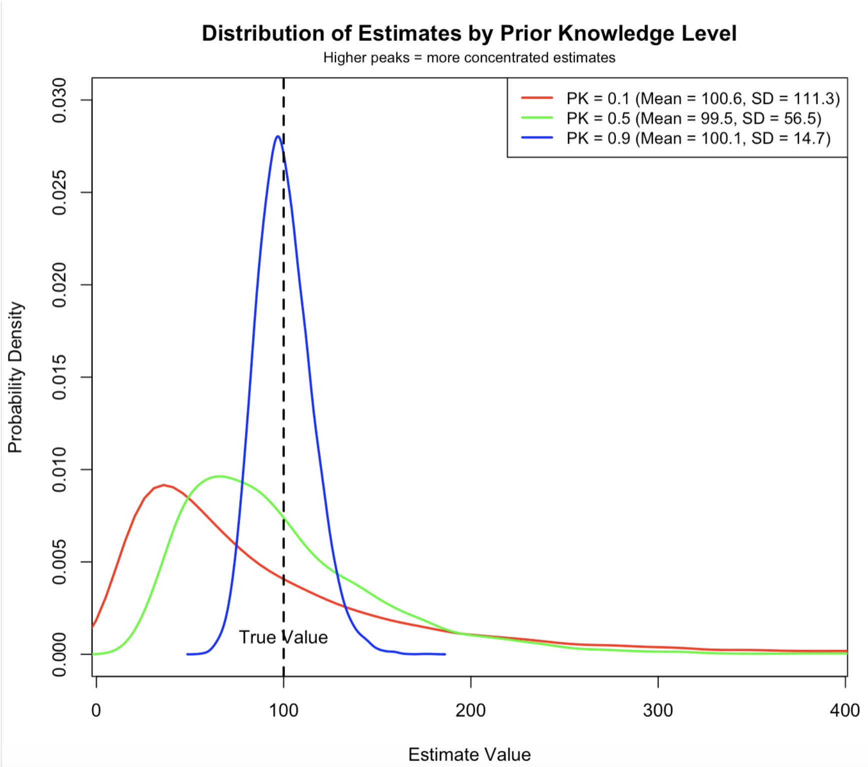


Figure 4

Formal Model Evaluation

To evaluate our model's predictions, we conducted simulations examining key phenomena: accuracy improvement through social influence, potency of Wisdom of Crowds (WOC) effects, and egocentric discounting. We used a truncated normal distribution for prior knowledge (mean=0.5, SD=0.15) across all simulations, with 100 individuals and 100 trials per condition.

- **Group Distance**: The average absolute error of the group estimate (|group mean - 100|) across all trials
- **Individual Distance**: The average absolute error made by individuals (averaging |individual estimate - 100| for each person)

- **WOC Benefit**: The advantage gained by using the group's judgment over individual judgments (Individual Distance - Group Distance)
- **% WOC Benefit**: What percentage of individual error is eliminated through aggregation

Table 1

Comparison of Normal vs. Dunning-Kruger Results

Metric	Normal	DK
Group Distance (First)	4.87	4.94
Group Distance (Second)	4.59	4.67
Individual Distance (First)	41.49	41.02
Individual Distance (Second)	14.22	22.40
WOC Benefit (First)	36.62	36.08
WOC Benefit (Second)	9.63	17.73
WOC Benefit Change	-26.99	-18.35
% WOC Benefit (First)	88.18	87.94
% WOC Benefit (Second)	68.91	79.34

Weight of Advice

Our results indicate that our basic model, with a direct mapping of PK to CONF, results in a WOA of 0.58, higher than the optimal 0.5. Interestingly, our revised mapping based on the initial paper on the Dunning-Kruger effect replicates the tendency for egocentric discounting, with the same WOA found by (Bailey et al., 2023) at 0.39.

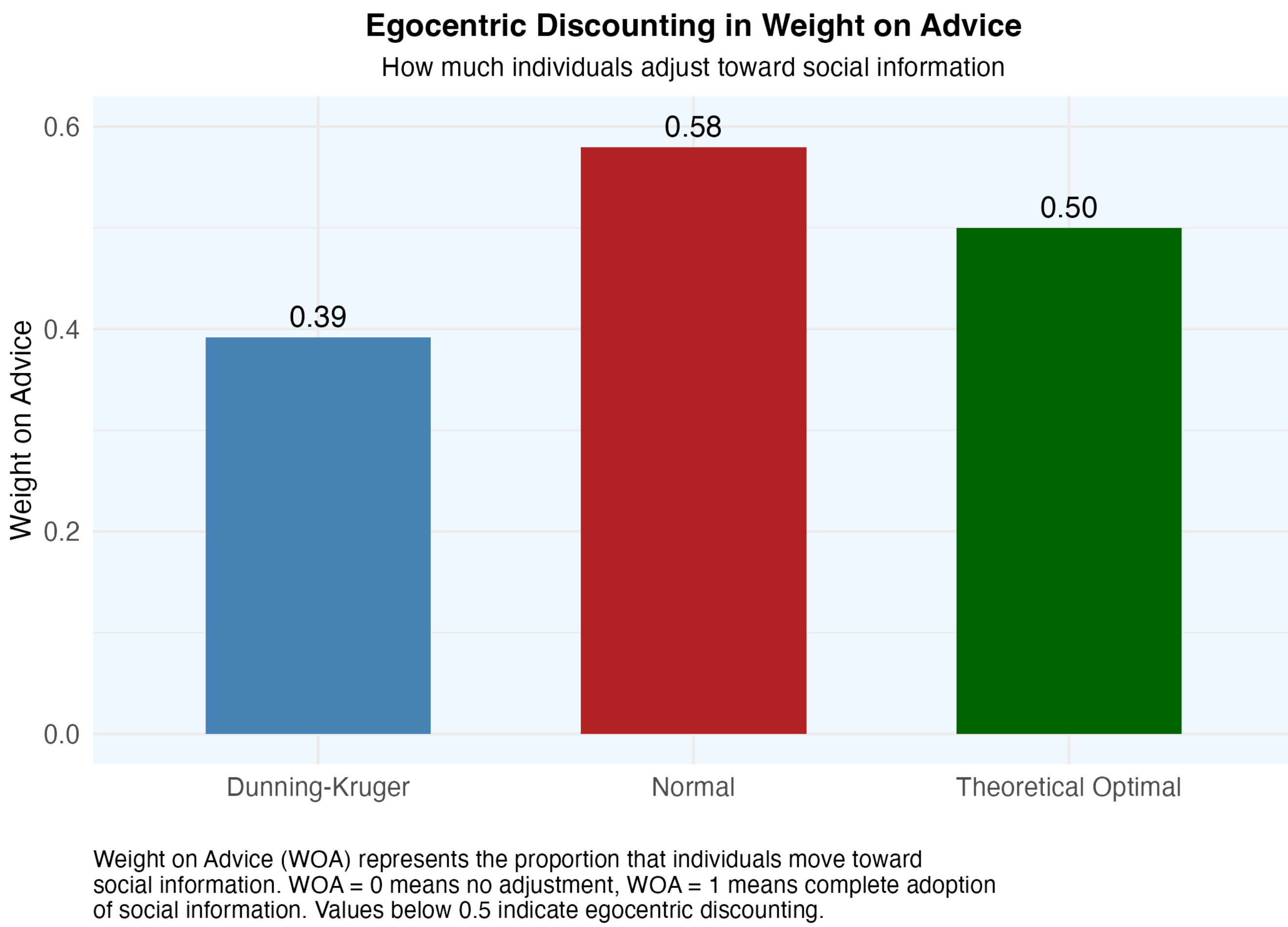


Figure 5

Do groups become more accurate after social influence?

Social influence does not improve the already accurate group mean, the averages of first and second estimates are extremely close. Our results do show that both simple and Dunning-Kruger confidence calculations lead to individual accuracy improvements, with the Dunning-Kruger effect significantly reducing benefits from social influence. Additionally, individual estimates always improve through social influence across all simulated trials.

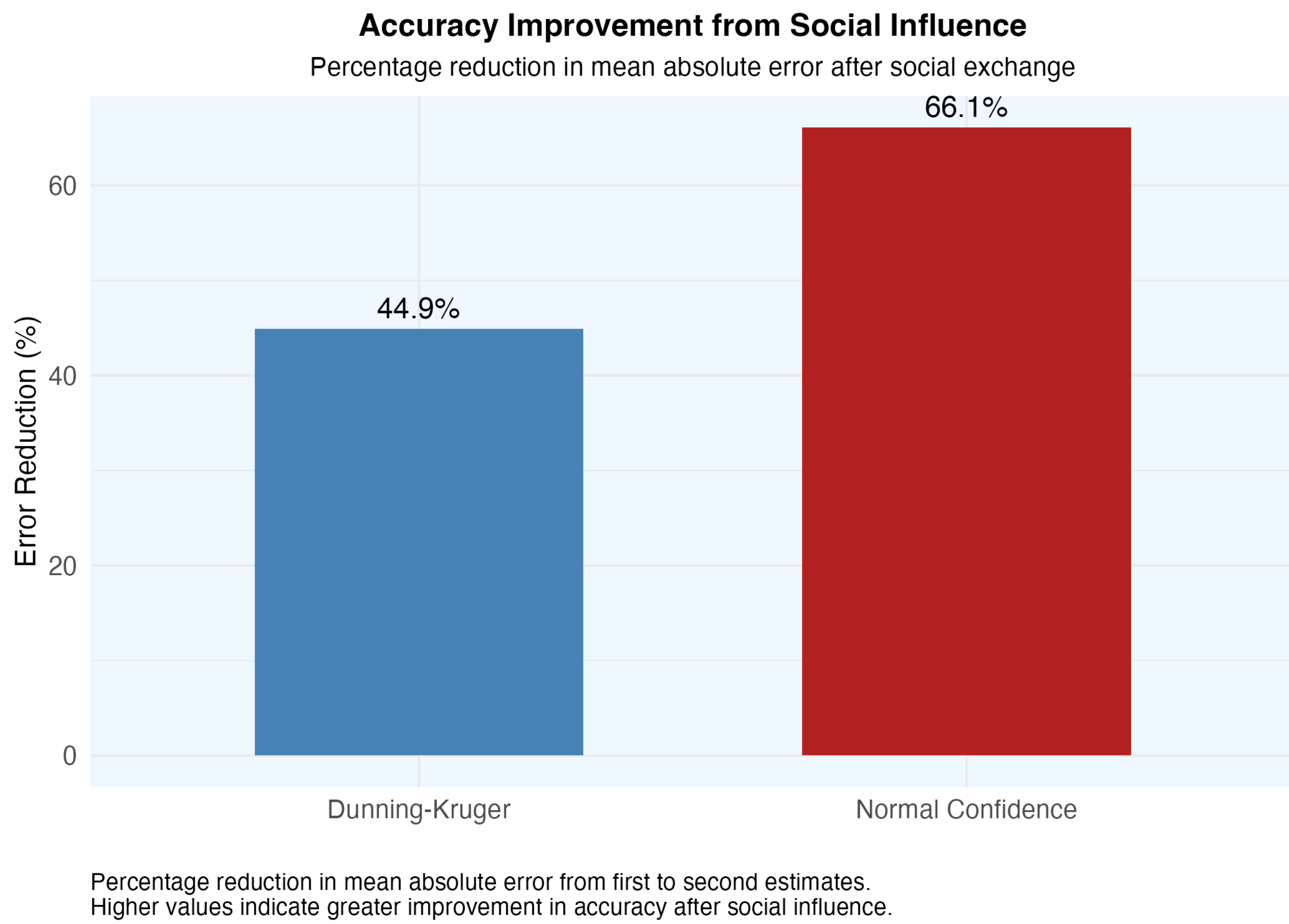
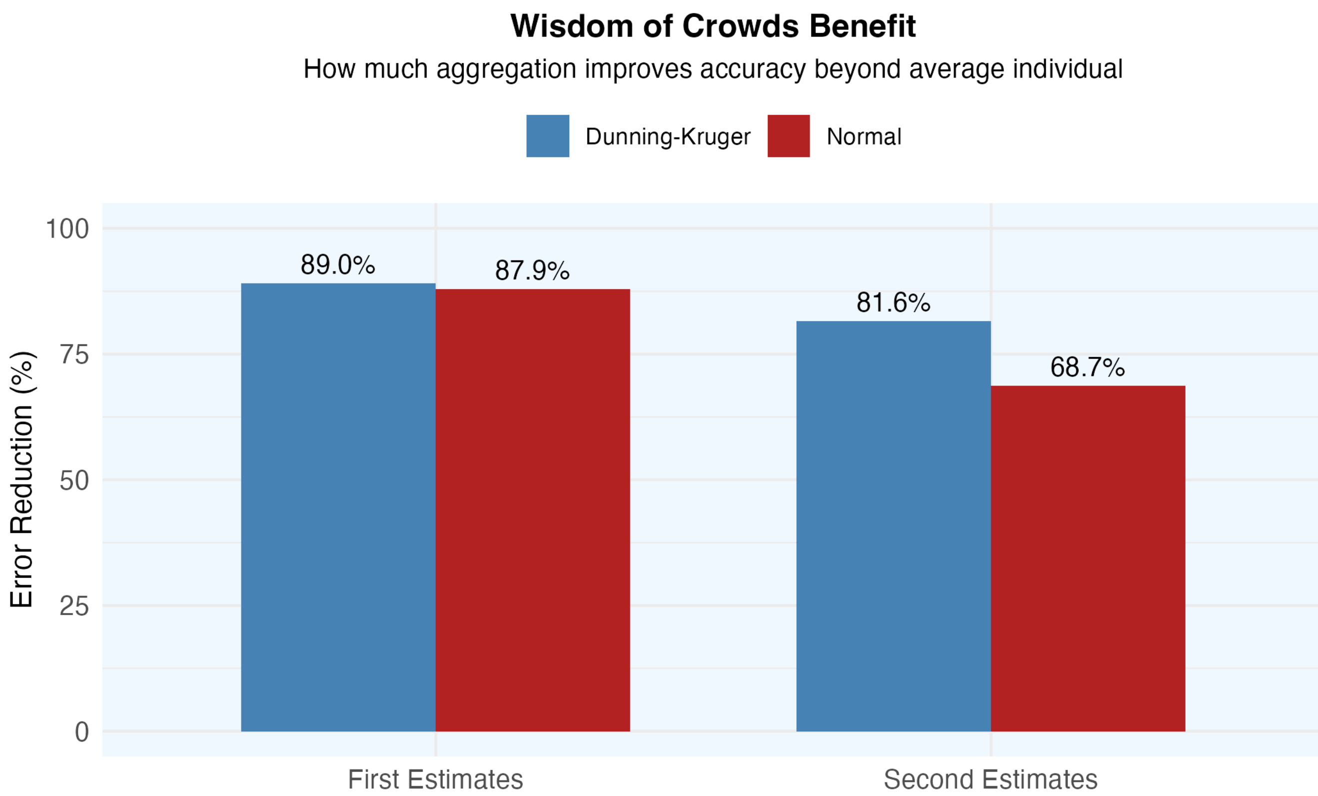


Figure 6

Does WOC potency decrease after reception of social information?

Yes, the benefits of the Wisdom of Crowds decrease after social information exchange in both simple and Dunning-Kruger confidence models. This reduction occurs because social influence decreases estimate diversity, weakening error cancellation effects while simultaneously improving individual accuracy. The fact that we see more of a benefit of WOC in the Dunning-Kruger model is explained by the greater diversity preservation that occurs when some individuals (overconfident novices) resist social influence while others (underconfident experts) are influenced more. This heterogeneity in advice integration partially preserves the diversity necessary for error cancellation.



Percentage reduction in error achieved by using the aggregated group estimate instead of the average individual estimate. Higher values indicate stronger Wisdom of Crowds effect. The decline from first to second estimates shows how social influence reduces diversity-driven error cancellation.

Figure 7

Reflection

Even though the literature already had a high degree of formalization, it was still challenging to extract out theoretical elements. We faced the problem of not being clear enough on the phenomenon we wanted to model, whether it was on the individual or on the group level. It would have been simpler to just look at the work of Bailey et al. (2023) and model only the mechanisms behind shifting toward advice, without concerning ourselves with group level accuracy and Wisdom of Crowds. This made our model and our research objective significantly more complex. Nonetheless, it is still rewarding to now have a more comprehensive model and also to be able to find the same egocentric discounting factor in our simulated data, with the Dunning-Kruger effect implemented.

It was very unexpected just how many tiny decisions go into formalizing a theory, how many additional assumptions need to be agreed upon and how these seemingly small decisions can lead to vastly different outcomes. The fact that formalization feels so overwhelming also goes to show how real-world studies have immense degrees of freedom, which can easily lead to different results, depending on methods, frameworks and measures used. We also found different effects in the literature, for example the reactance effect of high distance, which was not found by all papers surveyed.

Our group discussed a lot about how to properly integrate distance, confidence and in the beginning even other factors into a weight of advice calculation. It was challenging to find functions in this multi-dimensional space, which fit all the criteria and which everyone was happy with. Even though the VAST Model was helpful initially as a tool to organize our thinking, we found it more and more limiting as time went on. At times we stopped thinking about the actual phenomenon and just treated the VAST framework as a ground truth, which artificially limited our creativity and ability to connect the dots. All things considered though, formalizing a complex phenomenon like this has been a challenging but also very enlightening endeavor.

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Appendix A

Construct Source Table

ID	**Type** (**P**henomenon, **C**oncept, **R**elationship)	**Short Name**	**Quote**	**Reference**	**Relationship-Type** (n, p, i, r, c, …)	**Comment** (e.g., identified gaps or inconsistencies)	**Include?** (Y/N) (+ Extension)
WOC1	P	wisdom of crowds	Galton's original work (10) on estimation tasks shows that the median of indepen-dent estimates of a quantity can be impressively close to its true value. This phenomenon has been popularized as the wisdom of crowds (WOC) effect (11), and it is generally used to measure a group's performance.	(Jayles et al., 2017, p.1)	n	*Warum der Median? Nicht auch das arithmetische oder geometrische Mittel?)* *Was heißt "impressively close"?*	
WOC2	P	wisdom of crowds	Since then, collective estimations, computed as mean, median or geometric mean values of the group, have been shown to improve upon the estimations of most individuals of a group in several different contexts, an effect popularly known as wisdom of crowds (WOC)	(Madirolas & De Polavieja, 2015, p.2)	n	*Belegt, dass WOC nicht nur durch den Median zustande kommen kann, sondern auch durch das arithmetische oder geometrische Mittel*	
WOC3	P/C	wisdom of crowds	Cognitive diversity is the key ingredient for aggregation schemes such as majority rule and averaging to outperform most individuals (Clemen, 1989, p. 2008)—a phenomenon popularly	(Rader et al., 2017, p.8)	n	*Cognitive Diversity als inhaltliche Erklärung für WOC (über Diversität der Schätzungen)*	

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			called "the wisdom of crowds" (Suroweicki, 2004).				
SINFL1	P	social influence	Social interactions can have an additional negative effect in biased crowds [8, 9]. When individuals learn the estimations of the other members of the group, they typically change their own estimation towards the more common values. After social influence, the collective has thus a distribution of estimations more strongly peaked around the biased solution. This can give the collective perception of an agreement but the value agreed upon can be far from the truth [9].	(Madirolas & De Polavieja, 2015, p.2)	p	*Liefert Erwartungen für die Simulation: Prinzipiell sollte sich die Diversität verringern und dadurch die Distribution zuspitzen. Das macht Gruppen, in denen viele Mitglieder in derselben Richtung falsch liegen (bias), noch schlechter.*	
JAS1	C	JAS paradigm	The current meta-analysis synthesises studies using the judge–advisor system (JAS) paradigm (Sniezek & Buckley, 1995), which is the most commonly applied measure of advice-taking. In this paradigm, the judge is asked to provide a numerical estimate (e.g., distance between two cities) before receiving an advisor's (or advisors') estimate(s). Then the judge is invited to revise their estimate, and sometimes an incentive is provided for accuracy.	(Bailey et al., 2022, p.1)	n		
FE1	P	first estimates	Previous works have shown that distributions of independent	(Jayles et		*Beschreibt die individuelle Verteilung von FE einer*	

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			individual estimates are generally highly right-skewed, while distributions of their common logarithm are much more symmetric (12, 13, 18).	al., 2017, p. 2)		*Person.* *Kein Relationship-Type, da einfach nur eine Eigenschaft der dFE-Verteilung im VAST-Display.*	
FE2	C	first estimates	This is because humans think in terms of orders of magnitude, especially when large quantities are involved, which makes the logarithmic scale more natural to represent human estimates (20).	(Jayles et al., 2017, p. 2)	c	*Erklärt die individuelle Verteilung von FE einer Person.*	
WOA1	P	weight on advice	The natural way for humans to aggregate estimates is to use the median (22) or the geometric mean (18), which both tend to reduce the effect of outliers.	(Jayles et al., 2017, p. 3)		*Kein Relationship-Type, weil es lediglich eine Berechnungsformel ist.*	
WOA2	C	weight on advice	Agreement among advisors is viewed as indication of accuracy rather than possible shared error	(Rader et al., 2017, p.5)	p	*Könnte Verhalten unter full information condition erklären (agreement als Indikator für advice quality).*	(Extension 1)
WOA3	C	weight on advice	This suggests that expert advice is valued more highly than novice advice, perhaps due to an expectation of it being high quality and leading to an improvement in performance. We included descriptions of the advisor that suggest advice quality as a task characteristic that was not previously specified as an input factor in the JAS IPO model	(Bailey et al., 2022, p.3)	p		(Extension 1)

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WOA4	C	weight on advice	The most significant predictor of advice-taking was information about the advisor suggesting the potential quality of the advice.	(Bailey et al., 2022, p.21)	p		(Extension 1)
WOA5	R	weight on advice	It may also suggest that the judge perceives that their own knowledge of the estimate is uncertain and potentially reduced relative to the knowledge of the advisor, and this in turn may increase advice-taking (Gino & Moore, 2007; Yaniv & Kleinberger, 2000; Yaniv, 2004a, b). This type of knowledge comparison may occur more frequently when judges do not have information about the advisor that suggests the potential quality of the advice.	(Bailey et al., 2022, p.22)	p		
WOA6	C	weight on advice	As discussed above, each individual's social influence weight in the network is determined in part by their self-weight, so that individuals who place more weight on their own estimate are also more influential in the collective estimate.	(Becker et al., 2017, p.5073)	p		
WOA7	C	weight on advice	We find that the subjects' behavioral reactions are highly consistent, reflecting robust differences in personality or general knowledge: in each session, according to the way that subjects modified their estimates on average in the first 24 questions, we split the subjects into three subgroups.	(Jayles et al., 2017, p. 3)	p		

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SINFO1	R	social information	We expect a deterioration of the collective performance and accuracy as V moves too far away from zero and as a greater amount of incor-rect information is delivered to the group (by increasing ρ)	(Jayles et al., 2017, p. 5)	p	*Kein direkter Link im VAST-Display, aber Erwartung über den Einfluss von Social Information auf die Group Accuracy.*	
PK1	C	prior knowledge	Indeed, human groups are often composed of individuals with heterogeneous expertise; [...]	(Jayles et al., 2017, p. 2)		*Verdeutlicht, dass Personen in der Gruppe unterschiedliches Vorwissen bei einer Schätzaufgabe haben.* *Kein Relationship-Type, da einfach nur eine Eigenschaft der Prior-Knowledge-Verteilung im VAST-Display.*	
PK2	C	prior knowledge	A second and complementary explanation of individuality is that individuals have different levels of expertise on the subject or even in general exercises of estimation. This level of expertise is probably not high enough for the individuals to declare it, but it would be enough to act upon it when confronted with social influence.	(Madirolas & De Polavieja, 2015, p.12)	c		
PK3	P/C	prior knowledge	We have here proposed to extract information from the collective using those individuals resisting social influence. The methods proposed extract the information a collective considers of high private quality. We obtained better	(Madirolas & De Polavieja, 2015, p.12)	p, c		

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			collective estimations than the 'wisdom of crowds' [1–9] using the data from [9], especially for cases in which the crowd shows a very large bias. The methods work because resistance to social influence correlates with closeness to the true value. The correlation does not need to be very strong, that is, we do not need experts [10–12]. Instead, we use the geometric mean of those individuals that get influenced less by social information and this group can still show a large standard deviation.				
CONF1	P	confidence	In weighting opinions, people rely on cues to an advisor's accuracy. They take more advice from advisors who are more confident (Soll & Larrick, 2009), experienced (Harvey & Fischer, 1997), accomplished (Yaniv, 2004), and trusted (Sniezek & Van Swol, 2001) and less advice when they themselves are more confident (Gino & Moore, 2007).	(Rader et al., 2017, p.3)	p	*Verdeutlicht den Zusammenhang zwischen Confidence und Social Weight.*	
CONF2	P	confidence	Given previous evidence for a negative association between confidence and advice-taking (Bonaccio & Dalal, 2006), it is also possible that an uncertain estimate reduces the judge's confidence which in turn increases advice-taking.	(Bailey et al., 2022, p.22)	p		

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CONF3	C	confidence	Resistance to social information may be viewed as a behavioral measure of confidence, and the estimation of those resisting social influence as 'wisdom of the confident'.	(Madirolas & De Polavieja, 2015, p.10)	n, t		
D1	C	deviation	Our results show that the subjects' reaction to social influence is heterogeneous and depends on the distance between personal and group opinion.	(Jayles et al., 2017, p. 2)	p		
D2	R	deviation	The farther away the social information M is from a subject's personal estimate Xp, the more likely the latter is to trust the group as S increases.	(Jayles et al., 2017, p. 3)	p		
D3				Becker			
D4	P	deviation	People also shift less toward advice in close agreement with their initial opinion (Ecken & Pibernik, 2016; Schultze et al., 2015) than toward moderate advice, perhaps because near advice makes little difference for improving accuracy.	(Rader et al., 2017, p.3)	p		
D5	R	deviation	Near advice nevertheless has impact by engendering increased confidence (Schultze et al., 2015).	(Rader et al., 2017, p.4)	p		
D6	P	deviation	Although people often ignore far advice (Ecken & Pibernik, 2016;	(Rader et al., 2017,	p		(Extension 2)

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			Schultze, Rakotoarisoa, & Schulz-Hardt, 2015; Yaniv, 2004), they do so at their own peril (Yaniv & Milyavsky, 2007).	p.4)			
REV2	R	revision coefficient	Before social influence, keeping leads to the best accuracy, while adopting and overreacting behaviors are associated with the worst accuracy. However, as more reliable information is indirectly provided by the experts, and in particular for ρ ≥ 40 %, adopting and overreacting lead to the best accuracy after social influence (14, 19). The contradicting behavior is the only one for which the accuracy is deteriorating after social influence. Finally, compromising leads to a systematic improvement of the accuracy as the percentage of experts increases (better than keeping for ρ ≥ 40 %), very similar to that of the whole group. (p.4-5)	(Jayles et al., 2017, p. 4-5)		*Kein Relationship-Type, da es sich nur um eine Erklärung für den Einfluss unterschiedlicher Social Weight Verteilungen in einer Gruppe auf die Group Accuracy in Abhängigkeit von der Güte der sozialen Information handelt.*	
REV3	C	revision coefficient	In addition, more expert advice seekers can use the content of the advice itself to judge its accuracy and the ability of the advice giver	(Rader et al., 2017, p.9)		*Kein Relationship-Type, da es einfach nur erklären könnte, warum Personen mit gutem Vorwissen auch bei ferner SI auf ihr erstes Urteil vertrauen.*	
REV4	P/C	revision coefficient	The results (Fig. 2) show that initially accurate individuals made smaller revisions to their	(Becker et al., 2017, p.5073)	p		

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			estimates, whereas initially inaccurate individuals made larger revisions. Consistent with the DeGroot model, one explanation for this revision pattern is that individuals who were more accurate had greater self-weight in their revisions than individuals who were less accurate.				
REV5	C	revision coefficient	To control for this potentially confounding effect [i.e., deviation as explanation of correlation btw. accuracy and revision], we measured the partial correlation between error and revision magnitude, while holding constant the distance between the subject's initial estimate and the initial neighborhood estimate. Inset in Fig. 2 shows that, even with this statistical control, more accurate individuals still made smaller revisions to their estimates than less accurate individuals (n = 4,340 estimates by 1,040 subjects, ρ = 0.25, 95% CI [0.22, 0.28], P < 0.001, analysis of covariance). This result suggests that accurate individuals placed more weight on their own estimates and less weight on social information (SI Appendix). By contrast, less inaccurate individuals had a lower self-weight and were more influenced by	(Becker et al., 2017, p.5073)	n, p		

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			social information. For clarity, we refer to this partial correlation between accuracy and self-weight as the revision coefficient.				
REV6	C	revision coefficient	When considered in the context of our theoretical model, the correlation shown in Fig. 2 indicates that more accurate individuals had a larger social influence weight in the network, which can pull the group estimate toward a more accurate mean (SI Appendix). These analyses suggest a direct positive relationship between the average revision coefficient among the members of a group and the expected improvement in the accuracy of the group mean. [...] Fig. 3A indicates that, in decentralized networks, the greater the correlation between individual accuracy and self-weight, the more likely it is that the group mean will improve.	(Becker et al., 2017, p.5073)	p		
REV7	C	revision coefficient	Because this sum includes the subject's self-weight, each subject's influence in the collective estimation process is determined in part by how heavily they weight their own opinion compared with the social information they receive. This concept of social influence weight comes from the properties of the DeGroot model,	(Becker et al., 2017, p.5071)	p		

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			in which members of a population revise their estimates indefinitely according to the process above. Through this revision process, the DeGroot model predicts that, in a wide range of network structures, all members of the population will asymptotically converge on a single shared estimate (19). The collective estimate after social influence is a weighted mean of the initial independent estimates (20). Each individual's social influence weight is defined by the size of the contribution that their initial (independent) estimate makes to the final collective estimate (20). The relationship between selfweight and social influence weight reflects the fact that when a subject places more weight on their own individual belief, they adjust their belief less in response to others, and thereby contribute more weight to the group estimate (20).				
EGO1	P	egocentric discounting	A robust finding from studies using the judge–advisor paradigm with quantity estimates is egocentric discounting—the tendency to favor one's own opinions over those of others (Harvey & Fischer, 1997; Yaniv & Kleinberger, 2000). The weight on advice (WOA) is typically	(Rader et al., 2017, p.3)	n		

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			measured as the proportional shift toward another's opinion. Mean WOA is typically around 20% to 40%, which falls short of the 50% needed for ego-neutral equal weighting.				
EGO2	P	egocentric discount	We find that the median of S is 0.34, in agreement with previous results (15, 18, 25), meaning that individuals tend to give more weight to their own opinion than to information coming from others (14, 19).	(Jayles et al., 2017, p. 3)	n		
EGO3	R	egocentric discount	In part, people may discount advice because the reasons for their own answers are better understood or because they overestimate their own abilities (Harvey & Harries, 2004; Minson et al., 2011; Yaniv & Kleinberger, 2000).	(Rader et al., 2017, p.4)	c		
EGO4	R	egocentric discount	Consistent with this, many people hold a misperception that averaging equals average performance, endorsing aphorisms such as "compromise leads to mediocrity" (Larrick & Soll, 2006; Mannes, Soll, & Larrick, 2014). Thus, when it comes to weight on advice, people's lay theories of how to increase their accuracy often do not optimize these benefits in reality.	(Rader et al., 2017, p.5)	c		

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EGO5	C	egocentric discount	Taking advice can threaten the self-concept by undermining perceived autonomy and evoking concerns about self-presentation (Brooks et al., 2015; Brown & Levinson, 1987; Tost et al., 2012). This need to maintain the self-concept may be one of the main reasons people dislike unsolicited advice (Goldsmith, 2004) and egocentrically discount advice.	(Rader et al., 2017, p.12)	c		
EGO6	C	egocentric discount	The informational asymmetry account suggests that egocentric discounting occurs because people have greater access to their own reasons for a judgment relative to the reasoning behind another person's judgment (Yaniv, 2004b; although see Trouche et al., 2018). This assumption is supported by evidence for increased advice-taking when self-reported knowledge is low (Duan et al., 2021; Yaniv & Choshen-Hillel, 2012) or the decision is difficult (Gino & Moore, 2007).	(Bailey et al., 2022, p.3)		*Kein Relationship-Type, da es einfach eine Erklärung für Egocentric Discounting ist.*	
DK1	P	novice overconfidence	"Participants scoring in the bottom quartile on tests of humor, grammar, and logic grossly overestimated their test performance and ability. Although their test scores put them in the 12th percentile, they estimated themselves to be in the 62nd."	(Kruger & Dunning, 1999, p. 1)	p	*Direct evidence for our function's large positive gap between confidence and competence at low knowledge levels (PK≈0.324 maps to confidence≈0.62, PK=0.324 -> 12 percentile for specific truncnorm used)*	Extension 3
DK2	P	expert	"As Figure 1 illustrates, participants in other quartiles did	(Kruger &	p	*Direct evidence for our function's slight negative gap*	Extension 3

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		underconfidence	not overestimate their ability to the same degree. Indeed, those in the top quartile actually underestimated their ability relative to their peers, paired t(15) = -2.20, p < .05."	Dunning, 1999, p. 33)		*between confidence and competence at high knowledge levels (PK≈0.692 maps to confidence≈0.75, below identity line).*	
DK3	C	metacognitive skills	"In essence, we argue that the skills that engender competence in a particular domain are often the very same skills necessary to evaluate competence in that domain—one's own or anyone else's. Because of this, incompetent individuals lack what cognitive psychologists variously term metacognition, metamemory, metacomprehension, or self-monitoring skills."	(Kruger & Dunning, 1999, p. 30)	c	*Conceptual explanation for why the confidence-competence relationship follows this pattern. Low-knowledge individuals can't accurately assess their own abilities.*	Extension 3

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Variable Table

Construct	Short Name	Scale Level	Range/ Values	Anchors	Distribution	Formulas/Parameter-Anchors
Distribution of prior knowledge in the group	GPK	continuous	[0, 1]	Für eine Realisation pk gilt: 0 = kein Vorwissen 1 = Absoluter Experte	truncnorm(n, a=0 b=1, mean = μ, sd = 1) wobei μ für das erwartete Vorwissen in der Gruppe steht und in der Simulation variiert wird	
A person's prior knowledge regarding the estimation task	PK	continuous	[0,1]	0 = kein Vorwissen 1 = Absoluter Experte	Keine Verteilung	
Individual Confidence in First Estimate	CONF	continuous	[0,1]	0 = Kein Vertrauen in die eigene Schätzung 1 = Totales Vertrauen in die eigene Schätzung	Keine Verteilung	Simple Case: CONF = PK Dunning-Kurger: Uses cubic polynomial: $a + bPK + cPK^2 + d*PK^3$ with coefficients a=0.4, b=1.0, c=-1.2, d=0.7 Calibrated to match key percentile points from original study Low knowledge individuals (bottom quartile) overestimate their abilities High knowledge individuals (top quartile) slightly underestimate their abilities

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						Function transforms actual knowledge (PK) into perceived knowledge
Individual Distribution of independent First Estimates of a quantity	IFE	continuous (da eine quantity geschätzt wird)	(-Inf, +Inf)	Keine Anker, weil numerische Schätzung	IFE ~ Lognormal(μ, σ) $\mu = \ln(T) - \sigma^2/2$ Für PK = 0 ist σ = 1 und für PK = 1 ist σ = 0.05 σ = -0,95 * PK + 1	Orientierung an Jayles für PK = 0 und aufgrund fehlender Literatur haben wir für uns plausible Werte bei PK = 1 angenommen Lognormalverteilung (siehe Madirolas, Jayles)
Distribution of independent First Estimates in the Group	GFE	continuous (da eine quantity geschätzt wird)	(-Inf, +Inf)	Keine Anker, weil numerische Schätzung	Calculated via first estimates	
Social Information a person receives	SI	continuous	(-Inf, +Inf)	Keine Anker, weil numerische Schätzung	Keine Verteilung	mean of i-1 first estimates, where i is the index of the person receiving the social information
Individual Distribution of revised second estimate of a quantity	ISE	continuous	(0, +Inf)	Keine Anker, weil numerische Schätzung	truncnorm(n, a=0, mean = μ, sd = 1)	IFE *realisiert sich für eine Person in* ife μ = WOA * SI + (1 - WOA) * ife (aus Jayles, Madirolas)
Distribution of Second Estimates in the Group	GSE	continuous	(-Inf, +Inf)	Keine Anker, weil numerische Schätzung	Calculated via first estimates	
Weight of Advice	WOA	continuous	[0,1]	0 = Bleiben bei erster Schätzung 1 = Übernehmen der sozialen Information	Keine Verteilung	The log-based distance creates a symmetrical measure that treats ratios equivalently (e.g., SI being double or half the first estimate). The hyperbolic

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						tangent (tanh) function smoothly scales the influence of divergent estimates, approaching but never quite reaching its maximum for extremely different values. Low confidence (close to 0) leads to high weight of advice, near 1 High confidence (close to 1) results in minimal influence, even for divergent estimates As distance increases, weight increases but plateaus, preventing complete adoption for high-confidence individuals When estimates match exactly (distance = 0), weight equals 1 - confidence
True Value	T	continuous	(-Inf, +Inf)	Keine Anker, weil numerische Schätzung	Keine Verteilung	
Collective Accuracy	ACC	continuous	(0, +Inf)	0 = Maximale Accuracy, alle Estimates stimmen mit T überein	Keine Verteilung	mean(abs(c(D1, D2, D3, …))) D = T - FE or T - SE