**The Robust Benefits of Social Exchange for the Wisdom of Individuals in the Crowd**

**Abstract.** The accuracy of group beliefs measured as the average (“crowd”) numeric estimate can sometimes benefit from conversation and information exchange, but the process must be carefully managed to prevent herding and related behavior—it is generally better to keep people independent. Importantly, individuals are not the average, and it is possible for group members to become more accurate even while the crowd estimate becomes less accurate. Thus while decisions where the crowd belief really matters (e.g., a vote) might be highly sensitive to social processes, the benefits of social learning may be more robust for situations where individuals come together to share opinions but then make decisions independently. In contrast with the fragility of group accuracy, I show that social exchange nearly always benefits individuals in a crowd even when it simultaneously reduces group-level accuracy. I examine two theoretical models and reanalyze previously published experimental data to show that individuals can and usually do become more accurate, even as their groups become less accurate.

# 1. Introduction

A central question in research on numeric belief accuracy is whether and when communication between individuals improves accuracy or increases error. This question has become a particularly popular topic of research in recent years (Almaatouq, Noriega-Campero, et al. 2020, Atanasov et al. 2017, Becker et al. 2017, 2021, Da and Huang 2020, Minson et al. 2018) following growing interest in the “wisdom of crowds” (Page 2007, Surowiecki 2004). However, nearly a century of research (for much older examples see e.g. Jenness 1932, Sherif 1935) has produced a plethora of often contradictory experimental evidence, sometimes showing that social exchange improves accuracy and sometimes showing that it decreases accuracy (see Hastie 1986 for a partial review). This research thus generates a picture of groups as a highly fragile system: communication can improve numeric belief accuracy, but only when it is carefully structured and mediated as in the highly popular “Delphi Method” (Dalkey and Helmer 1963).

Critically, however, this research focuses on the accuracy of the average belief in a group, not the average accuracy of the individuals in that group (e.g. Almaatouq, Rahimian, et al. 2020, Atanasov et al. 2017, Becker et al. 2017, Da and Huang 2020, Gigone and Hastie 1997, Gustafson et al. 1973, Jenness 1932). Despite the practical value of group averages, decisions are of course often made by individuals—who perhaps can benefit from the wisdom of the crowd through social learning before ultimately making their own independent decisions. Thus the important question in many practical contexts is not how communication impacts the wisdom of the crowd, but how such exchange impacts the wisdom of individuals in the crowd—i.e., whether and when individuals can learn from the crowd. Mathematically speaking, it is entirely possible for the group to become less accurate even as individuals within the group, on average, become more accurate.

In the context of this popular focus on crowd accuracy, the present paper asks: how does social exchange shape individual accuracy? While some empirical evidence already suggests that social exchange can improve individual accuracy under pristine conditions that also improve group accuracy, this paper examines the robustness of this effect. Specifically, I study two theoretical models and reanalyze prior experimental data to examine whether individuals can reliably learn from the wisdom of the crowd, even under conditions that reduce crowd accuracy.

## Social Exchange, Crowd Wisdom, and Belief Accuracy

Research on belief accuracy all generally follows the same methodological paradigm: subjects generate numeric estimates such as the count of candies in a jar or some economic forecast, then engage in some social process such as a conversation or written numeric exchange, and finally provide the estimate a second time. This paradigm has been in use for nearly a century (Jenness 1932, Sherif 1935) becoming popular in the mid-20th century (e.g. Dalkey and Helmer 1963, Gustafson et al. 1973, Ven and Delbecq 1974) and continuing recently (see e.g. Atanasov et al. 2017, Becker et al. 2021, Da and Huang 2020, Frey and van de Rijt 2020, Mannes 2009, Palley and Soll 2019).

Concern about the fragility of belief accuracy is popular because it is intuitive. Interaction can genuinely undermine group processes (Kerr and Tindale 2004) such as brainstorming, where people often perform better when working independently (Diehl and Stroebe 1991). In committee decision-making, normative pressure to conform can generate “groupthink” wherein individuals suppress information that disagrees with established consensus, leading groups to produce decisions based on inaccurate beliefs where individuals might independently make have made better choices (Janis 1982). Even the simple act of making decisions publicly observable can lead to “herding” in decisions where beliefs determine subsequent information gathering, generating detrimental feedback processes (Banerjee 1992, Frey and van de Rijt 2020).

Where verbal theorizing offers limited insight or even misleading conclusions, formal theoretical models can help to clarify expectations and test intuitive hypotheses. By combining formal theoretical arguments with empirical data, research has begun to offer a clear picture of how social exchange shapes belief accuracy. Fortunately, models of numeric opinion exchange can be readily quantified (Becker et al. 2020, 2021, DeGroot 1974, Golub and Jackson 2010).

Importantly, the trajectory of individual accuracy can be de-coupled from the trajectory of group accuracy. Consider for example one seminal paper (Lorenz et al. 2011) showing some of the risks associated with group communication. Subsequent reanalysis of their data found that, despite the risks to the group as a whole, individuals in the study received greater monetary compensation when working together than when working independently (Farrell 2011). However, this study engaged people under relatively ‘pristine’ conditions: decentralized networks where everyone was equally influential and could communicate only by sharing numbers, rather than engaging in free conversation—precisely those conditions expected to minimize risks (Becker et al. 2017, 2020, Golub and Jackson 2010). The present paper thus seeks to determine whether Farrel’s (2011) analysis represents the exception or the rule. Just how hard is it for individuals to learn from crowd wisdom?

## Proof of Principle.

For such ‘pristine’ conditions as analyzed by Farrel (2011), individual improvement is nearly guaranteed. To see this, first note that DeGroot (1974) showed formally that groups embedded in decentralized social networks (where everyone is equally influential) will converge on the simple mean of pre-discussion beliefs. Second, note that when groups converge on the mean belief as a result of social exchange (such that the mean belief itself is unchanged) then individuals are statistically guaranteed to improve on average. To see why, consider the “crowd beats averages law” (Page 2007). This law mathematically guarantees that the error of the group average is lower than the error of an average individual—the basis for the wisdom of crowds. (The equation proving this result is formally comparable to the “variance bias tradeoff” in mathematical statistics.) Thus, any process leading to convergence around the mean will necessarily reduce individual error!

Importantly, prior empirical analyses and this theoretical statement consider the effect of social exchange under relatively pristine conditions. Lorenz et al.’s (2011) experiment is comparable to the “Delphi method” specifically designed to improve accuracy (Dalkey and Helmer 1963). A similar result was reported by Gurcay et al.’s (2015), where groups had discussions in a controlled text-based environment. These conditions ensured that all participants were equally influential, leading the group to converge on the mean of pre-discussion beliefs. (Lorenz at al showed risks associated with communication but they were in where beliefs “bracketed” the truth—they found null results regarding outcomes for the group average.)

Even outside such pristine conditions, this simple principle underlies the results presented in this paper. Suppose there is some social process that causes the average belief to become less accurate. When the crowd estimate is expected to hold a large accuracy benefit compared to individuals, and the change in crowd error is small relative to this benefit, then the individuals will become more accurate even as the group becomes less accurate. This condition can be stated formally: let δ be the distance between the average individual error and the crowd error prior to conversation (i.e. the amount individuals would improve if they converged on the pre-discussion mean); and let ω be the distance between in pre-conversation and post-conversation crowd error (i.e. the amount by which the crowd gets worse); finally, assume that post-conversation variance is zero i.e. individuals reach consensus. Then, whenever ω<δ, then the group average will become less accurate even as individuals become more accurate.

**2. General Analysis**

Notably, ‘reaching consensus’ is an implausible simplifying assumption, and ω generally cannot be known in advance—thus while this formal statement demonstrates the intuition behind this paper, it is not in itself sufficient to determine whether communication will help or harm individuals in a crowd. The goal of the present work is to assess when individual improvement is likely to occur under empirically plausible conditions—i.e. just how robust are the benefits of social learning for individuals in the crowd. This paper presents the results of three analyses: two theoretical analyses and one empirical re-analysis of prior experimental data.

The first theoretical analysis adopts a simple and widely studied “opinion exchange” model (DeGroot 1974) in which individuals in a network can observe the opinions—i.e., the numeric estimates—of their network peers. Importantly, however people in practice exchange more than numbers—they exchange detailed information. Thus to increase generalizability I also study a second model representing information exchange. I adapt a model by Mann & Helbing (2017) where people receive “signals” that are informative of the thing to be estimated.

I study both theoretical models by simulating networks of N=50 nodes, with initial beliefs independently, identically distributed (i.i.d.) according to a log-normal distribution with parameters μ=6.68, σ=0.81. These parameters are based on an empirical study by Kao et al (2018) characterizing the shape of numeric estimate distributions, and represent a model estimation task—counting gumballs in a jar with 1,000 gumballs. To test the effect on a range both accurate and inaccurate crowds, I vary the location of the ‘truth’ to produce low or high initial group error. Our results do not depend on these exact parameter configurations.

**2.1. Opinion Exchange Model**

I begin with the DeGroot (1974) model of social exchange, which provides an effective approximation of empirical data (Almaatouq et al. 2022, Almaatouq, Noriega-Campero, et al. 2020, Becker et al. 2021, Friedkin and Bullo 2017). In this model, each individual starts with an independent estimate following some population distribution. Each individual then simultaneously observes the estimate of their peers in a social network. After observing peer estimates, each individual adopts a new opinion equal to a weighted average combining their own initial estimates with peer estimates. Following Becker et al (2017), I follow a simplified model in which each individual places the same amount of weight on all their peers, so that updates are parameterized only by the amount of weight on individual beliefs. This yields the following update rule:

Et+1 = Wself x Et + Wsocial x Epeer

where Wself is the weight each person places on their own initial estimate; Et is their estimate at time t; Wsocial is the weight each person places on their peer beliefs (and is equal to 1-Wself) and Epeer is the average of their peer beliefs.

**2.2. Information Exchange Model**

The DeGroot model, while empirically useful, assumes an anemic form of social exchange which is devoid of information. When people talk, rather than just exchange numbers, other mechanisms emerge which can shape beliefs. To study this possibility theoretically, I consider a simple model of information exchange in which individuals possess informative signals and exchange that information in a network. This model is inspired by theoretical (Mann and Helbing 2017) and empirical research (Pescetelli et al. 2019) on belief formation in which each individual in a population starts with an informative signal about the target being estimated. People then communicate by sharing information with peers in their social network. In this model, each agent begins with a random signal drawn from the distribution defined above. I assume the number of signals to be very large such that each agent starts with a unique signal. Each agent’s estimate is equal to the average of the signals they have observed. (At the initial time step, since they have only one signal, an agent’s estimate is equal to their signal.) At each time step, randomly select an edge in the network connecting two agents. Each Agent shares the chronologically first signal they observed which the other agent does not have.

To illustrate the social exchange process, consider two agents paired up: Agent 1 with signals [75, 105, 90] and Agent 2 with signals [87, 115, 75]. The order of each list indicates the chronological order, such that the first signal Agent 1 observed (their initial signal) is ‘75’. Then when they are paired up, Agent 1 will share the signal ‘105’ and Agent 2 will share the signal ‘ 87’, and each agent will add the newly observed signals to the end of their list.

**2.3. Empirical Analysis**

To support these theoretical results, I re-analyze previously published experimental data on belief accuracy in information exchange networks. I consider data from four sources: Becker et al. 2017, Becker et al. 2019, Gürçay et al. 2015, and Lorenz et al. 2011. I include these sources but not others (e.g. Becker et al. 2020) because they offer control groups who revise with no social influence, allowing me to separate the effects of random movement (especially regression to the mean) from the effects of social information where necessary. These experiments all follow the same basic paradigm described in the literature review: participants answer a numeric question, such as “how many candies are in this photograph” or “what is the budget of the US Department of Defense?” Participants then engage in some kind of information exchange such as discussion or mediated numeric exchange. In three experiments (Becker et al. 2017, 2019, Lorenz et al. 2011) participants were shown simple numeric information about each other’s estimates (as in the Delphi method (Dalkey and Helmer 1963) while in one experiment (Gürçay et al. 2015) subjects interacted through a computer-based text chat interface in open discussion. Each experiment also included an independent control group, in which individuals provided multiple revised estimates over time but without social exchange.

All experiments examined decentralized networks, either in the form of all-to-all networks or sparse networks, but (Becker et al. 2017) also included highly centralized networks of information with one central node and 39 peripheral nodes. In this condition, participants were shown the average of peer estimates, without any information about the network, meaning that everybody saw the central node’s estimate and the central node saw the average of everyone else. I note however that both theoretical and empirical evidence (Almaatouq, Rahimian, et al. 2020, Becker et al. 2020) suggests that discussion groups act as centralized networks, since factors such as talkativeness can make some people more influential and thus more central. I therefore report results for three types of networks: decentralized numeric exchange i.e. Delphi networks (“decentralized”), centralized numeric exchange networks from Becker et al. 2017 (“centralized”), and all-to-all unstructured discussion networks (“discussion”) from Gürçay et al. 2015.

Because the conditions provided by experimental data do not span the breadth of parameters that I study theoretically, I structure the empirical analysis somewhat differently than the theoretical analysis. To simplify the analysis and presentation, the primary results simply divide outcomes based on whether the group became more accurate or not. To test the possibility that some people improved and not others, I also examine how the initially most-accurate individuals fared compared with the initially least accurate. For this secondary analysis, results are strongly impacted by the regression to the mean—people with above-average accuracy in their initial estimates are expected to become less accurate just by random variation. Thus for these analyses, I report all outcomes compared against the independent control group.

For statistical testing, I use t-tests to estimate whether a given process improves accuracy, either testing that a mean is different from zero or testing whether an exchange condition is different from independent estimation. For conditions where I combine data from multiple datasets, I use weighted regression to equally weight each dataset (for one-sample comparisons, the intercept of this regression is equal to a manually weighted mean, just as the intercept of an unweighted regression is equivalent to a simple t-test).

**3. Results**

**3.1. Theoretical Results—Opinion Exchange**

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| Chart  Description automatically generated  ***Figure 1.*** *The effect of correlation (top) and centralization (bottom) on group error (left) and individual error (right) when initial group error is high or low.* |

For opinion exchange, prior research (Becker et al. 2017, Silver et al. 2021) has identified two key factors that can reduce group accuracy: (1) highly central nodes in a network who obtain a disproportionate influence over group beliefs, and (2) a population-level correlation between confidence and error.

I first consider the effects of network centralization by generating networks using a controllable preferential-attachment algorithm (Barabási and Albert 1999). Figure 1 (bottom left and right) shows the effect of social exchange on crowd error (left) and individual error (right) as a function of centralization. For all centralized networks, social exchange increases crowd error, with this effect increasing as centralization increases. At the same time, however, social exchange decreases individual error in all scenarios.

I next consider the effect of a correlation between confidence and accuracy—where people who are more accurate make larger revisions, and people who are less accurate make smaller revisions. Empirical data generally shows a positive correlation between accuracy and confidence (Becker et al. 2017, Laan et al. 2017, Silver et al. 2021) but the goal of this paper is to test the robustness of individual error to even the worst case scenarios. Figure 1 (left side) shows, as expected, that the error/confidence correlation determines the improvement of the mean, as high confidence individuals exert a pulling force and are thus more influential. When confident/influential individuals have high (low) accuracy, the group mean improves (gets worse). This effect is clearest when group error is high, as when error is low, there is no room for improvement (but a positive correlation offers the least risk).

Regardless of the complicated effect of social exchange on group outcomes, I find that individual accuracy generally improves during social exchange, including many cases where the group as a whole gets worse. Figure 1 (right side) shows that when initial group error is small, i.e. where there is “wisdom of crowds” (Galton 1907, Surowiecki 2004) individuals nearly always improve. When group error is high, extremely negative accuracy/confidence correlations (which increase group error) can in fact undermine individual accuracy. However even when there is a moderate negative correlation, sufficient to reduce crowd accuracy, individuals still improve in the high-group-error regime. Thus overall, individual accuracy improves in general conditions apparently consistent with empirical data, but people are not invulnerable: implausibly extreme conditions will reduce individual accuracy.

**3.2. Theoretical Results—Information Exchange**

To test the robustness of standard DeGroot results to alternative model specifications, I examine information exchange under a worst case scenario: highly centralized networks. Analytic consideration of this model suggests that if run to consensus—i.e. until every person holds every piece of information—then final group error will be the same as initial group error. (This occurs because both initial and consensus belief is the simple mean of the all informational signals.) Moreover, similar to the DeGroot model, variance at the end will be zero, as every individual holds identical opinions. Consensus dynamics, however, are not empirically plausible—people do not reach consensus, and communication in practice generally leaves considerable disagreement. Thus I focus the analysis on outcomes for short periods of time on an order of magnitude comparable to experimental data. To illustrate the dynamics of the model, I report the effect of information exchange over time. Figure 2 shows the accuracy over time for signal exchange in highly centralized networks. The main panel shows a close-up of an empirically plausible time period, and the inset shows the model run to consensus.

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| Chart  Description automatically generated  ***Figure 2.*** *The effect of information exchange on group error (left) and individual error (right). Main panel shows short term outcome, inset shows outcomes at consensus.* |

The left panel of Figure 2 shows the error of the crowd (i.e. of the mean belief) as a function of time, as signals spread. As expected for highly centralized networks, the error of the crowd increases (the crowd gets less accurate) as a result of information exchange. This result can be intuitively explained by the fact that prior to any information exchange, when each person has one unique signal, the mean belief of the crowd is equal to the mean of all the independent signals. As people begin to exchange information, however, the signal initially held by the most central nodes become disproportionately popular within the crowd—thus the mean belief of the crowd becomes biased towards the initial signals of the central node. Like individuals, any given signal is, in expectation, less accurate than that of the set as a whole, by the same logic as the crowd beats average law, i.e. the variance bias tradeoff. Thus the group becomes less accurate as it becomes biased towards the signals held by central individuals. As the inset shows, if the model runs until everybody holds every piece of information, crowd error drops eventually to zero, when the group estimate equals the simple mean of all the signals.

In contrast, however, individual error is entirely robust to this bias. The right panel of Figure 2 shows that as signals spread, the average error of individuals decreases monotonically until it reaches zero, even in highly centralized networks. This reliable effect can be explained by considering diffusion from the individual perspective. As an individual, one simply observe’s an increasing number of signals over time. The expected error of an individual’s belief decreases as the number of signals they observe increases, again by the same logic as the crowd beats error law i.e. the variance bias tradeoff (and the way in which the sample error in statistics decreases as the number of observations increase). Thus over time the number of signals observed increases and individual error on average decreases.

**3.3. Empirical Results**

To empirically assess the robustness of individual belief accuracy against the effects of social exchange, I re-analyze previously published experimental data with three primary conditions: numeric opinion exchange in decentralized networks (“decentralized exchange”); exchange in centralized networks (“centralized exchange”); and simple conversation (“open discussion”). While these empirical datasets do not cover the full range of conditions considered in the theoretical models, I do examine cases where the group got worse.

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| Diagram, schematic  Description automatically generated  ***Figure 3.*** *The effect of information exchange on individual accuracy across four experiments (bottom row), analyzed at the overall level (top left) and conditional on the improvement of the group as a whole (top right).* |

I first consider the overall effect of social exchange under the three communication conditions. As shown in Figure 3 (upper left panel) all communication formats (decentralized exchange, centralized exchange, and open discussion) led to reduced error for individuals (P<0.001, all three conditions, see methods). In contrast, an independent estimate-revise-estimate process produced some small nominal improvement, indistinguishable from zero (P>0.21, Fig. 3 upper left). I then consider the effect of social exchange on individual outcomes under “worst case scenarios” by considering just those trials where the group as a whole became less accurate. Figure 3, upper right panel shows the change in individual error, for different communication formats, based on whether the group as a whole improves. Decentralized exchange networks significantly improve even when the group as a whole gets worse (P<0.001). Open discussion and centralized exchange networks both show nominal but insignificant improvement even when groups as a whole get worse (P>0.64, P<0.12). Thus while communication in these worse-case scenarios may not reliably improve outcomes, individuals seem relatively free from risk even when groups get worse.

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| Graphical user interface, diagram  Description automatically generated  ***Figure 4.*** *The effect of information exchange on individual accuracy broken down by initial accuracy (Q1 = top 25% most accurate, Q4 = bottom 25% least accurate).* |

One possible concern about the effect of social exchange on individual accuracy is that, even as individuals on average become more accurate, the very best individuals become less accurate. That is, it may be that average individuals improve but experts are worse off—so people who believe themselves to be above-average may wish to avoid participation in social exchange. To assess this possibility, I divide individuals into quartiles based on their initial accuracy relative to their specific group. Figure 4 shows the average change in individual error broken down by quartile of initial accuracy. For example, bars for Q1 show the change in error for people who had the most accurate initial estimates, averaged across all the trials for a given condition in a given dataset. (A given trial is thus represented four times—once for each quartile.) Higher values indicate worse outcomes (greater increases in error).

With regard to the most accurate people—simply due to the mathematically guaranteed effect of regression to the mean, the best people will get worse and the worst will get better. Thus it is critical for this analysis to compare outcomes against the control condition. In comparing independent to social conditions, I find no clear effect of social exchange on the initially accurate individuals. In two of the four experiments, solo estimators saw worse outcomes while the other half showed that social exchange generated worse outcomes. This uncertainty at the experimental level is also reflected in a summary statistical analysis: neither decentralized exchange (estimate=0.069, se= 0.20, P>0.7), centralized exchange (estimate=-0.02, se=0.03, P>0.41), nor discussion (estimate=0.14, se=0.21, P>0.48) show a significant difference from independent estimation. It’s important to be careful when interpreting a null result. While I cannot reject the alternative hypothesis that social exchange harms those who are initially accurate, I interpret these results to mean that if there is any risk to initially accurate individuals, it is small.

**4. Discussion**

Whereas social interaction is highly risky for the wisdom of the crowd, information exchange nonetheless provides a robust opportunity for individuals to learn from the crowd. Across two theoretical models and four published datasets, I find evidence that social exchange can be helpful to individuals in a wide range of circumstances, even as group accuracy decreases. These findings offer three specific contributions to literature on belief accuracy. First, I draw novel conclusions from a standard theoretical model by analyzing outcomes for individuals under scenarios that make groups get worse. Second, I offer a novel alternative model which shows that the benefits of social exchange for individuals in the crowd are not limited to one specific set of assumptions. Third, paralleling the theoretical analysis, I draw new conclusions from existing experimental data by showing the robust benefits of social influence for the wisdom of individuals in the crowd. Overall, I find that social exchange positively improves accuracy measured at the individual level for empirically plausible conditions. Even considering specific cases where the groups became less accurate, I find that social exchange rarely if ever poses a threat to individuals. While the statistical results were null, I had a relatively large sample size across four studies, so I can reasonably infer that any risk—if it exists—is negligible from a practical perspective. Taken together, this evidence supports the argument that social exchange does not need to be avoided, or carefully managed, in order to minimize risk and maximize the potential for social learning.

**4.1. Limitations and Related Research**

I present an array of evidence on numeric estimates from a wide range of sources, all of which consistently indicate that social exchange is not harmful to individual accuracy, and often beneficial. Nonetheless, I cannot (and would not) argue that social exchange is never harmful. The theoretical analysis shows that some conditions can reduce individual accuracy, and there may yet be additional theoretical conditions that reduce accuracy. Empirical evidence largely supports the robust benefits of social exchange for individuals, but there are many varied forms of human interaction, and these experiments reflect only limited conditions. While the theoretical model shows that extreme negative correlations between accuracy and confidence can sometimes reduce individual accuracy, empirical data of the kind examined here tends to show positive correlations (Laan et al. 2017, Silver et al. 2021). Some of the results are inconclusive: while social exchange does not seem to pose a risk even to the most accurate individuals, I must be cautious in interpreting null results. Importantly, neither the theoretical model nor the empirical data addresses the possibility that some people have demonstrably more expertise than the rest of the group, which may not be fully reflected in the accuracy-based analysis. Further research would be useful to investigate whether special guidelines are necessary for experts, who may have more to lose from bad information but may also be better at filtering quality.

One important scope condition of this research is the focus on numeric accuracy. While I find robust benefits, the effect of social exchange can have unexpected effects on dichotomous decisions, such that group decisions become less accurate even as numeric accuracy increases, a paradox termed the “crowd classification problem” (Becker et al. 2021). This effect is related to research on herding, in which social exchange can undermine accuracy (Frey and van de Rijt 2020) and generate cascades of agreement which distort the relationship between true opinions and expressed opinions (Banerjee 1992). Importantly, these effects can be easily avoided in the context of quantitative accuracy: simply focus attention on quantitative estimates and avoid discussing black-and-white opinions (Becker et al. 2021)—i.e., nuance matters. This recommendation is consistent with the assumptions and scope conditions of the model presented here, which reflects opinion and information exchange.

**4.2. Practical Implications**

When quantitative accuracy matters, this argument has substantial implications for managerial practice, primarily in the form of constraint relaxation. The wisdom of crowds may be fragile, but this research suggests that for individuals in the crowd, social exchange poses minimal risk in most common scenarios and usually offers a great opportunity to learn from the crowd. Thus in a situation such where individual decision-makers must make decisions and recommendations based on their beliefs, it is more meaningful to consider individual error as I do here than the error of the average opinion.

Importantly, this analysis does not indicate that managers and decision-makers don’t need to pay attention at all to how communication happens. Rather, this analysis indicates that communication itself is not inherently risky, and the benefits to individuals are robust to many factors which do in fact pose risks for group level accuracy. For example, discussions in a financial context about topics such as the conditions of a market (as in the information model) or specific valuations (as in the opinion model) can improve individual accuracy even in apparently risky contexts such as centralized influence or poor confidence calibration. While managing communication remains important for group decisions, this analysis gives organizations of individual decision-makers one less thing to worry about.

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