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)*	

			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.*	
SINFL2	P	social influence	A mean weighting of 48% was evident in response to advice from advisors perceived to provide high quality advice. This is closely approaching Larrick and Soll’s (2006) suggested rational weighting of 50%	(Bailey et al., 2022, p.21)	p		
SINFL3	P	Social influence	The mean weight of advice in response to advisors perceived to provide low quality advice (i.e., 32%) did not differ from the degree of advice-taking from advisors who were described in neutral terms (i.e., 37%). This is consistent with asymmetry of reputation formation over repeated interactions, which in turn is	Bailey et al., 2022, p.21)	p		

			explained by risk aversion theories (Yaniv & Kleinberger, 2000).				
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 individual estimates are generally highly right-skewed, while distributions of their common logarithm are much more symmetric (12, 13, 18).	(Jayles et al., 2017, p. 2)		*Beschreibt die individuelle Verteilung von FE einer 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	(Jayles et al., 2017,		*Kein Relationship-Type, weil es lediglich eine*	

			median (22) or the geometric mean (18), which both tend to reduce the effect of outliers.	p. 3)		*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)
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	(Bailey et al., 2022, p.22)	p		

			the potential quality of the advice.				
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		
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 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.	(Madirolas & De Polavieja, 2015, p.12)	p, c		
CONF1	P	confidence	In weighting opinions, people rely on cues to an advisor's accuracy.	(Rader et	p	*Verdeutlicht den Zusammenhang zwischen*	

			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).	al., 2017, p.3)		*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		
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; Schultze, Rakotoarisoa, & Schulz-Hardt, 2015; Yaniv, 2004), they do so at their own peril (Yaniv & Milyavsky, 2007).	(Rader et al., 2017, p.4)	p		(Extension 2)
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 $\rho \geq 40$ %, 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,	(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.*	

			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)				
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 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.	(Becker et al., 2017, p.5073)	p		
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	(Becker et al., 2017, p.5073)	n, p		

			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 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	(Becker et al., 2017, p.5073)	p		

			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.				
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, 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	(Becker et al., 2017, p.5071)	p		

			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 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.	(Rader et al., 2017, p.3)	n		
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	(Rader et al., 2017, p.4)	c		

			(Harvey & Harries, 2004; Minson et al., 2011; Yaniv & Kleinberger, 2000).				
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		
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-	(Bailey et al., 2022, p.3)		*Kein Relationship-Type, da es einfach eine Erklärung für Egocentric Discounting ist.*	

			reported knowledge is low (Duan et al., 2021; Yaniv & Choshen-Hillel, 2012) or the decision is difficult (Gino & Moore, 2007).				