Abstract

We introduce individual bias to the simulation model of exploration and exploitation and examine the joint effects of individual bias and other parameters, aiming to answer two questions: First, whether reducing individual bias can increase organizational objectivity? Second, whether measures, such as increasing organization size, can increase organizational objectivity in the presence of individual bias? Our results show that individual bias has both positive and negative effects, and reducing individual bias may be not beneficial when organization size is large or environment is turbulent. Diverse knowledge resulting from large organization size can help avoid the negative effects of individual bias when the bias is strong enough so that the individuals who are less limited by bias can be distinguished as the source of learning. Our results also suggest that increasing interpersonal learning, decreasing learning from the organization, task complexity, and environmental turbulence, and maintaining personnel turnover can improve organizational objectivity in the presence of individual bias.

Keywords:
Individual Bias, Agent-Based Modeling, Diversity, Exploration, Exploitation

Introduction

1.1 Acquiring high quality knowledge is central for organizational adaptation (Ferreira et al. 2011; Flores et al. 2012; Hernandez-Espallardo et al. 2011). However, individuals, who create, retain, and transfer knowledge (Argote & Eiron-Spektor 2011), are subject to an array of biases (Bhandari et al. 2008; Mojzisch et al. 2010; Tversky and Kahneman 1974), such as insensitivity or oversensitivity to certain knowledge (see Oreg and Bayazit (2009) for a bias taxonomy). Knowledge is therefore contaminated within the diffusion process, and this is generally viewed as detrimental to the objectivity of organizations.

1.2 Despite the belief that bias is rooted in human nature (Urbieta et al. 2011) and difficult to be reduced (Wilson & Brekke 1994), there still exist two intuitions in organizational practice about how to control individual bias. One is that reducing individual bias, for example, by using a decision support system (Bhandari et al. 2008), will increase organizational objectivity. The other is that objectivity can emerge in large organizations, because individual biases of different directions in a large organization can cancel each other out on the analogy of the law of large numbers (Zollman 2011). Based on these intuitions, organizations expend a lot in technologies of rationality that help reduce individual bias and encourage more people to share knowledge. The underlying logic behind these intuitions is that the macro behavior of a system is simply a linear combination of the micro behaviors of its elements. Unfortunately, it is not always true for social systems, as noted by many researchers (e.g. Davis 1992; Mohammed & Ringseis 2001; O'Leary 2011). In this paper, we intend to examine these two intuitions and answer the following two questions:

1. Whether reducing individual bias can increase organizational objectivity?
2. Whether measures, such as increasing organization size, can increase organizational objectivity in the presence of individual bias?

1.3 An agent-based simulation model is constructed based on the classic models of exploration and exploitation (March 1991; Miller et al. 2006). We focus mainly on investigating how individual bias affects organizational objectivity under different conditions and how other parameters affect organizational objectivity in the presence of individual bias.

Related work
2.1 Bias is usually defined as departure from objective standards that one can specify (Funder 1987), and is therefore viewed as
inaccuracy. Wilson and Brekke (1994), based on a subjective criterion, defined bias as an unwanted response that results from
unconscious or uncontrollable mental processes. According to this definition, bias is independent of the accuracy of results.
However, this does not mean that bias is harmless to the holder's performance. It definitely limits the holder's rationality and may
rule out better solutions. Herein, we focus on the subjective definition, because we believe that organizations are mainly
confronted by judgmental tasks, where correct standards usually cannot be specified (Kerr et al. 1996).

2.2 Despite the efforts made by psychology researchers on both individual and group biases, only limited literature has focused on
the impact of individual bias on group performance and has identified complicated patterns (Hinsz et al. 2008). Bias can possibly
lessen at group level as participants in the group may correct the biases of one another (Hill 1982; Hinsz 1990; Kerr et al. 1996;
Kerr & Tindale 2011). It is therefore believed that important decisions should be made in group settings (Hastie & Kameda 2005;
Kerr & Tindale 2004). However, bias may also be enhanced at group level when it is prevalent among individuals, leading to a
worsened group performance (Hinsz et al. 2008; Menegatti & Rubini 2012). Kerr et al. (1996, 2011) argued that it is impossible to
draw simple conclusions on the relationship between individual and group biases, and suggested investigations into the factors
that influenced the relationship, such as group size and the degree of individual bias. Kerr et al. (1996, 2011) also carried out
simulation experiments and provided valuable insights into the effect of individual bias on group bias. However, their studies
focused on group decision making rather than organizational adaptation, of which there are differences in mainly two respects:
First, organizations usually have larger population sizes than groups and thus have more diversified knowledge and stronger
information processing capability, which may help avoid the negative effects of individual bias (Bonabeau 2009). Second, organizational adaptation involves constant adjustment of individual judgments and evolution of the participants, while group
decision making is dedicated to aggregating individual preferences to form a group preference. Therefore, research on the
relationship between individual bias and organizational adaptation is needed.

2.3 Literature about the effect of irrationality on knowledge diffusion has indicated that bias may have positive effect on organizational
knowledge under certain conditions. Since the pioneering work of March (1991) on organizational learning, it has been widely
accepted that organizations have to balance the exploration of the novel and the exploitation of the known to gain superior
knowledge in the long run (He & Wong 2004; Gupta et al. 2006; Lavie et al. 2010). However, organizations usually incline to
exploitation because of its immediate returns as well as the risks existing in exploration (Groysberg & Lee 2009; March 1991;
Walrave et al. 2011). March (2006) has pointed out that irrationality, a result of bias, provides a source of exploration. Further,
Siggelkow and Rivkin (2005; 2006) analyzed the exploration of low-level managers in multi-level organizations and found that the
bounded rationality of low-level managers may prevent the organizations from reaching sub-optimal consensus rapidly and thus
increases the overall exploration. Therefore, a seemingly reachable conclusion is that individual bias may help balance
exploration and exploitation and improve objectivity in organizations where exploitation is overused. Previous research, though
has identified various factors influencing exploration and exploitation, is not yet enough to answer our questions. For one thing,
individual bias lowers the potential of individuals to reach higher objectivity despite that it may increase exploration. For another,
it is not clear whether the presence of individual bias changes the relationships between those factors and organizational
exploration and exploitation. In consideration of the ubiquity of individual bias, research on the joint effects of individual bias and
the factors on organizational objectivity will deepen our understanding of knowledge diffusion within organizations and help
improve organizational adaptation.

Simulation model

3.1 An agent-based model is constructed based on the model of exploration and exploitation, which is built initially by March (1991)
and extended by many scholars such as Fang et al. (2010), Kane and Alavi (2007), Kim and Rhee (2009), Kunz (2011), Lazer
and Friedman (2007), and Miller et al. (2006). An amount of empirical research (e.g. He & Wong 2004; Rothaermel & Alexandre
2009; Uotila et al. 2009) has proved that the model is powerful for understanding knowledge diffusion and organizational
adaptation.

3.2 March (1991) modeled mutual learning between organizations and their participants, while Miller et al. (2006) introduced
interpersonal learning to March's (1991) model. Their models characterize the critical processes of knowledge diffusion within
organizations. We retained their major features as the four basic features of our model. Then, we introduced individual bias as
the fifth feature.

Four basic features based on the classic models

3.3 (1) There exists an external reality with \( D \) dimensions, each of which is assigned a value of 1 or \(-1\) with independent equal
probability. \( D \) reflects task complexity. In each round, each of the values can shift from \(1 \) to \(-1\) or \(-1\) to \(1\) with probability \( P_T \).

3.4 (2) Beliefs about each dimension of the reality are held by each of \( S \) individuals in an organization and by an organizational code.
The beliefs reflect the knowledge of environment. Each belief has a value of 1, \(-1\), or 0. A value of 1 or \(-1\) means a specific belief
about the corresponding dimension of the reality; a value of 0 means the absence of a belief. Initially, the beliefs of the
organizational code are all assigned 0, and those of the individuals are 1, \(-1\), or 0 with independent equal probability. In each
round, each individual may be replaced by an initialized individual with probability \( P_I \).
3.5 The extent to which the beliefs match the reality reflects the objectivity of these beliefs. Individuals may hold uncertain beliefs, those with the value of 0, which have equal probability in matching or not matching the reality. Calculating objectivity simply as the proportion of the beliefs matching the reality may underestimate the real possible objectivity. To avoid this, we calculate the objectivity as the proportion of the beliefs matching the reality minus that of the non-matching ones, where the positive and negative effects of the uncertain beliefs cancel out. This is consistent with Miller et al. (2006). Organizational objectivity is represented by the objectivity of the organizational code.

3.6 (3) The organizational code learns from the individuals in each round to reflect best practice. Specifically, the organizational code is modified by replacing, with probability $P_{OL}$, the corresponding belief of the code with the dominant belief of the individuals who have higher objectivity than the organization. Subsequently, each individual learns from the organizational code by replacing each of her beliefs with the corresponding belief of the code with probability $P_{LO}$. The individuals do not change their beliefs if the corresponding belief of the organizational code has a value of 0.

3.7 (4) The individuals are located in a circle and each individual links with two on her left and two on her right. Each individual searches for the linked neighbor who has higher objectivity than the rest neighbors and herself, and learns from this neighbor by copying each belief of the neighbor with probability $P_{IL}$. If there are no neighbors with higher objectivity, the person chooses four individuals randomly, identifies the proper individual in the same way as described above and learns from her. If she still cannot find a suitable individual, her beliefs remain unchanged.

3.8 The circle network here has the same average degree as Miller et al.’s (2006) grid network, yet is more clustered. We adopt this setting because a special feature of real social networks is that people’s friends may also be friends with each other, which results in a highly clustered structure (Newman & Park 2003; Watts & Strogatz 1998). Nevertheless, we also performed simulation in a grid network and the results showed no qualitative difference.

Introduction of individual bias as the fifth feature

3.9 According to the subjective definition, bias is the unwanted response resulting from unconscious or uncontrollable mental processes. Here we view bias as an information filtering mechanism, similar to the bias named the sin of commission or omission by Kerr et al. (1996). Cognitive psychology has long compared the human mind to an information processor (Massaro & Cowan 1993), which receives and processes information, and outputs responses. The bias holders stick to some beliefs that can be either right or wrong, and are insensitive to contrary evidence. That is to say, bias filters the information learned from others and makes the mind produce responses that depart from rationality. The proportion of the filtered information reflects the degree of individual bias. Accordingly, we introduced individual bias as the fifth feature of the model.

3.10 (5) Each individual has a bias vector with $D$ dimensions, each of which is assigned initially a value of 1 with probability $P_B$ and 0 otherwise. The value of 1 means the corresponding dimension is biased and the belief will not be influenced by contrary beliefs held by the organization or other individuals. The value of 0 means the absence of bias.

Table 1: Parameters in our model

| Parameter | Description                                      | Default setting |
|-----------|--------------------------------------------------|-----------------|
| $S$       | Organization size                                | 100             |
| $D$       | Task complexity                                  | 30              |
| $P_{CL}$  | Rate of learning by the organization from individuals | 0.5             |
| $P_{LO}$  | Rate of learning by individuals from the organization | 0.5             |
| $P_{IL}$  | Rate of interpersonal learning                   | 0.5             |
| $P_{IT}$  | Degree of environmental turbulence               | 0               |
| $P_{IR}$  | Personnel turnover rate                          | 0               |
| $P_B$     | Degree of individual bias                        | [0-0.5]         |

Results

4.1 The model was constructed using Netlogo (Wilensky 1999). The code is available at http://www.openabm.org/model/3742.

4.2 Systematic simulation experiments with different parameter specifications were carried out. In the work of Miller et al. (2006), each experiment stopped when equilibrium where all individuals had the same objectivity was reached. However, this equilibrium may never be reached in our model because learning is restricted by individual bias. We believe that the same time limit should be adopted across all the experiments, as in Kane and Alvi (2007), Kim and Rhee (2009), and March (1991), because it is meaningless to investigate the balance between exploration and exploitation if there is no time limit (Niizato & Gunji 2011). Since bias slows knowledge diffusion, we set the time limit of each experiment at 200 rounds, the same as Kim and Rhee (2009), but
much more than the 80 rounds in March (1991) and Kane and Alvi (2007). The default setting (see Table 1) is used as a baseline across all experiments. Each experiment was iterated 100 times with different random seeds to avoid stochastic effect. The number of iterations was chosen arbitrarily. The results are based on averaging the last-round objectivity of the 100 iterations. We carried out pairwise multiple comparisons using the LSD method for homogeneous variance samples and the Dunnett’s T3 method for heterogeneous variance samples. Most of the pairs have statistically significant difference at the 0.05 level. To be accurate, we have also pointed out the pairs with no statistically significant difference in the figure captions. The conclusions are drawn based on statistically significant results.

Effects of organization size and individual bias

4.3 It is believed that the diversity resulting from large organization size helps avoid the negative effects of individual bias (Bonabeau 2009), because large organizations are more likely to include outstanding individuals (Lee & Van den Steen 2010) and include individuals holding biases of different directions, which may cancel each other out (Zollman 2011). It is thus seemingly reasonable to expect higher objectivity of large organizations.

4.4 Figure 1 illustrates the effects of organization size (S) and individual bias (P_B) on organizational objectivity. In Figure 1, we found three influencing patterns of organization size: (1) when P_B=0, the organizational objectivity increases with S; (2) when 0<P_B<0.25, the objectivity of the large organizations (S≥200 and 250) is similar to that of the small ones (S=50), but significantly lower than that of the moderate ones (S=100 and 150); (3) when P_B≥0.25, the organizational objectivity also increases with S, similar to the first pattern.

4.5 The first and the third patterns are consistent with the expectation, while the second is inconsistent. To explain this inconsistency, we have to find out why one pattern transforms to another with the increase of P_B. Detailed investigation reveals that the balance between exploration and exploitation accounts for the transformation from the first pattern to the second, while the "chemical reaction" of large size and strong bias accounts for the transformation from the second to the third.

4.6 First, let us focus the attention on why the first pattern transforms to the second when P_B increases from 0 to 0.05.
4.7 We tracked the organizational objectivity of the large (\(S=250\)) and moderate (\(S=150\)) organizations when \(P_B=0\) or 0.05 and showed the results in Figure 2. Organizational learning literature has suggested that exploration maintains diversity and may find better solutions, while exploitation results in convergence and yields consensus (Kim & Rhee 2009; March 1991; Miller et al. 2006). As a result, excessive exploration exhibits slow improvement because of inefficiency (as illustrated by the red line in Figure 2(b)), while excessive exploitation exhibits quick improvement at first and then gets trapped in a static state (as illustrated by the blue line in Figure 2(a)). Organizations that achieve balance between exploration and exploitation can improve the performance continually (as illustrated by the red line in Figure 2(a) and the blue line in Figure 2 (b)). Accordingly, moderate organizations exploit overly while large ones achieve balance when \(P_B=0\); large organizations explore overly while moderate ones achieve balance when \(P_B=0.05\).

4.8 The results are summarized and given in Figure 3. It can be seen that exploration increases with organization size. This is because large organizations contain more diverse beliefs and thus have more difficulties in reaching consensus. Exploration also increases with the degree of individual bias, indicating bias as a source of exploration, as implied by March (2006). Therefore, when \(P_B\) increases from 0 to 0.05, more exploration is introduced to large organizations, which have already achieved balance when \(P_B=0\). This makes the large organizations explore overly and fail to increase objectivity because of inefficiency.

| \(P_B=0\)          | \(S=150\)                        | \(S=250\)                        |
|---------------------|----------------------------------|----------------------------------|
| Excessive exploration | Balance between exploration and exploitation | html://jasss.soc.surrey.ac.uk/17/2/2.html |

![Figure 2. Effects of organization size (S) on organizational objectivity at different degrees of individual bias (P) with exploration and exploitation patterns.](http://jasss.soc.surrey.ac.uk/17/2/2.html)
by the organization, indeed decreases when $P_B$ increases from 0 to 0.05, as expected by organizational learning literature, and then increases when $P_B$ increases from 0.05 to 0.3.

4.10 We contribute the unexpected increase of learning efficiency of large organizations to their ability to distinguish the individuals whose biased beliefs are more objective than those of others in the presence of strong individual bias. As we define bias as an information filtering mechanism and assign its value randomly, there may be individuals whose biased beliefs match the reality better than others. These individuals, namely, the "outstanding" individuals, are less limited by their bias and have the potential to reach higher objectivity. To distinguish the "outstanding" individuals and learn from them is the only way for organizations to avoid the negative effects of bias. However, we presume that the biased dimensions are unperceivable, because biases will be corrected and disappear once they are perceived. It is thus impossible for an organization to directly clarify the extent to which biased beliefs match the reality and distinguish the "outstanding" individuals. However, with the increase of bias, the correlation between the internal potential and the external performance (i.e. the objectivity of overall beliefs) of individuals is enhanced, and as a result, the probability that the individuals distinguished by external performance are exactly the "outstanding" ones increases. Since an organization distinguishes the members who are more objective than the organization as best practice in this model, the objectivity of the biased beliefs in best practice reflects the organization's ability to distinguish the "outstanding" individuals. As shown in Figure 5, the objectivity of the biased beliefs in best practice of the large organizations increases with the degree of individual bias, while that of the moderate organizations decreases. This means that when $P_B$ increases from 0.05 to 0.3, the ability of large organizations to distinguish the "outstanding" individuals indeed increases more, providing the organizations with an advantage of better quality of learning source. This is how large organizations avoid the decrease of efficiency caused by strong individual bias.
Simply put, the probability of including "outstanding" individuals increases with the organization size, while the distinguishability of these individuals increases with the degree of bias. Large organization size and strong individual bias together result in a "chemical reaction" (see Figure 6), making organizations able to avoid the efficiency decrease resulting from large size and strong bias through trading off learning speed for the quality of the learned beliefs and the potential for reaching higher objectivity. Therefore, increasing organization size to a high level is beneficial only when individual bias is strong, while decreasing individual bias to a low level is not beneficial for large organizations.

Figure 6. "Chemical reaction" of large organization size and strong individual bias

Notes. The "outstanding" individuals mean those whose biased beliefs match the reality more than others. In other words, their potential is less limited by bias so that they are able to reach higher level of objectivity.

Effects of learning rates and individual bias

Learning rates reflect the effectiveness of socialization to the organization or other participants. The rates of learning by the organization ($P_{OL}$) and from the organization ($P_{LO}$) reflect the effectiveness of centralized learning, while the rate of interpersonal learning ($P_{IL}$) reflects the effectiveness of decentralized learning. Rapid learning accelerates knowledge convergence and is thus viewed as exploitation (March 1991; Miller et al. 2006). Figure 7 illustrates the effects of different learning rates ($P_{OL}$, $P_{LO}$, $P_{IL}$) and individual bias ($P_B$) on organizational objectivity. When $P_B$ is low, organizational objectivity decreases with the rise of $P_{OL}$ and $P_{LO}$ but increases with the rise of $P_{IL}$; whereas when $P_B$ is high, varying $P_{OL}$ or $P_{LO}$ or increasing $P_{IL}$ from 0.5 to 0.8 yields no statistically significant difference, because the number of changeable beliefs decreases when individual bias increases. The reason centralized learning has negative effects is that it results in rapid convergence of knowledge and gets the organization trapped in a sub-optimal solution. On the contrary, it is difficult to reach consensus through decentralized learning, and thus the organization avoids getting trapped in a sub-optimal knowledge and is able to improve continually.

Figure 7. Effects of three learning rates ($P_{OL}$, $P_{LO}$, and $P_{IL}$) and individual bias ($P_B$) on organizational objectivity
When $P_B$ is high (i.e. $P_B > 0.2$ in (a); $P_B > 0.35$ in (b); $P_B > 0.1$ in (c)), varying $P_{OL}$ or $P_{LO}$ or increasing $P_{IL}$ from 0.5 to 0.8 yield no statistically significant difference at the 0.05 level.

Figure 8. Effects of individual bias ($P_B$) and the interactions between two learning rates on organizational objectivity}

4.13 To further compare the effect strengths of the learning rates, we examined the effects of individual bias ($P_B$) and the interactions between two learning rates and showed the results in Figure 8. It can be seen in Figure 8(a) that the setting $P_{OL} = 0.8$ and $P_{LC} = 0.2$ yields more difference than the setting $P_{OL} = 0.2$ and $P_{LC} = 0.8$, compared with the setting $P_{OL} = 0.2$ and $P_{LC} = 0.2$. This means that the increase of $P_{OL}$ yields more negative effect than the equal amount of increase of $P_{LO}$, suggesting a stronger negative effect of increasing $P_{LO}$ than $P_{OL}$. In Figure 8(b), when $P_B < 0.05$, organizational objectivity at the setting $P_{IL} = 0.8$ and $P_{LC} = 0.8$ is significantly lower than that at $P_{IL} = 0.2$ and $P_{LC} = 0.2$; when $P_B > 0.05$, the two settings are similar to each other. This suggests that the negative effect resulting from increase of $P_{LO}$ is roughly stronger than the positive effect resulting from the equal amount of increase of $P_{IL}$. Similarly, it can be seen in Figure 8(c) that the positive effect of increasing $P_{IL}$ is roughly stronger than the negative effect of increasing $P_{OL}$. The effect strengths of the learning rates can be summarized as follows:

Negative effect of increasing $P_{LO}$ $\geq$ Positive effect of increasing $P_{IL}$ $\geq$ Negative effect of increasing $P_{OL}$

4.14 This result can be attributed to the roles these learning processes play within organizations. Learning by the organization influences the knowledge source not directly but through individual learning, and thus has the weakest effect on organizational objectivity; whereas, learning of individuals from the organization is centralized and more rapid than interpersonal learning, and thus has a stronger effect. Further, when individual bias is strong, the difference between the effects of the learning rates vanishes.

4.15 As regards the effect of individual bias, it is shown in both Figure 7 and 8 that there exists non-zero degree of individual bias that results in optimal organizational objectivity.

Effects of task complexity and individual bias

4.16 In the model, task complexity represents the number of possible combinations of beliefs. The specific combination that matches the reality is required for organizational adaptation. Therefore, the difficulties of the task of adapting to the environment increase with task complexity. Figure 9 illustrates the effects of task complexity ($D$) and individual bias ($P_B$) on organizational objectivity.
4.17 It is not surprising that the organizations facing tasks with lower complexity always perform better, which is consistent with the general understanding that complex knowledge is learned more slowly than simple knowledge (Miller et al. 2006; Rivkin 2000). This is because that lower task complexity means fewer combinations of beliefs, and thus it is easier to find an optimal solution. Reducing task complexity, for example, by automatic technologies or labor division, can therefore improve organizational objectivity.

4.18 As regards the effect of individual bias, Figure 9 shows an inverted-U relationship between organizational objectivity and the degree of individual bias. This is because certain degree of bias maintains diversity, which avoids getting trapped in sub-optimal knowledge.

Effects of environmental turbulence and individual bias

4.19 Environmental turbulence captures the idea that standards of objectivity are changing in many social decision settings. Figure 10 shows the effects of environmental turbulence ($P_T$) and individual bias ($P_B$) on organizational objectivity. It can be seen that, when $P_B$ is low, various non-zero $P_T$ generally results in little difference in organizational objectivity; when $P_B$ is high, organizational objectivity decreases with the increase of $P_T$. As environmental turbulence is represented by the probability of changing a dimension of the reality, it actually decreases the accuracy of the learned beliefs and results in ineffective learning. This is why organizational objectivity decreases with the increase of environmental turbulence.

4.20 Figure 10 also shows the positive effect of strong individual bias in turbulent environment. This is because that the more rapidly the beliefs converge, the more prevalent a specific belief is among the population, and thus the more people will be influenced when the corresponding dimension of the reality changes. Individual bias filters information and maintains diversity, which may
decrease the number of influenced people. This also explains why varying $P_T$ from 0.03 to 0.12 yields little difference when $P_B$ is low. Therefore, reducing individual bias by using technologies of rationality is not beneficial to organizational adaptation in turbulent environment.

Effects of personnel turnover and individual bias

4.21 Personnel turnover is common in most organizations and has usually been viewed as a source of new knowledge and exploration (Schreyogg & Sydow 2010). Since bias also provides a source of exploration as we have discussed above, organizations may explore overly and thus lower their objectivity when both the turnover rate and the degree of individual bias are high. This expectation is supported by the results shown in Figure 11. The presence of turnover increases organizational objectivity no matter how strong the individual bias is. This is because new-coming individuals bring diverse beliefs that may be more objective, while the organizational code is not affected by leaving individuals. As for the effect of individual bias, it can be seen that slight individual bias is beneficial in the presence of personnel turnover. Reducing individual bias thus may be beneficial when there is personnel turnover.

![Figure 11. Effects of personnel turnover ($P_R$) and individual bias ($P_B$) on organizational objectivity](http://jasss.soc.surrey.ac.uk/17/2/2.html)

Notes: Various non-zero $P_R$ generally yields no statistically significant difference at the 0.05 level.

Discussion

5.1 Advancement in information and communication technology provides organizations with tools to reduce individual bias or to avoid its negative effects. In this paper, we investigate the rationality of these practices by examining organizational objectivity as a function of individual bias and the factors involved in previous models of exploration and exploitation, such as organization size, learning rates, task complexity, environmental turbulence, and personnel turnover. Our results demonstrate that there exists non-zero optimal degree of individual bias, and the effectiveness of avoiding the negative impact of individual bias by increasing organization size depends on the degree of bias.

Individual bias

5.2 Our results show that individual bias has two-sided effects on organizational adaptation. On the one hand, slight bias is beneficial for moderate and small organizations and strong bias is for large organizations in stable environment. In addition, strong bias is also helpful in turbulent environment. This supports the evolutionary perspective on individual bias, which argues that bias limits information and may improve adaptation (Haselton et al. 2009). The results also confirm March’s (2006) proposition that irrationality is a source of exploration, which maintains diversity among individuals. Therefore, individual bias can benefit organizations that overuse exploitation or need more exploration. On the other hand, individual bias also has negative effects. It makes individuals stick to certain beliefs, may rule out optimal solutions, and limits individuals’ potential for reaching higher objectivity. Besides, since consensus is also needed to result in organized actions (Fiol 1994; Woolley & Fuchs 2011; Zollman 2010, 2012), the diversity resulting from individual bias may lead to inefficiency. The tradeoff between the positive and negative effects usually results in non-zero optimal degree of individual bias.

Organization size

5.3 Since it is believed that the negative effect of individual bias can be avoided by the diversity resulting from large organization size, research on collective performance usually ignores individual bias. Our results suggest that this benefit of large organization
size functions only when individual bias is strong enough so that the individuals with potential for reaching higher objectivity can be distinguished through external performance. Otherwise, diversity may lead to inefficiency.

5.4 Our results contribute to the dispute over the optimal organization size. Williamson (1967) pointed out that managers’ bounded capability for processing information limits the optimal organization size since it may get overloaded when the organization size increases. His inference is persuasive from a static perspective, yet he overlooks the role of selection mechanism in avoiding the limitation of individual capability. Our results are consistent with Williamson (1967) when individual capability is slightly limited, but add that diversity resulting from large size can help overcome the limitation when capability is strongly limited. This also implies an advantage of agent-based simulation over static analysis.

Learning rates

5.5 Learning rates, which reflect the effectiveness of socialization to the organization or other participants, have been a major concern in the research on exploration and exploitation. However, previous research has not taken individual bias into consideration. Still, their results are not completely consistent with ours under the setting of $P_B=0$. We agree with most research (March 1991; Miller et al. 2006; Kim & Rhee 2009) in that a high rate of learning by individuals from the organization does harm to organizational adaptation. Similar to Kim and Rhee (2009), we also find a high rate of interpersonal learning beneficial; but this is different from Miller et al. (2006), who argued that a moderate rate of interpersonal learning is more helpful. This inconsistency, we conjecture, is caused by their concern for tacit knowledge that transfers only through interpersonal learning. In our separate experiments, the results of which are not shown here, we find that the presence of tacit knowledge accelerates the improvement in the objectivity of beliefs, and thus weakens the role of interpersonal learning in maintaining diversity. Therefore, a high rate of interpersonal learning may result in excessive exploitation when tacit knowledge is considered. As for learning by the organization, March (1991) and Miller et al. (2006) argued that a high learning rate would be beneficial, but we suggested the opposite. We also carried out separate experiments using the same setting as March (1991), results of which are not shown in this paper, and found that the effect of increasing the rate of learning by the organization may be positive yet insignificant. Considering that March (1991) did not carry out significance test, and Miller et al. (2006) only found slight difference yielded by varying the rate, we believe that the inconsistency can be attributed to the fact that the effect of the rate of learning by the organization is so weak that it is easily influenced by stochastic factors.

5.6 When the degree of individual bias increases, the difference resulting from varying the learning rates vanishes. The effect of the rate of learning by the organization, the weakest among the three, vanishes the most quickly. Accordingly, we suggest that organizations rely on promoting interpersonal learning to improve their objectivity.

Other factors

5.7 Some other factors also play roles in organizational adaptation in the presence of individual bias. It is not surprising that reducing task complexity or environmental turbulence can help increase organizational objectivity. Therefore, it is beneficial to reduce task complexity using automatic technologies or labor division, and to reduce environmental turbulence by decreasing unnecessary changes of task standards.

5.8 Our results are also consistent with Lee and Van den Steen (2010) in that organizations with personnel turnover perform better. This is because new-coming individuals bring diverse beliefs, while the organization code is not affected by the leaving individuals. It is thus beneficial to maintain personnel turnover. This conclusion, however, depends on the presumption that all knowledge can be coded by the organization. Tacit knowledge, which cannot be coded, may be lost with its owners' leaving. Further research on the effect of tacit knowledge and personnel turnover in the presence of individual bias is needed.

Implications

6.1 This study contributes to the research on bias and organizational learning by demonstrating that even individual biases of different directions cannot cancel each other out at the organization level and their presence may change the way other factors influence organizational knowledge. Therefore, individual bias should be an unneglectable factor to consider. The model can be extended in future research to deepen the understanding of the relationship between individual bias and organizational adaptation in several ways. First, previous literature focuses mainly on systematic bias that is widespread among individuals (Kerr et al. 1996), while the bias addressed in our model is presumed to be random. In future investigation, both random and systematic biases can be included. Second, network structure has been proved to be an important factor in knowledge diffusion (Lazer & Friedman 2007; Zollman 2012). Although we have found no qualitative difference between circle networks (the default setting in our model) and grid networks (the setting in Miller et al. (2006)) in separate analysis, the structure in reality is much more complex. It is worthwhile to further explore the effects of more complex network structures.

6.2 The practical implication of our results lies in that we have identified the application conditions for several popular practices for promoting organizational adaptation. For example, more and more organizations train their members to use statistical technologies or decision support systems in order to reduce individual bias. Some organizations also resort to other measures to avoid the negative effects of individual bias, such as engaging more people in tasks and facilitating communication by using internet. We investigate the rationality of these practices by answering the two questions put forward at the beginning of this
1. Whether reducing individual bias can increase organizational objectivity? We find that there usually exists non-zero optimal degree of individual bias. Although it is difficult to specify the optimal degree of individual bias and maintain the bias exactly at the degree, we are confident to claim that reducing individual bias is not beneficial when organization size is large or the environment is turbulent. Organizational learning literature argues that organizations usually incline to exploit overly (Groysberg & Lee 2009; March 1991; Walrave et al. 2011). Since individual bias slows down the convergence to consensus and impedes exploitation, non-intervention to individual bias may be a helpful and economic way to achieve balance between exploration and exploitation for most organizations.

2. Whether measures such as increasing organization size can improve organizational objectivity in the presence of individual bias? We find that a moderate organization size is helpful when there exists slight individual bias, while a large size is helpful when the bias is strong. In addition, increasing interpersonal communication, decreasing learning from the organization, task complexity, and environment turbulence, and maintaining personnel turnover can also improve organizational objectivity when individual bias is present.

Acknowledgements

We acknowledge the support of the National Natural Science Foundation of China (grant No.71271166) and the Doctoral Fund of Ministry of Education of China (grant No.20120201110068).

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