COGNITION, NETWORK STRUCTURE, AND LEARNING IN TOP MANAGERS' INTERPERSONAL NETWORKS

ABSTRACT

In an uncertain, complex and competitive business landscape, top managers' ability to quickly and effectively learn from others in their interpersonal networks could give their companies a competitive edge. We propose an anchoring mechanism to explain how their interpersonal learning outcomes might be shaped by the interplay between cognitive attributes, such as impatience and conservatism, and the degree to which extremely well-connected individuals, or hubs, is probable in their networks. Using an agent-based model, we find that impatience and conservatism may lead to poor interpersonal learning outcomes, particularly if top managers belong to less "hubby" networks. In addition, distorted information has the potential to compromise learning, regardless of the level of impatience or conservatism and network "hubbiness". Moderate to high levels of initial knowledge variety may also hamper interpersonal learning if top managers are highly impatient or conservative, and operate in networks with a certain degree of hubbiness. Although the adoption of less-than-ideal standards for judging the accuracy of beliefs may expedite learning, it is generally costly in terms of low learning performance levels. However, more impatient or conservative top managers may improve their learning performance by primarily targeting hubs, or some mix of hubs and nearby contacts.

Keywords: agent-based model, anchoring, interpersonal learning, network structure, social capital, top managers

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INTRODUCTION

It is generally recognized that firms may gain a competitive edge if they excel at acquiring, integrating and using knowledge (Argote and Ingram 2000, Grant 1996, Kogut and Zander 1992). But the basic task of accumulating knowledge is not as clear-cut as one might initially believe. A resource-based logic suggests that knowledge may lead to superior performance if it is rare, unique and imperfectly imitable (Penrose 1959, Barney 1991, Wernerfelt 1984). We also know from previous knowledge management research that the most valuable knowledge tends to be in a tacit form; that is, as experience-based "know-how" knowledge which is generally difficult to share in the absence of repeated face-to-face interactions (Nonaka 1994, Leonard and Sensiper 1998, Polanyi 1966, Wellman 2009). Interestingly, top managers, such as chief executive officers (CEOs), are likely to have a particularly strong need for this kind of knowledge. After all, they are typically pressed to spot emerging opportunities, solve difficult problems, and ward off threats from rivals by making strategically important decisions—e.g., adoption of emerging technology, acquisitions, international market entry—under time pressure and uncertainty (Eisenhardt 1989; Garg et al. 2003).

We expect top managers to have a network of personal contacts outside their organizations. Thus, they may turn to their interpersonal networks for help when faced with time-sensitive and difficult decisions. More generally, we recognize that top managers have an important role to play when it comes to gathering external knowledge. However, strategic management research does not tell us as much as we need to know to assess whether, how and precisely why they and their firms might actually benefit from such efforts (Collins and Clark 2003, Hambrick 1982, Vera and Crossan 2004). Specifically, we do not have a definitive answer to this fundamental question: Do top managers learn from their network members in ways that enrich their firms' knowledge base? It is difficult to answer this question because there are still major gaps in our understanding about the underlying factors that influence the value of knowledge that individuals acquire from their interpersonal networks. In terms of theoretical guidance, much of what we currently know comes from a network-based perspective.

As a starting point, network-based research generally presumes that interpersonal networks contain valuable social capital in general, and particularly in the form of knowledge resources (Adler and Kwon 2002, Burt 1992, Granovetter 1973, Nahapiet and Ghoshal, 1998). When it comes to explaining the process of external knowledge acquisition or interpersonal learning, network theorists primarily focus on the role of network- or dyad-level structural characteristics (i.e. brokerage versus cohesive network structures; strong versus weak ties), as well as relational characteristics (i.e. more or less trusted relationships) (Argote and Fahrenkopf 2016, Argote et al. 2003, Burt 1992, Granovetter 1973, Inkpen and Tsang 2005). For example, if individuals deliberately maintain a mix of strong and weak ties, or know trustworthy weak ties, they are expected to acquire novel and valuable tacit information from others (Hansen 1999, Levin and Cross 2004, Ozdemir et al. 2016, Reagans and McEvily 2003). Another line of network research proposes that the aggregate interpersonal learning performance of individuals is determined by the degree to which extremely well-connected individuals, or hubs, dominate the network. Specifically, if a network has a moderate number of hubs, superior ideas will emerge over the long term because diverse ideas are preserved long enough to engender numerous combinatorial possibilities (Schilling and Fang 2014).

Although a network perspective offer important insights, there remain major gaps in our understanding about the underlying factors that shape the interpersonal learning outcomes in individuals in general, and top managers in particular. But an emerging cognition research stream provides helpful insights that are beginning to fill these gaps (Anderson 2008; Augier and Vendelø 1999). Importantly, we are beginning to understand why it is inappropriate to assume that even privileged access to interpersonal networks will translate into the acquisition of valuable knowledge. Also being called into question is the conventional conceptualization of social capital merely as benefits (i.e. information, influence, or support) that people accrue on the basis of the "goodwill that is engendered by the fabric of [their] social relations" (Adler and Won 2002, p. 17). Whether people obtain useful information from others does not depend only on how well their social relations are configured. After all, we know that individuals may realize different levels of informational benefits even when they have similar network positions that promise the same potential informational benefits (Adler and Kwon 2002). Another important source of variation in informational benefits across network members rests on individual differences (Casciaro 1998; Emirbayer and Jeff Goodwin 1994; Stevenson and Greenberg 2000). Specifically, we recognize that the cognitive aspects of individuals play a distinct and contingent role in interpersonal learning or social capital outcomes. This could mean that top managers' ability to learn quickly and well from their social connections could depend on both the structural characteristics of their interpersonal networks and their cognitive attributes. Research can make important contributions by further clarifying and confirming this basic insight.

Therefore, we seek to advance prior related strategic management research by drawing on a cognitive framework to investigate why and how top managers' cognitive attributes and interpersonal network structures might jointly shape their interpersonal learning outcomes. We specifically focus on the following two cognitive attributes: a) *impatience*, as reflected in an individual's tendency to perceive immediate information from others as more valuable than delayed information, and b) *conservatism*, as reflected in an individual's tendency to hold on to prior beliefs or ignore new information. We focus on these cognitive attributes because prior research indicates that top managers exhibit differences in terms of impatience (e.g., Smith et al. 1988; Wiklund et al. 2016) and conservatism (e.g., Christensen et al. 2015); and such differences have major implications for organizational decisions, processes and outcomes. However, we know very little about how impatience or conservatism affects top managers' interpersonal learning outcomes. We evoke an anchoring logic to theorize about the interpersonal learning effects of impatience and conservatism. In general terms, anchoring is a form of heuristic or simple rule. Its presence is manifested in cases where some initial value or reference point excessively influences the final decisions or judgments that individuals progressively make over time (Tversky and Kahneman 1974). Anchoring behavior is pervasive and difficult to avoid because individuals may even subconsciously exhibit such behavior (Furnham and Boo 2011). As with other forms of heuristic decision making, individuals are trying to simplify their decisions as a way of coping with the demands that complexity and uncertainty place on their limited mental resources (Gigerenzer and Gaissmaier 2011, Kahneman 2011, Simon 1955). However, a major concern is that heuristics may lead to poor decisions because they tend to distort how people reason and make judgments (Kahneman 2011). We conceptualize impatience and conservatism as a form of anchoring heuristic. In the case of impatience, we recognize that impatient top managers are likely to adopt a present-future temporal heuristic that engenders a fixation on present information even when delayed information becomes available (Ebert and Prelec 2007, Malkoc et al. 2010). Present information effectively serves as an anchor in this case. When it comes to conservatism, there is a fixation on one’s prior beliefs even when current information is available; hence, prior beliefs effectively serve as a form of anchor. Importantly, neither present information nor prior beliefs might constitute accurate representations of reality. They may undermine interpersonal learning in top managers because they exert a major influence on what they ultimately believe and act on. Thus, we expect impatience and conservatism to be associated with poor interpersonal learning outcomes.

When it comes to network structures, we build on Schilling and Fang (2014) by focusing on their degree of “hubbiness”; that is, the extent to which the presence of extremely well-connected individuals or hubs in the network is probable. We conceptualize the network structure as the social environment in which top managers scan and seek external information. Since uncertainty is key driver of error-prone heuristic decision making, we are particularly interested in how the hubbiness of top managers’ network affects their search behavior and interpersonal learning outcomes. When they seek information in more hubby networks, we propose that they may identify the most reliable sources of information more easily, and with greater confidence. This could mean that they are less inclined to engage in heuristic decision making as their network becomes more hubby. As a result, it is possible that the anticipated negative learning effects of impatience- and conservatism are less pronounced in more hubby networks. However, we show that the story is more complicated because Schilling and Fang (2014) have linked the dominance of hubs to sub-optimal aggregate learning outcomes in networks.

Our cognitive framework allows us to specifically shed light on the following three questions: a) Do impatience and conservatism lead to poor interpersonal learning outcomes? b) Are the learning performance effects of such cognitive attributes contingent on the hubbiness of one's networks? c) What environmental conditions, actions or behaviors, particularly hamper or foster interpersonal learning when individuals are impatient or conservative, and seek information in more or less hubby networks? To address these questions, we develop and apply an agent-based (simulation) model. We do so because it is costly and analytically difficult to address these questions based on survey data and conventional statistical techniques. More generally, prior research suggests that a simulation approach is appropriate because it can handle the complex and analytically intractable nature of the issues we have raised better than either verbal theorizing, or pure mathematical modeling (Crawford et al. 2015; Harrison et al. 2007). To foster confidence in our simulation results, we deliberately address widely recognized concerns about simulation modeling, including the potential sensitivity of simulation results to experimental conditions and assumptions (Harrison et al., 2007; Leombruni and Richiardi 2005, Manzo 2014).

Our study makes two major important theoretical contributions. First, it contributes by lending support to a cognitive perspective that calls for greater attention to learning-relevant factors at both the individual and network level in organizational learning research (Anderson 2008, Levin and Cross 2004). Second, our findings also lend support to the view that individual cognition constitutes an important boundary condition for resource-based and social capital perspectives on organizational performance (Anderson, 2008; Morgan et al. 2018). In doing so, we also contribute to recent efforts to strengthen the microfoundations of strategic management research (Felin et al. 2015; Minbaeva 2016).

The remainder of this article is organized as follows. The next section presents a review of the relevant literatures. Drawing on our cognitive framework, we then articulate propositions about how each cognitive attribute and network hubbiness separately and jointly impact interpersonal learning performance at the individual level. To evaluate these propositions, we develop and implement an agent-based model. We report the relevant simulation results for a baseline model, followed by an extended version of this model. In the final section, we conclude by discussing our theoretical contributions, limitations and potentially fruitful directions for future research.

THEORETICAL FRAMEWORK

External knowledge resources, organizational learning and performance

Strategic management scholars have long relied on a resource-based logic to explain why some firms consistently outperform others (Penrose 1959). The basic proposition is that firms will achieve and sustain superior performance if they own resources that are rare, valuable and imperfectly imitable (Barney 1991, Wernerfelt 1984). Building on this basic insight, proponents of a knowledge-based perspective stress the relative importance of knowledge resources (Grant 1996, Kogut and Zander 1992). Such resources may impact firm performance through a variety of strategic decisions and organizational processes. Consider firms that want to compete by offering differentiated or branded products at premium prices. To achieve superior performance, they generally need to ensure that their capabilities and resources are well-aligned with the prevailing conditions in their external environment (Bourgeois 1985). Therefore, as part of their internal scanning process (Andrews 1980; Learned et al. 1965), managers need to assess the resource requirements of their strategy in general, and particularly in relation to emerging opportunities, threats or problems. But to perform these and other related tasks well, they also need to properly scan their external environment. Specifically, they need to gather relevant information about specific sectors (i.e. customers, suppliers, competitors, technology) and general sectors (economic, political, social and regulatory conditions); and interpret or make sense of such data even the face of uncertainty (Daft and Weick 1984, Kiesler and Sproull 1982, Thomas et al.1993). The collective insights or meanings they derive from this process are reflected in their firms' knowledge base. This knowledge base also includes managers' experience and know-how, as well as ideas about new combinations for creating new products, or improving existing ones (Deeds et al. 1999, Ilinitch et al. 1996).

The most successful firms will be those that excel at enlarging their knowledge base, and generating value from it (Zander and Kogut 1995). In other words, firms whose learning process facilitates the timely accumulation, integration and application of performance-enhancing knowledge

(Argote and Ingram 2000, Daft and Weick 1984, Huber 1991, Teece et al. 1992). This organizational learning process is not confined to internal sources of knowledge. After all, other organizations can be important sources of knowledge (Huber 1991; Kreiner and Schultz 1993, Powell 1998). At the same time, we know from prior research that firms with greater absorptive capacity are better positioned to learn from external knowledge (Cohen and Levinthal 1990). Specifically, they have an enhanced ability to identify, assimilate and apply external knowledge because their knowledge base is sufficiently related to knowledge generated by others.

Managers’ interpersonal networks and the acquisition of external knowledge

Strategic management and organization science researchers have sought to build on these insights by clarifying how managers specifically contribute to the enlargement of their organizations’ knowledge base. An important insight is that their role is linked to the underlying nature of advantageous external knowledge. In keeping with a resource-based logic, we generally expect such knowledge to be rare, valuable and imperfectly imitable. Based on prior knowledge management research (Brown and Duguid 1998, Cook and Brown 1999, Nonaka 1994, Wellman 2009), we specifically recognize that advantageous knowledge outside the firm is unlikely to appear in a fact-based or “know-what” form that can be easily captured, stored, modified and retrieved. In other words, it is unlikely to be explicit knowledge stored in documents at different organizations (e.g., memos or manuals). Instead, it is likely to be in a tacit form; specifically, as “know-how” knowledge or intuitions that individuals gain from experience, and specific to certain functions, tasks or contexts (Nonaka 1994, Leonard and Sensiper 1998, Polanyi 1966, Wellman 2009). Although tacit knowledge is difficult to put into words, it can be transferred over the course of repeated, time-consuming, face-to-face interactions among individuals who trust each other (Nonaka 1994). Under these conditions, knowledge seekers can progressively understand relevant contextual information, and gain more shared experiences with those who possess tacit knowledge. Specifically, they may acquire know-how knowledge from others as they repeatedly observe and imitate their practices over time, and in different contexts. More generally, individuals will acquire tacit knowledge as they develop the required individual- and situation-specific absorptive capacity (Domurath and Patzelt 2016).

Given the important role that social relations play in the transfer of tacit knowledge among individuals, prior research has sought to link managers’ access to interpersonal networks to the acquisition of knowledge-based social capital (e.g., Carroll and Teo 1996). More generally, previous network research helps us understand how the structural aspects of managers’ interpersonal networks (i.e. brokerage vs cohesive network structures; tie-strength heterogeneity), combined with relational characteristics (i.e. level of trustworthiness), might shape what they come to know from their interactions with others. For instance, as previously discussed, we expect managers to acquire more novel and valuable tacit information when they interact with others in larger networks inhabited by trustworthy weak ties (Hansen 1999, Levin and Cross 2004, Ozdemir et al. 2016, Reagans and McEvily 2003). We also know that they might be exposed to superior ideas if hubs moderately dominate their interpersonal networks (Schilling and Fang 2014).

Joint impact of managerial cognition and network structure on external knowledge acquisition

Although a network perspective offers important insights, the configuration of social relations among individuals does not tell us everything we need to know when theorizing about the informational benefits they might acquire from such relations. More recent research suggests we also need to take into account the psychological aspects of individuals (Augier and Vendelø 1999, Garud and Rappa 1994). For example, Anderson (2008) makes a notable contribution by showing that the informational benefits realized by managers who embrace mentally demanding activities are particularly large when they belong to large networks. Researcher can build on, and extend this research stream by raising the level of understanding about the role and consequences of managerial cognition and heuristics in top managers’ interpersonal learning process and outcomes. It is important to do so because the process of seeking knowledge and learning from others is part of a larger strategic decision-making process that is unfolding under time pressure, complexity and uncertainty. Furthermore, what top managers come to know, believe or perceive may influence what information they seek, whom they seek such information from and when; and ultimately, what they understand, believe and act on when they receive diverse or conflicting information (Bogatti and Cross 2003, Carley 1991). For all these reasons, it is important to clarify and assess how managerial cognition and heuristics shape interpersonal learning in top managers.

Managerial cognition and heuristic decision making

Top managers deserve special attention when accounting for managerial cognition in network-based theories of knowledge accumulation or interpersonal learning. The upper echelons perspective suggests that their cognitive characteristics significantly influence a wide range of strategic decisions, organizational processes, performance outcomes (Barney et al. 2018, Carpenter et al. 2004, Hambrick 1982, Hambrick and Mason 1984). Behind such decisions, processes and outcomes is the formidable task of solving problems or evaluating opportunities under time pressure and genuine uncertainty (Knight 1921). When confronted with such challenges, behavioral economics research suggests that top managers are unlikely to undertake information-intensive, time-consuming and mentally burdensome analyses (Rabin 2013, Simon 1955); instead, they may try to simplify and speed up their decisions by adopting simple rules or heuristics (Gigerenzer and Gaissmaier 2011; Gigerenzer and Goldstein 1996, Kahneman 2011).

We specifically recognize that top managers might be predisposed to heuristic decision making in the form of anchoring (Tversky and Kahneman 1974). By this we mean, they could be drawn to some initial value or reference point that excessively influence the final decisions or judgments they progressively make over time. Experimental psychology and strategic management research indicate that the phenomenon of anchoring is pervasive (Furnham and Boo 2011; Malhotra et al. 2016). It is underpinned by the selective recall of, or attention to, the initial value or reference point in question (Mussweiler 2003, Mussweiler and Strack 1999, 2000). However, a dominant view is that anchoring and other forms of heuristics are associated with cognitive biases that may lead to systematic errors in reasoning and judgments (Kahneman 2011). At the same time, others argue in favor of heuristics on the grounds that they can expedite decision-making when information deficiencies are acute, without necessarily leading to worse outcomes than more sophisticated approaches (Gigerenzer and Gaissmaier 2011).

Building on a behavioral economics perspective, behavioral strategy and entrepreneurship researchers support the application of insights from cognition research in strategic management theories. In particular, they argue that cognitive resources (i.e. prior knowledge and experience) and cognitive representations or mental models (Grégoire et al. 2011, Gavetti and Levinthal 2000, Kaplan 2011, Narayanan et al. 2011, Priem et al. 2011) deserve special attention. On the point of mental models, an important observation is that senior executives’ mental models embody simplified knowledge structures that reflect how they perceive themselves, others, time, and their environment (Gary and Wood 2011; Nadkarni and Barr 2008, Nadkarni and Chen 2014).

Learning performance effects of impatience and conservatism

Drawing on insights from the postulated cognitive framework, we will theorize how cognitive attributes, such as impatience and conservatism, affect interpersonal learning performance in top managers. Specifically, we will invoke an anchoring logic to do so, and take up these cognitive attributes in turn.

As stated earlier, impatience is manifested in an individual’s tendency to perceive immediate information from others as more valuable than delayed information. At high levels of impatience, individuals may exhibit present-biased preferences (O’Donoghue and Rabin 1999), where a one-day delay between now and tomorrow is perceived to be considerably worse than the same one-day delay in a future period (i.e. waiting 91 versus 90 days from today). We also know from prior behavioral research that impatient top managers might be predisposed to adopt a temporal heuristic that rests on a present-future dichotomy (Ebert and Prelec 2007; Malkoc et al. 2010). This present-future heuristic dramatically contracts the time horizon by crudely dividing it into two periods: today and the future. Top managers will resort to this form of temporal heuristic as they try to cope with the mental strain associated with uncertain times and time pressure. The information that is available today is more salient or concrete; and hence, attracts their attention, compared with information that is linked to an abstract future period (Marcel et al. 2011, Thomas et al. 2001). Today’s information is also more accessible from memory than delayed information that is relegated to an abstract future period. All of this could mean that impatient top managers who adopt a present-future heuristic are effectively using present information as an anchor. However, as discussed earlier, anchoring can lead to errors in reasoning or judgment because of the tendency for individuals to inadequately adjust away from it as more relevant or accurate information becomes available (Kahneman 2011). This implies that impatient top managers may end up with inaccurate beliefs about reality because they hold on to what they know based on present information, even when delayed, but better information becomes available. It is also possible that they might prematurely end their search for external information. Other things being equal, we assume that if the information-gathering period is shortened, as reflected in a lower average search time, the speed of learning will be accelerated. But if the learning process is accelerated because less time is spent searching for high-quality information, then learning outcomes could be poor. Based on these foregoing arguments, we propose the following:

> **Proposition 1**: A top manager's level of impatience will negatively impact his or her interpersonal learning performance.

The second cognitive attribute is conservatism. We have already defined it as an individual's tendency to hold on to prior beliefs or ignore new information (Edwards 1982). In general, we expect more conservative individuals to be preoccupied with self-preservation or threat-mitigation, as reflected in a tendency to embrace rigid principles, rules, and/or values (Jost et al. 2003). In organizational settings, this could mean that more conservative senior executives are more defensive than others; and also more inclined to avoid new experiences, or undertakings, they perceive to be risky (Christensen et al., 2015; Sturdivant et al. 1985). Taken together, these dispositions may entrench prior beliefs, such they effectively serve as a form of anchor heuristic. Again, we expect this heuristic to give rise to bias in reasoning or judgment at levels that hamper interpersonal learning. Specifically, by virtue of their underreaction to new information, conservative top managers will not adjust away from their prior beliefs as much as they should when more accurate information becomes available. Therefore, they are expected to end up holding on to inaccurate beliefs when they stop gathering information from others; hence our proposition:

Proposition 2: A top manager's level of conservatism will negatively impact his or her interpersonal learning performance.

Learning performance effects of impatience and conservatism under different network structures

An interesting question is whether the postulated learning performance effects of impatience and conservatism are contingent on the network structures within which top managers seek information from others. Given the prevalence of extremely well-connected individuals, or hubs, in real-world networks (Barabási 2009, Barabási et al. 2002), and the important role they play in network-level learning outcomes (Schilling and Fang, 2014), we are particularly interested in uncovering the interplay between cognitive attributes and network hubbiness in top managers' interpersonal learning performance.

Impatience, network hubbiness, interpersonal learning. Our first proposition suggests that top managers' interpersonal learning performance will be poorer when they are more impatient. Is this anticipated outcome contingent on the hubbiness of their network? To address this question, we need to determine whether more hubby networks are associated with more cognitively demanding conditions—such as high levels of uncertainty—that induce greater reliance on heuristics in impatient top managers.

We propose that there will less uncertainty about which information providers are more reliable as more hubs dominate the network. It follows that the chance of having an early knowledge-sharing interaction with a well-informed person is higher in a more hubby network. This could mean that the chance of anchoring on relevant or accurate present information is higher too. If so, the anticipated adverse learning effects of anchoring might be less pronounced in more hubby networks. At the same time, hubs may also hold inaccurate beliefs, albeit at a lower rate than less connected individuals. Furthermore, we know from prior research that highly hubby networks are associated with premature convergence around initially superior ideas that turn out to be sub-optimal over the long term (Schilling and Fang, 2014). Therefore, it is possible that anchoring on early information provided by hubs might lead to poor interpersonal learning performance in impatient top managers. To capture the ambiguity about the moderating effects on network hubbiness, we postulate the following two opposing propositions:

> **Proposition 3a**: When a top manager's network is highly hubby, the anticipated negative effect of impatience on his or her interpersonal learning performance will diminish.

> **Proposition 3b**: When a top manager's network is highly hubby, the anticipated negative effect of impatience on his or her interpersonal learning performance will be amplified.

Conservatism, network hubbiness, interpersonal learning. According to our second proposition, higher levels of conservatism will result in poorer interpersonal learning in top managers. It would be helpful to know whether the hubbiness of their network moderates the postulated relationship between conservatism and interpersonal learning performance. We have argued that conservative top managers effectively anchor on prior beliefs. Thus, the relevant question is: Are the anticipated adverse learning effects associated with such anchoring behavior more or less pronounced in a more hubby network? Based on our earlier arguments, we recognize that conservative top managers might find it easier to identify, and connect with well-informed individuals in a more hubby network. However, because conservative top managers underreact to new information, it is unclear whether they will benefit from their interactions with hubs as much as they can. One case in which they might do so is when their prior beliefs are consistent with the accurate beliefs of hubs. In this case, they would have anchored on prior beliefs that happen to be accurate. As a result, the adverse learning effects of anchoring could diminish in more hubby networks. On the contrary, if hubs have accurate beliefs that are at odds with top managers' prior beliefs, they might have hurt their interpersonal learning performance even more by persistently anchoring on inaccurate prior beliefs. As did before, we postulate the following two propositions to convey the ambiguity that surrounds the interplay between conservatism and network hubbiness in their interpersonal learning performance:

> **Proposition 4a**: When a top manager's network is highly hubby, the anticipated negative effect of conservatism on his or her interpersonal learning performance will diminish.

> **Proposition 4b**: When a top manager's network is highly hubby, the anticipated negative effect of conservatism on his or her interpersonal learning performance will be amplified.

Figure 1 summarizes our conceptual model.

[**Insert Figure 1 about here**]

ANALYTICAL MODELS

To investigate the interpersonal learning effects of impatience and conservatism in top managers under different levels of network hubbiness and other contingent factors, we draw on the seminal work of March (1991), and more recent studies such as Schilling and Fang (2014). Like these prior studies, our model contains the following three components: a) external reality, b) individuals or agents, and c) a network or informal organizational structure. In line with disparate research streams (Aiello et al. 2008, Barabási and Albert 1999, Barabási et al., 2002, Schilling and Fang, 2014), we also draw on a hub- and distance-based preferential attachment mechanism to evolve the network structures that we analyze. A notable feature of our model is that agents may hold accurate or inaccurate beliefs. More recent organizational and management research that applies agent-based modeling emphasize the practical relevance of this feature (e.g., Levine and Prietula 2014). We also allow information-seeking agents to acquire inaccurate beliefs from others because they misjudge the relative performance of alternative beliefs (i.e. one's current beliefs versus beliefs shared by another agent in a subsequent interaction). Following Schilling and Fang (2014), we examine the implications of faulty judgments when information-providing agents truthfully report their beliefs, and when they report distorted information. However, Schilling and Fang (2014) focus on the implications of network hubbiness for interpersonal learning outcomes at the network level. Thus, we extend their approach by accounting for the interplay between network structure and individual cognitive attributes in learning performance outcomes at the individual level.

Altogether, we have taken an important step towards validating our agent-based model because we have clarified exactly how it builds on, and extends prior related studies that apply validated models (Adner et al. 2009, Burton and Obel 1995, Davies et al. 2007, Harrison et al. 2007). More importantly, our agent-based model can yield useful insights because it rests on theoretically and empirically grounded assumptions, within a coherent cognitive framework (Mason and Watts 2012).

Baseline Model

Initial network structure: We consider a population of 100 agents (i.e. $N = 100$). This population size is adequate for the purpose of our analysis because it facilitates a sufficiently large number of knowledge-sharing interactions while keeping the level of computational difficulty at a minimum. In line with prior research (i.e. Schilling and Fang 2014), we apply a preferential attachment approach to model the following three stylized network structures: a) highly hubby (scale-free) network, b) moderately hubby (truncated scale-free) network, and c) non-hubby (random) network (See Figure 2). They represent three potential social environments in which individuals may seek information from others.

[**Insert Figure 2 about here**]

Agents' roles, reality, beliefs, and cognitive attributes: Our information-seeking (top-manager) agent—e.g., CEO of an established corporation, or the founding-CEO of a new venture—is randomly selected. All other agents are information providers. Reality constitutes an objectively true set of beliefs, with each belief representing a separate dimension of a problem or opportunity domain, and assigned a value of one (as opposed to zero). We choose four dimensions because doing so keeps the analysis simple, yet non-trivial. A set of beliefs constitutes an agent's mental representation of reality. Initial beliefs are randomly assigned to the agents in our model. In line with our foregoing discussion, an agent may exhibit impatience and conservatism. We will show how we operationalize these cognitive attributes when we discuss the interpersonal learning process later on.

Learning performance: We define the level of (final) learning performance that an agent achieves as the sum of the following two components: a) systematic component, and b) a random component. We operationalize the systematic component as a linear relationship between learning performance and information of a certain quality, where quality reflects the degree of correspondence between an agent's belief and reality, ranging from 0 (i.e. completed misinformed agent) and 1 (i.e. perfectly informed agents). Importantly, this proposed linear relationship rests on the assumption that an individual's learning performance improves at a constant rate as she accumulates information of a given quality. (As part of our sensitivity analysis, we later relax this baseline assumption by changing the value of a scaling parameter, α, from 1 to 0.5). The random component captures the amount of noise in the agent's learning performance. We generate values for this component as outcomes of a normally distributed random variable. (See the online Appendix S1 for an illustration of how an agent's learning performance is determined in our analysis).

Exchange partner selection strategy: We know from prior cognition research (e.g., Gigerenzer and Gaissmaier 2011, Gigerenzer and Goldstein 1996) that faster and less information-intensive, heuristic decision-making rests on the following three building blocks: a) process for initiating a search ("search rule"), b) process for stopping the search ("stopping rule"), and c) process for making a final decision ("decision rule"). In the context of our study, a key component of the search rule is an *exchange partner selection strategy*, where the key objective is to obtain high-quality information from others. When individuals are seeking information from their social ties, they need to decide which potential exchange partners should be prioritized for knowledge-sharing interactions. Our earlier discussion also suggests that individuals may be particularly drawn to hubs or neighbors when deciding which information sources they should primarily target. Therefore, we express agent i's exchange partner identification strategy, $Seek_j$, as their propensity to seek information from agent j:

$$Seek_j = h_j e^{-\theta d_{i,j}} \tag{1}$$

where the term h_j is a measure of the degree to which agent j is a hub in the network. An underlying assumption is that agent j will continue to provide high-quality information no matter how hubby he becomes. (As part of our sensitivity analysis, we later relax this baseline assumption by changing the value of a scaling parameter, η, from 1 to 0.5—which translates into a change from h_j^1 to $h_j^{0.5}$). The term $d_{i,j}$ is a measure of the network distance between a pair of agents; e is an Euler's constant approximately equal to 2.71828; and θ is a non-negative parameter that governs the choice between hubs and nearby contacts or neighbors. Specifically, values of θ closer to zero indicate that an individual is primarily targeting hubs (i.e. *hub-focused partner selection strategy*), while higher values of θ imply a preference for neighbors (i.e. *neighbor-focused partner selection strategy*), regardless of their level of connectivity in the network.

Interpersonal learning, stopping and final decision rules: The heuristic approach we have described in our postulated cognitive framework is also helpful for understanding how agent i might go beyond the search process, and progressively learn through a belief updating scheme that she terminates at some point. In line with the satisficing principle (Simon 1955) and related evidence from experimental psychology and entrepreneurship research (Choi et al. 2008, Hausmann and Läge, 2008, Soll and Larrick, 2009, Yaniv and Milyavsky 2007), we expect a cognitively constrained agent to conduct a non-exhaustive, sequential search for information from others. We propose that agent i will end her search as soon as she appraises her chance of attaining correct information to exceed a given probability threshold level—that is, the standard she adopts for judging the accuracy of her beliefs. At the final stage of the heuristic decision-making process, the information-seeking agent will follow a final decision rule that dictates what she ultimately believes. In the context of our study, agent i's stopping and decision rules may be linked to her subjective probability of attaining beliefs that perfectly correspond with reality, given her cognitive attributes (i.e. impatience and conservatism). The ideal standard against which a given set of beliefs is judged to be correct is the optimal probability threshold, T^*, which ranges from zero to one. Importantly, the application of such an ideal standard should not be interpreted to mean that an information-seeking agent will never hold inaccurate beliefs when she commits to it; instead, it keeps the likelihood of doing so at a minimum. In line with prior research (e.g., Camerer and Ho 1998, Stahl and Wilson 1995), we assume that agent i's subjective probability of attaining correct beliefs has a logistic form. Taken together, these considerations suggest that agent i will end her search for external information, and stop updating her belief, in accordance with the following stopping rule:

$$Prob_{i,t}(correct\ beliefs) = \frac{e^{C+\rho_i KON_{i,j}/N+\beta_i\left(P_{i,t}-P_{i,0}\right)}}{1+e^{C+\rho_i KON_{i,j}/N+\beta_i\left(P_{i,t}-P_{i,0}\right)}} > T^* \qquad (2)$$

where C is a constant term whose value is set to optimize the chance of being correct when making the least informed guess—without information on relevant individual attributes—about the probability that the average network member holds beliefs that correspond well with reality (See online Appendix S2 for the derivation of the constant C). In keeping with the practice of using implicit measures of psychological attributes when it is not feasible to obtain explicit ones (Gawronski 2014), the parameter ρ_i serves as an implicit measure of the level of impatience an agent exhibits. We assume that $\rho_i < 0$. A larger absolute value of ρ_i implies that an agent is more dismissive toward information received from later knowledge-sharing exchanges when appraising her chance of attaining correct beliefs. The parameter β_i serves as an implicit measure of the level of conservatism that an agent exhibits. We assume that $\beta_i > 0$. A smaller value of β_i implies that an agent's appraisal of her chance of attaining correct beliefs, based on performance feedback, is weaker than would be expected from an objective evaluation that places less weight on her prior beliefs. $KON_{i,j}$ denotes the order number of agent i's knowledge-sharing interactions with other agents. In this case, $\rho_i < 0$ specifically captures the subjective probability effects of impatience in terms of an agent's tendency to view her chance of attaining correct beliefs to be lower when she receives information from later knowledge-sharing interactions. The term $\left(P_{i,t} - P_{i,0}\right)$ denotes the difference between current possible learning performance level and the initial learning performance level (i.e. performance level associated with an agent's initial set of beliefs). Our use of the initial learning performance level as a benchmark for assessing an agent's perceived learning progress is consistent with the use of an anchoring heuristic (Tversky and Kahneman 1974). As noted before, this could mean that there is a selectivity accessibility mechanism at work (Mussweiler 2003), such that the performance level associated with an agents' initial set of beliefs is recalled more easily from their memory or an external source. This relative performance component of the stopping rule is consistent with prior research that associates cognitive attributes (i.e. overconfidence) in individuals (e.g., Krueger and Dunning 1999), and CEOs in particular (e.g., Hiller and Hambrick 2005), with an observed pattern of faulty judgments due to poor relative performance assessments. Specifically, the stopping rule captures the potential for an information-seeking agent to obtain and keep inaccurate beliefs because her cognitive attributes (i.e. impatience and conservatism) and choices (i.e. adopted standard for judging the accuracy of beliefs) predispose her to misjudge the relative performance of her current beliefs, and those later shared by another agent.

Simulation results based on the baseline model

In accordance with our baseline model, we implemented simulations in Julia Language (Bezanson et al. 2017) with the LightGraphs package (Bromberger et al., 2017). Online Appendices S3 and S4 show the initial parameter values for the key variables, as well as the pseudocode for the simulation algorithm, respectively. We now turn to the main simulation results.

Figure 3 plots the effects of impatience and conservatism on final learning performance across networks that differ in degree of hubbiness.

[**Insert Figure 3 about here**]

In general, higher levels of impatience (i.e. values of ρ closer to -1) or conservatism (i.e. values of β closer to 0) are associated with lower levels of learning performance, as well as a relatively long search time on average. These findings are consistent with propositions 2 and 3. However, as can be seen in Figure 3 (i.e. top-right and top-left plots), the adverse performance effects of impatience and conservatism are contingent on the hubbiness of the network; specifically, learning performance is particularly poor in non-hubby networks compared with either highly hubby or moderately hubby ones. When it comes to average search time, the moderating effects of network hubbiness is relatively weak in the case of impatience; and virtually immaterial in the case of conservatism. These findings are more consistent with propositions 3a and 4a.

EXTENSION OF BASELINE MODEL

In this section, we explore the extent to which the learning performance effects of individual cognitive attributes and network hubbiness might be affected by the presence of external environmental conditions, such as distorted information and initial knowledge variety; as well as individual actions or behaviors, such as the standards adopted for judging the accuracy of one's beliefs and exchange partner selection strategies.

Based on our baseline model, an information seeker can initially hold correct or wrong information before seeking information from another individual. In this case, such an information seeker may obtain wrong information from a knowledge-sharing exchange if a) the information provider truthfully reports incorrect beliefs, and b) the information seeker replaces her initially correct beliefs with the incorrect ones because she misjudges the relative performance outcomes of alternative beliefs. By extending our baseline model to allow information providers to misinform others by lying and making mistakes, we may evaluate the learning performance effects of additional sources of distorted information in networks. By lying, we mean the intentional reporting of distorted information to others. When information providers lie in our model, they report the opposite of what they know or believe about the attribute of a given dimension of a problem or opportunity with the intention to mislead others. When it comes to mistakes, we are concerned about the inadvertent reporting of distorted information to others. When information providers make a mistake in our model, they report the incorrect attribute of a given dimension of a problem or opportunity based on random human error (i.e. recall and/or reporting of the wrong information by chance). To capture the potentially harmful effects of small departures from truthful reporting on learning performance, we consider cases in which information providers lie or make mistakes when reporting information to others with a probability of a) 0.001, and b) 0.01. Interestingly, an emerging view is that a small amount of misinformation can be performance enhancing at the network level (Schilling and Fang 2014); however, this may not necessarily be the case at the individual level. Figure 4 illustrates the learning performance effects of impatience and network hubbiness when there is distorted information. Importantly, even when information providers lie or make mistakes at low rates, the resulting departures from truthful reporting may significantly undermine the learning performance of an information seeker, regardless of her level of impatience or the hubbiness of her networks. It is notable that an information seeker’s learning performance tends to suffer more when information providers lie as opposed to make mistakes. As can be seen in Figure 4, search times can be relatively long when a highly impatient information seeker has to deal with distorted information. This outcome is virtually the same across networks ranging from non-hubby to highly hubby; and hence, not contingent on network hubbiness.

[**Insert Figure 4 about here**]

Figure 5 illustrates the learning performance effects of conservatism and network hubbiness in the presence of distorted information. The findings are qualitatively similar to those previously reported for impatience: slight departures from truthful reporting inhibits learning, independent of the level of conservatism or network hubbiness; and conservatism can lead to long search times when an information seeker is confronted with distorted information, regardless of the hubbiness of her network.

[**Insert Figure 5 about here**]

Prior research indicates that initial knowledge variety (or knowledge dissimilarity) up to a certain level can be performance enhancing at the network level (Schilling and Fang 2014). But this may not necessarily be the case for every information-seeking agent in the network at a given point in time. To investigate the implications of initial knowledge variety for individual interpersonal learning, we first measure it as the total number of mismatched belief dimensions across pairs of agents divided by the total number of such pairs (Schilling and Fang 2014). However, since initial beliefs are randomly assigned in our model, we specifically capture initial knowledge variety as follows: step 1, run 20000 replications of the simulation; step 2, compute the associated values for initial knowledge variety; step 3, order (from smallest to largest) and divide the 20000 initial knowledge variety values into five bins, each with 4000 values; drop the second and fourth bin (so that bins one, three and five are more separated); and step 5, use the midpoints of the ordered values in each of the three bins to categorically measure a low, medium and high level of initial knowledge variety. As can be seen in Figure 6, an information-seeking agent tends to perform better at lower levels of initial knowledge variety, and the hubbiness of the network plays a complex contingent role. Interestingly, higher levels of impatience are associated with longer search times, virtually independent of the level of initial knowledge variety or the hubbiness of the network.

[**Insert Figure 6 about here**]

Similar to an impatient information seeker, a conservative one tends to achieve higher performance levels at lower initial knowledge variety levels. In addition, the search times tend to be long when the level of conservatism is high, regardless of the level of initial knowledge variety or the hubbiness of the network.

[**Insert Figure 7 about here**]

Building on our earlier discussion, we explore how the interpersonal learning outcomes arising from the interplay between cognitive attributes and network structures might be impacted by the decision to adopt a certain standard for judging the chance of having beliefs that perfectly correspond with reality. To do so, we numerically compute an optimal probability threshold—with respect to correct beliefs—that has the potential to optimize learning performance. Based on this ideal standard, we consider cases in which the acceptable standard is low (actual probability threshold is smaller than the optimal probability threshold), optimal (actual probability threshold is equal to the optimal probability threshold), and high (actual probability threshold greater than the optimal probability threshold). As captured in Figure 8, an information-seeking agent can achieve a relatively high level of performance by either operating at, or slightly above the optimal probability threshold. However, this enhanced performance is traded off against a relatively long search period.

[**Insert Figure 8 about here**]

We have a similar picture for conservatism in Figure 9: a less-than-ideal standard for judging the accuracy of one's beliefs can lead to relatively poor learning performance. Although lower standards can shorten the time required to search for external information, a highly conservative information-seeking agent does not save a substantial amount of search time.

[**Insert Figure 9 about here**]

Finally, we consider the case involving exchange partner selection strategies. In keeping with our earlier discussion, we investigate whether an impatient and conservative information-seeking agent may achieve better learning outcomes if she adopts a hub-focused ($\theta = 0$), equal opportunity (mixed) ($\theta = 1$), or neighbor-focused ($\theta = 2$) strategy in network structures ranging from non-hubby to highly hubby. We know from prior research that individuals may particularly derive advantages when they interact with well-connected individuals (Hasan and Bagde 2015). By virtue of their high level of connectivity and influence in a variety of networks (Barabási 2009, Barabási et al. 2002), hubs are presumed to be generally better informed than non-hub network members. We also recognize that some hubs may be more accessible and less demanding than others. Furthermore, some hubs may not have accurate information, and those who do, might inadvertently or intentionally misinform others (Schilling and Fang 2014). We presume that individuals who primarily target hubs do so with the expectation that the chance of getting accurate information from them is relatively high, and the potential challenges of dealing with hubs are manageable. In contrast to a hub-focused partner selection strategy, a neighbor-focused one prioritizes proximate social ties, regardless of their level of connectivity in the network. This neighbor-focused approach is consistent with the notion of cognitively constrained search in uncertain environments, where individuals primarily look for clues from recent information or proximate locations (Gavetti and Levinthal 2000, Levinthal and March 1993). Meanwhile, an equal opportunity approach may capitalize on the advantages of hub- and neighbor-focused strategies, while limiting the associated disadvantages. As can be seen in Figure 10, an impatient information-seeking agent can achieve a relatively high level of learning performance by primarily targeting hubs, or a mix of hubs and neighbors; however, the performance-enhancing benefits of such strategies are contingent on the hubbiness of the network. Interestingly, when an information seeker exhibits a high level of impatience, her search time will be relatively long, regardless of the partner selection strategy or network hubbiness.

[**Insert Figure 10 about here**]

As captured by Figure 11, the story is virtually the same for a conservative information-seeking agent: focusing on either hubs or some mix of hubs and neighbor can enhance performance, and the performance-effects of partner selection strategies are contingent on network hubbiness. Similarly, a highly conservative information-seeking agent will search for information over a relatively long period, regardless of her partner selection strategy.

[**Insert Figure 11 about here**]

Robustness checks

In additional analyses reported in online Appendices S5 to S7, we conducted sensitivity analyses with a focus on important experimental conditions. Specifically, we examined whether our main findings remain qualitatively the same when we incorporate more psychologically and organizationally realistic assumptions in our model. First, we relaxed the assumption that agents' beliefs constitute independent dimensions by allowing for correlation between the dimensions. In doing so, we capture the more appealing and realistic view of beliefs as simplified knowledge structures or actionable information (Shank and Abelson 1977). This necessarily requires the establishment of linkages or correlation between core belief dimensions. Second, we relaxed the assumption that the relationship between learning performance and externally acquired information is linear. Specifically, we account for the possibility of a non-linear relationship, where learning performance improves at a decreasing rate as external information accumulates. Third, we relaxed the assumption that hubs deliver high-quality information at the same rate as they become more connected in the network. We consider the case in which hubs become a progressively less reliable as source of high-quality information as they become more connected, and overburdened by excessive information. This situation is plausible because prior strategic management researchers view information overload as a serious problem in organizations (O'Reilly 1980). In all these variations, the findings are largely consistent with our main results. Given concerns about the practical significance and sensitivity of simulation results to manipulatable experimental conditions (Harrison et al. 2007, Leombruni and Richiardi 2005, Manzo 2014), this finding should bolster confidence in the theoretical insights that rest on our main results.

DISCUSSION

We presented a cognitive framework that invokes an anchoring logic to investigate why and how top managers' cognitive attributes and network structures might jointly shape their interpersonal learning outcomes. Based on the results from our agent-based model, the emerging picture is that more impatient or conservative top managers may learn less, and relatively slowly—due to a longer-than-necessary search period—than others, particularly in the context of less hubby networks. Interestingly, even low levels of distorted information—arising from mistakes and especially lies—may hurt top managers' interpersonal learning performance, independent of their level of impatience or conservatism, or access to hubs. However, such misinformation does not seem to significantly affect how quickly they learn from others because it does not materially add to the relatively lengthy search times that are associated with impatience or conservatism. In the case of initial knowledge variety, the hubbiness of the network plays a more important moderating role, but the basic observation is similar: more impatient or conservative top managers do not seem to handle moderate to high levels of initial knowledge variety well in their interpersonal networks—a challenge that apparently amplifies the tendency toward relatively low levels of interpersonal learning, but not necessarily long search times. Importantly, having shown that the adoption of ideal standards for judging the accuracy of one's beliefs are performance enhancing, more impatient or conservative top managers are likely to realize worse interpersonal learning outcomes if they try to expedite the search process by adopting less ideal standards. At the same time, such managers may improve their interpersonal learning outcomes by primarily targeting hubs, or some mix of hubs and neighbors.

Our study makes two major important contributions. First, we add to prior organization learning in the context of informal structures by clarifying the interplay between individual cognitive attributes, such as impatience and conservatism, and network structures in the interpersonal learning performance of leading corporate players such as top managers (Levine and Prietula 2012, Reagans and McEvily 2003, Schilling and Fang 2014). Our study specifically contributes by lending support to the view that contingent frameworks that simultaneously account for learning-relevant factors at the individual and network level can be helpful for explaining and predicting organizational learning behaviors and outcomes. We specifically build on, and extend prior research such as Anderson (2008). In his study, he reports evidence that more cognitively motivated managers will especially realize substantial informational benefits when they belong to large networks. We advance this research stream because we offer new and complementary analytical findings on the joint effects of impatience and conservatism and network hubbiness on interpersonal learning outcomes. We also point to a more complicated picture by identifying other important contingent factors at work (i.e. initial knowledge variety in the network, standards for judging the accuracy of one's beliefs).

These insights are also related to a network research stream that is primarily concerned with the challenge of pacing knowledge diffusion to optimize interpersonal learning. A well-received view is that aggregate interpersonal learning in informal organizational structures may be optimized over the long term if knowledge diffuses within them at a moderate pace (March 1991). However, we know that hubs are pervasive across a variety of networks; and because they may accelerate the speed of knowledge diffusion in networks, a major concern is that diverse ideas may not be preserved long enough to engender numerous combinatorial possibilities, and superior ideas over the long term (Schilling and Fang 2014). When it comes to top managers' interpersonal learning performance, we are mindful that they may turn to their most well-connected contacts for information because they are under pressure to quickly solve difficult problems, or spot opportunities, with limited information. Our findings suggest that they might find it difficult to optimize interpersonal learning by keeping access to diverse information and the speed of knowledge acquisition in balance. In practice, this could mean that top managers' cognitive attributes and the structural characteristics of their networks predispose them to terminate their search for external information long before superior ideas crystalize in their interpersonal networks. Thus, it is possible that organizations may not benefit as much as they can from senior executives' access to a variety of knowledgeable internal and external contacts. Taken together, these nuanced insights are particularly helpful for building organizational learning theories that rest on managerial cognition

Finally, our study has major implications for social capital research. We contribute to the development of social capital theory in strategic management (Adler and Kwon 2002, Nahapiet and Ghoshal 1998), and particularly in entrepreneurship, given the greater focus on new ventures or small firms that depend on their owners' networks for external resources (Gedajlovic et al. 2013, Stuart and Sorenson 2007). We know from Vissa (2012) that new venture owners (or founding CEOs) may progressively grow their network by soliciting and using the referrals provided by earlier, and potentially stronger contacts. At the same time, Ozdemir et al. (2016) point to a more active network development and management strategy; specifically, such owners may intentionally devote more time and energy toward the maintenance of close relationships with strategically important contacts, while structurally embedding less important contacts through mutual acquaintances. Our study adds to this line of research because the reported findings suggest that business owners may adopt appropriate partner selection strategies and standards that increase their chance of obtaining valuable information from others. More generally, the findings lend support to the view that business owners' cognition is a particularly important contingent factor or boundary condition for a social capital theory of entrepreneurship (Corbett, 2007). They also reinforce the point that individual cognition constitutes an important boundary condition for a resource-based view of the firm (Morgan et al., 2018). By making these contributions, our study also respond to recent calls for stronger microfoundations in strategic management concepts and theories (Felin et al. 2015, Minbaeva 2016). Specifically, we advance this initiative by linking a macro-level concept such a social capital to a mechanism that rests on the interplay between micro-level concepts (individual cognitive attributes) and macro-level concepts (network structures).

Limitations and areas for future research

Our study has limitations that provide opportunities for future research. First, while it is helpful to focus on the cognition of top managers as key decision-makers in interpersonal networks within organizations, the collective cognition of several players could be more relevant for interpersonal learning outcomes in highly cooperative or consultative networks. Researchers may build on our work by investigating the aggregation of individual cognitive attributes into collective ones, and draw implications for individual- and network-level learning under different network structures and other relevant contingencies. Second, we assumed that individuals arrive at their beliefs in a reasonable way. In addition, when they hold beliefs that are at odds with reality, we presume that the source of the inaccuracy could result from information seekers' tendency to misjudge the relative performance of alternative beliefs that are honestly reported; or based on their vulnerability to the lies or mistakes of information providers. However, we recognize that individuals need not form beliefs in a reasonable way, and that the source of inaccurate beliefs goes beyond what we have considered. Specifically, since top managers may persistently hold unreasonable or superstitious beliefs when making decisions under uncertainty (Tsang 2004), our model is silent on a potentially important source of inaccurate information. Researchers may build on our work by investigating the underlying mechanisms behind the emergence and persistence of superstitious beliefs, as well as their learning performance effects at the individual and network levels.

CONCLUSION

Well-connected top managers have the potential to give their companies a competitive edge by quickly learning from others in their interpersonal networks when confronted with strategically important decisions, under uncertainty and time pressure. However, we have theorized and shown that the interpersonal learning process is complicated by the interplay of learning-relevant cognitive attributes, such as impatience and conservatism, and network characteristics, such as the prevalence of hubs. The emerging picture is that how top managers think, strategically network and form judgments about what to believe from others can significantly affect how quickly and well they learn in their interpersonal networks. This calls for much more attention to the cognitive attributes of such managers when theorizing about their ability to identify, assimilate and apply valuable knowledge resources beyond the boundary of their organizations.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. An illustration of how learning performance is determined in our analysis.

Appendix S2. Derivation of the constant C.

Appendix S3. Initial parameter values of key variables in the model.

Appendix S4. Pseudocode for the simulation algorithm.

Appendix S5. First robustness check—More complex reality and belief structure.

Appendix S6: Second robustness check—Non-linear learning performance structure.

Appendix S7. Third robustness check—Declining quality of hubs as connectivity increases.

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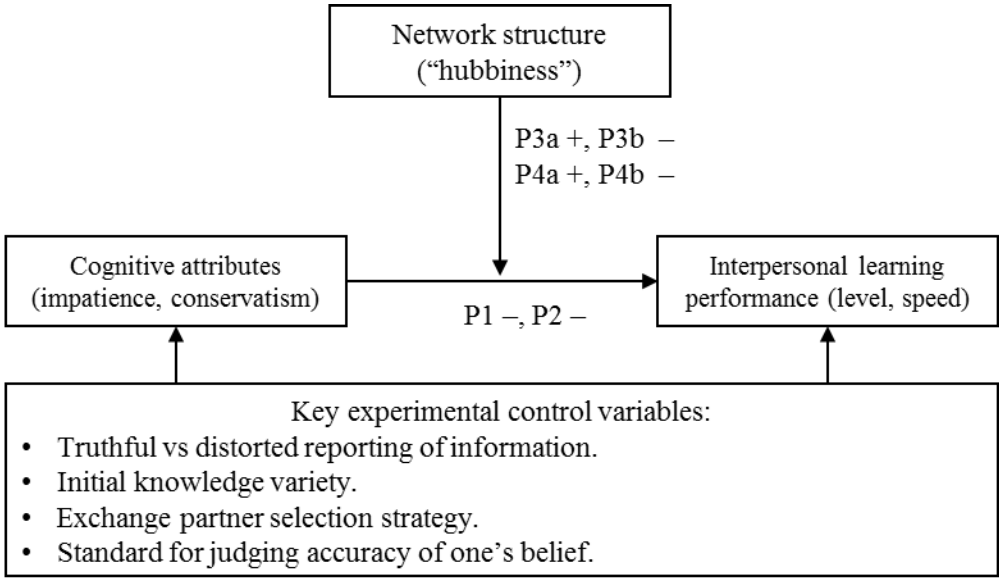
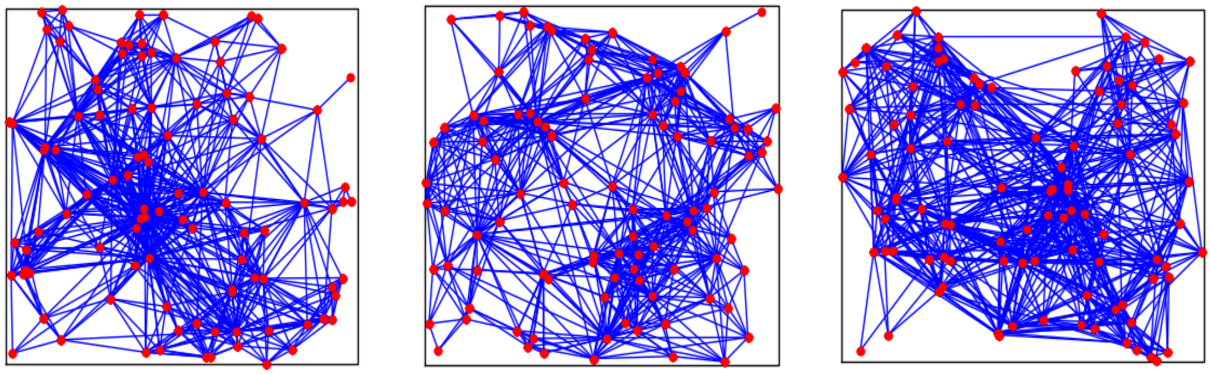


Figure 1. A conceptual model of the separate and joint effects of impatience and conservatism on interpersonal learning performance in top managers.



(a) (b) (c)

Figure 2. a) Highly hubby network (i.e. scale-free network), b) moderately (or medium) hubby network (i.e. truncated scale-free network) and c) non-hubby network (i.e. random network). There are 100 agents in each network. The average number of links received by the agents is the same in the three networks (approximately 7.5), but the variance is different—it decreases as we shift from the highly hubby network to the non-hubby one.

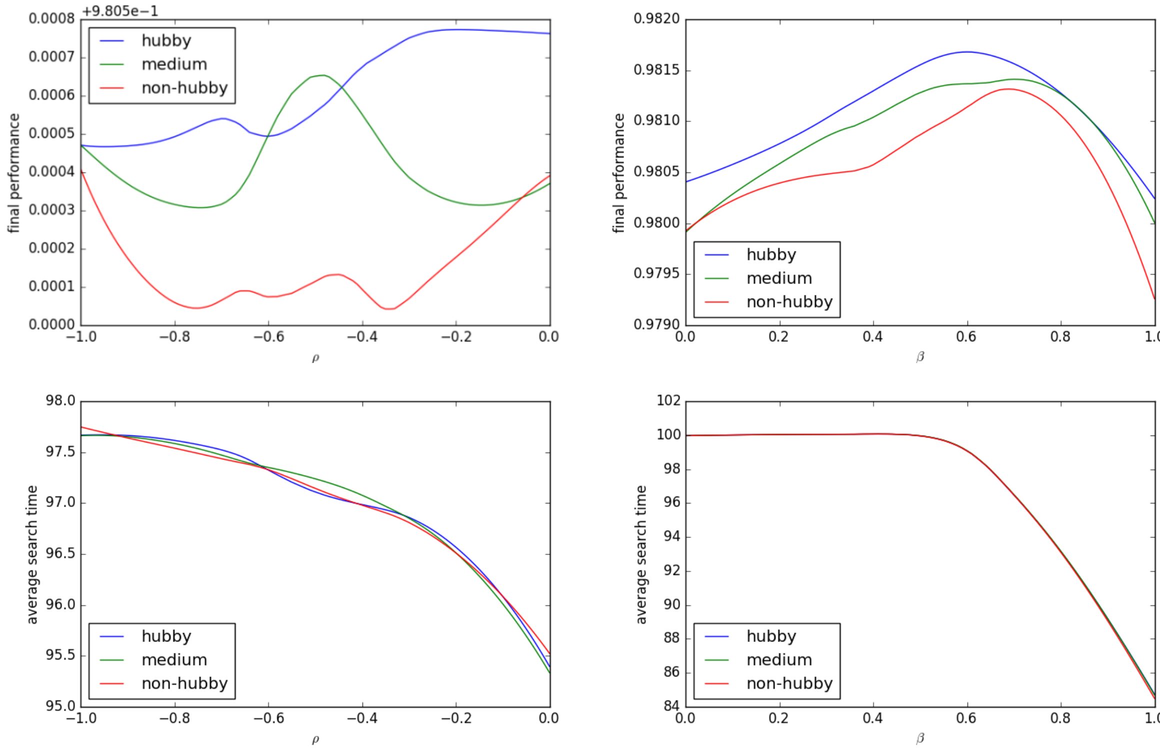


Figure 3. Learning performance effects of impatience (ρ) and conservatism (β) under different network structures. The abbreviated legend labels "hubby", "medium" and "non-hubby" denote highly hubby, moderately or medium hubby, and non-hubby networks, respectively. Experimental control variables used in all cases: a) truthful reporting, b) moderate initial knowledge variety, c) equal opportunity (mixed) partner selection strategy, and d) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

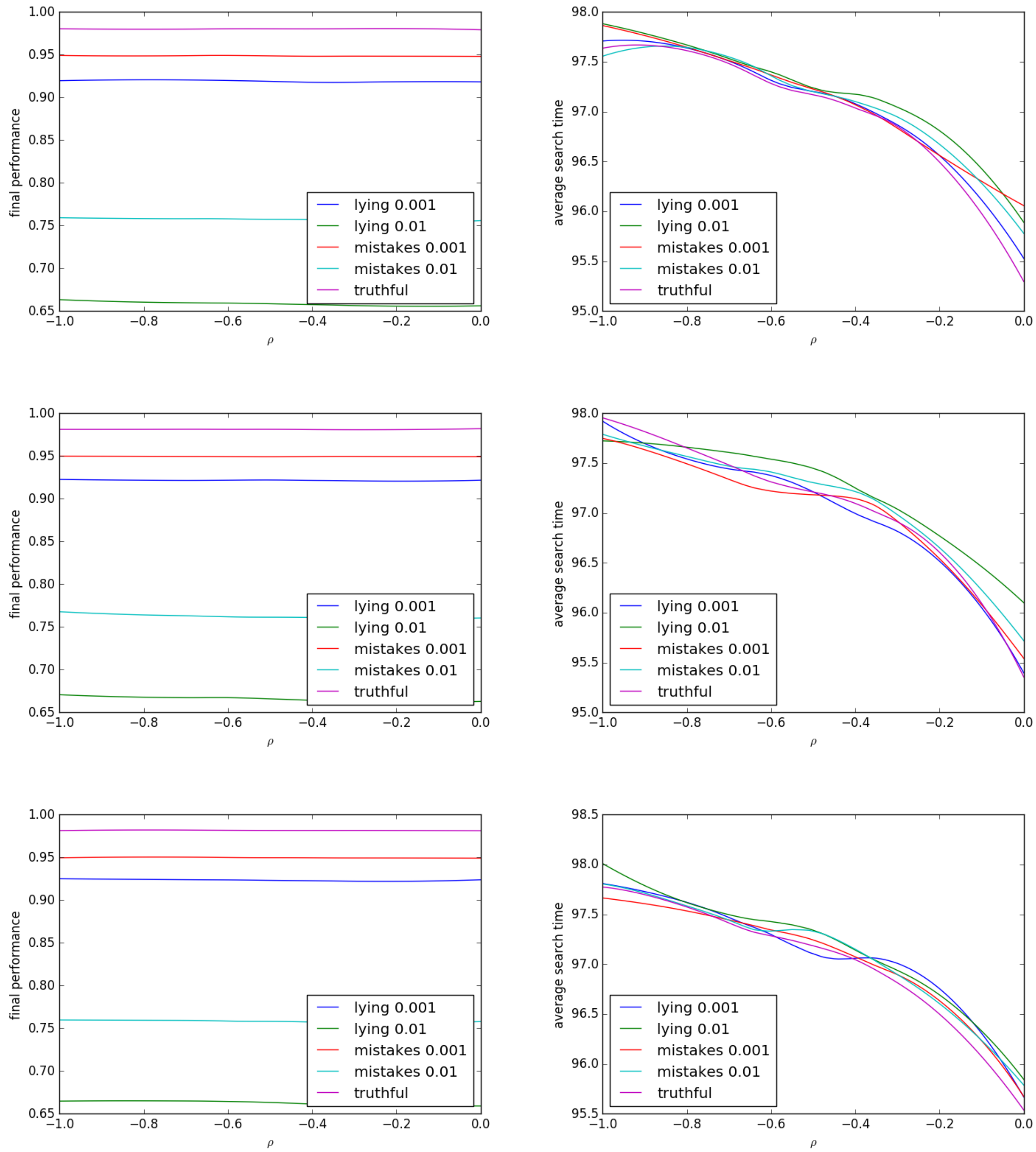


Figure 4. Learning performance effects of impatience (ρ) under different levels of network hubbiness and information distortion. Network structures used in left- and right-hand-side subplots: top, highly hubby networks; middle, moderately hubby networks, and bottom, non-hubby networks. Lying: intentional reporting of distorted information to others. Mistakes: inadvertent reporting of distorted information to others. Experimental conditions for lying and mistakes: information providers lie or make mistakes when reporting information to others with a probability of a) 0.001, and b) 0.01. Experimental control variables used in all cases: a) moderate initial knowledge variety, b) equal opportunity (mixed) partner selection strategy, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

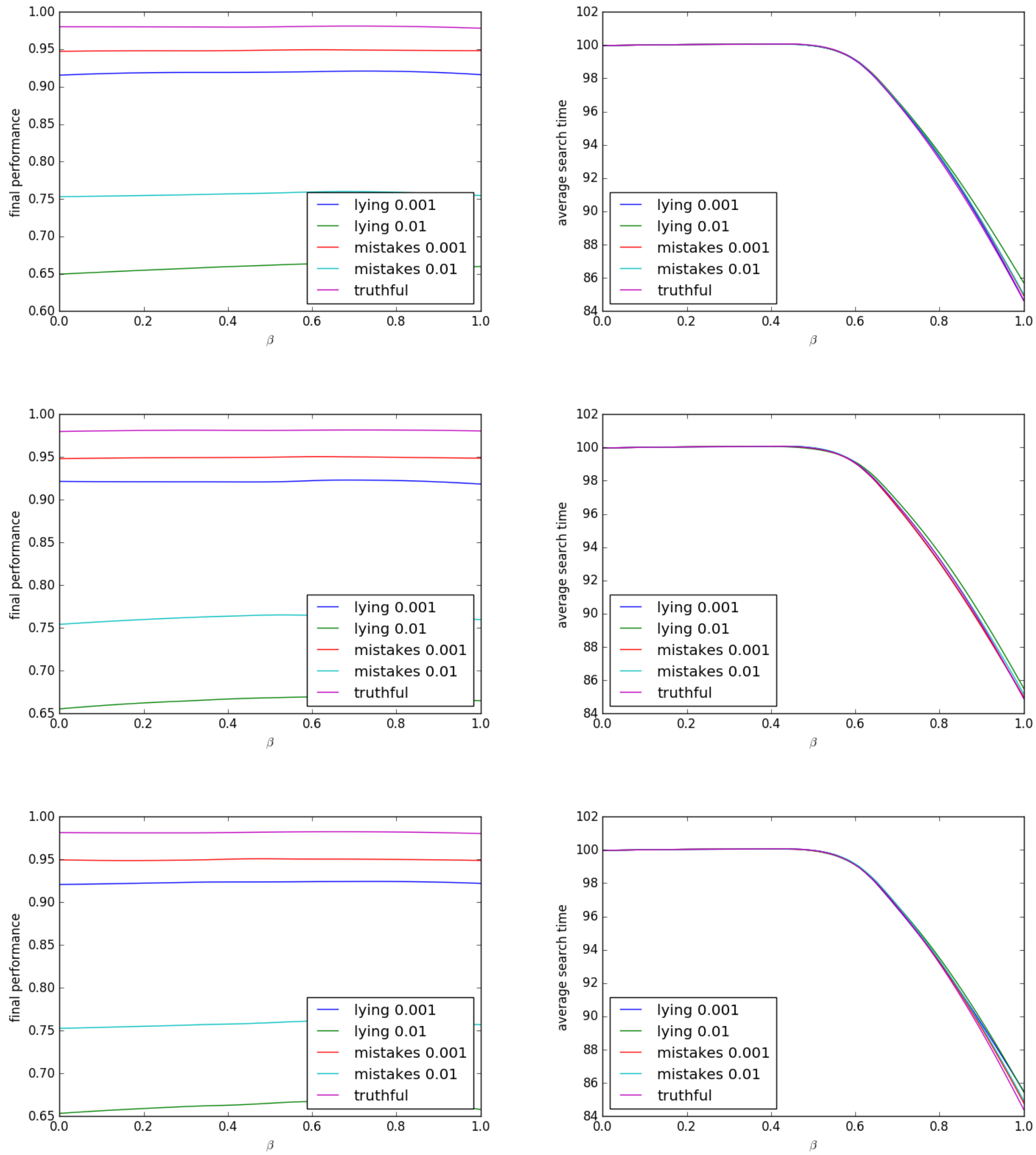


Figure 5. Learning performance effects of conservatism (β) under different levels of network hubbiness and information distortion. Network structures used in the left- and right-hand-side subplots: top, highly hubby networks; middle, moderately hubby networks, and bottom, non-hubby networks. Lying: intentional reporting of distorted information to others. Mistakes: inadvertent reporting of distorted information to others. Experimental conditions for lying and mistakes: information providers lie or make mistakes when reporting information to others with a probability of a) 0.001, and b) 0.01. Control experimental variables used in all cases: a) moderate initial knowledge variety, b) equal opportunity (mixed) partner selection strategy, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

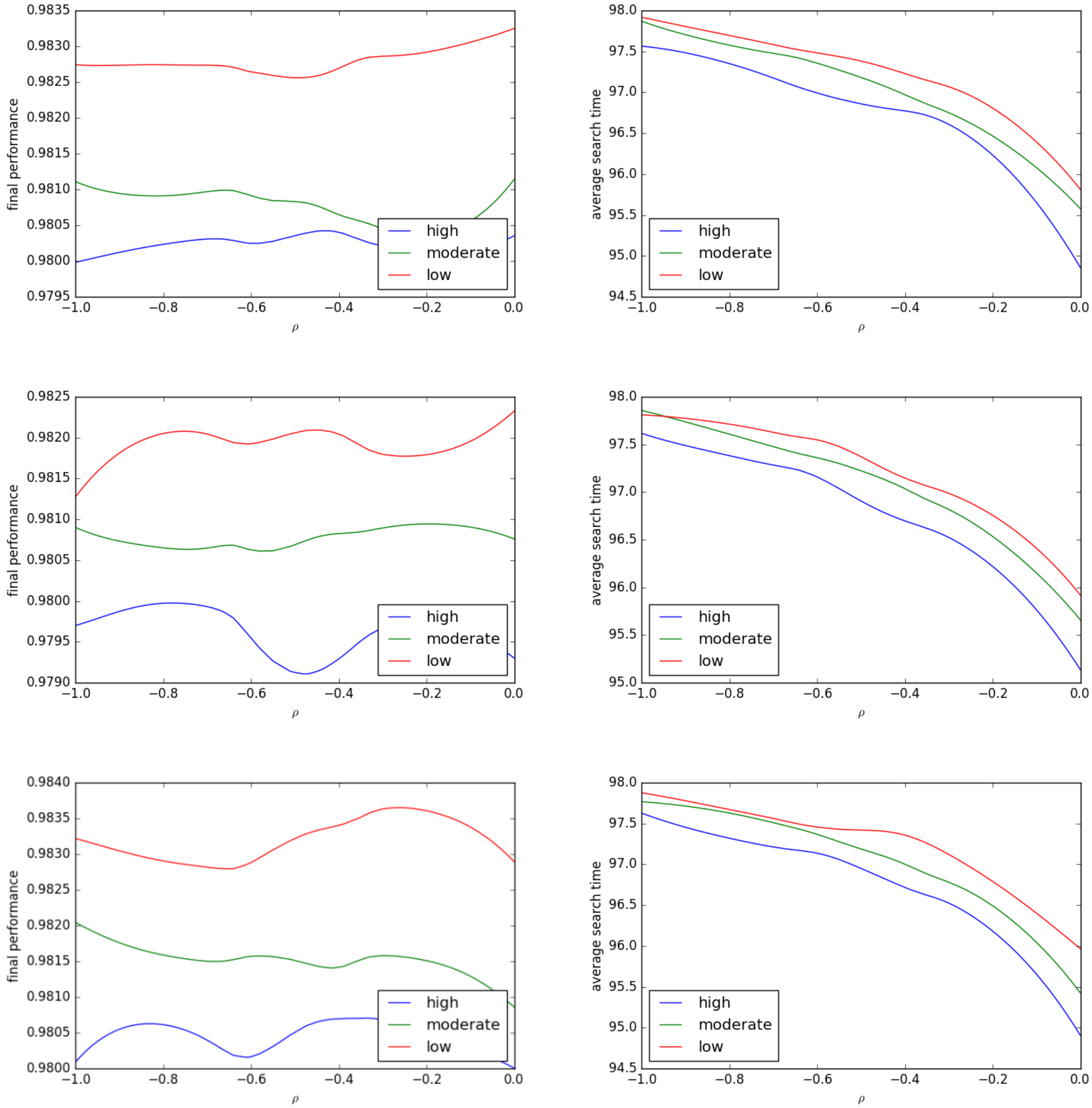


Figure 6. Learning performance effects of impatience (ρ) under different levels of network hubbiness and initial knowledge variety. Network structures used in the left- and right-hand-side subplots: top, highly hubby networks; middle, moderately hubby networks, and bottom, non-hubby networks. The figure legends indicate high, moderate and low levels of initial knowledge variety. Low to high initial knowledge variety implies low to high degree of variation in the agents' initial beliefs about the dimensions of a problem or opportunity. Experimental control variables used in all cases: a) truthful reporting, b) equal opportunity (mixed) partner selection strategy, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

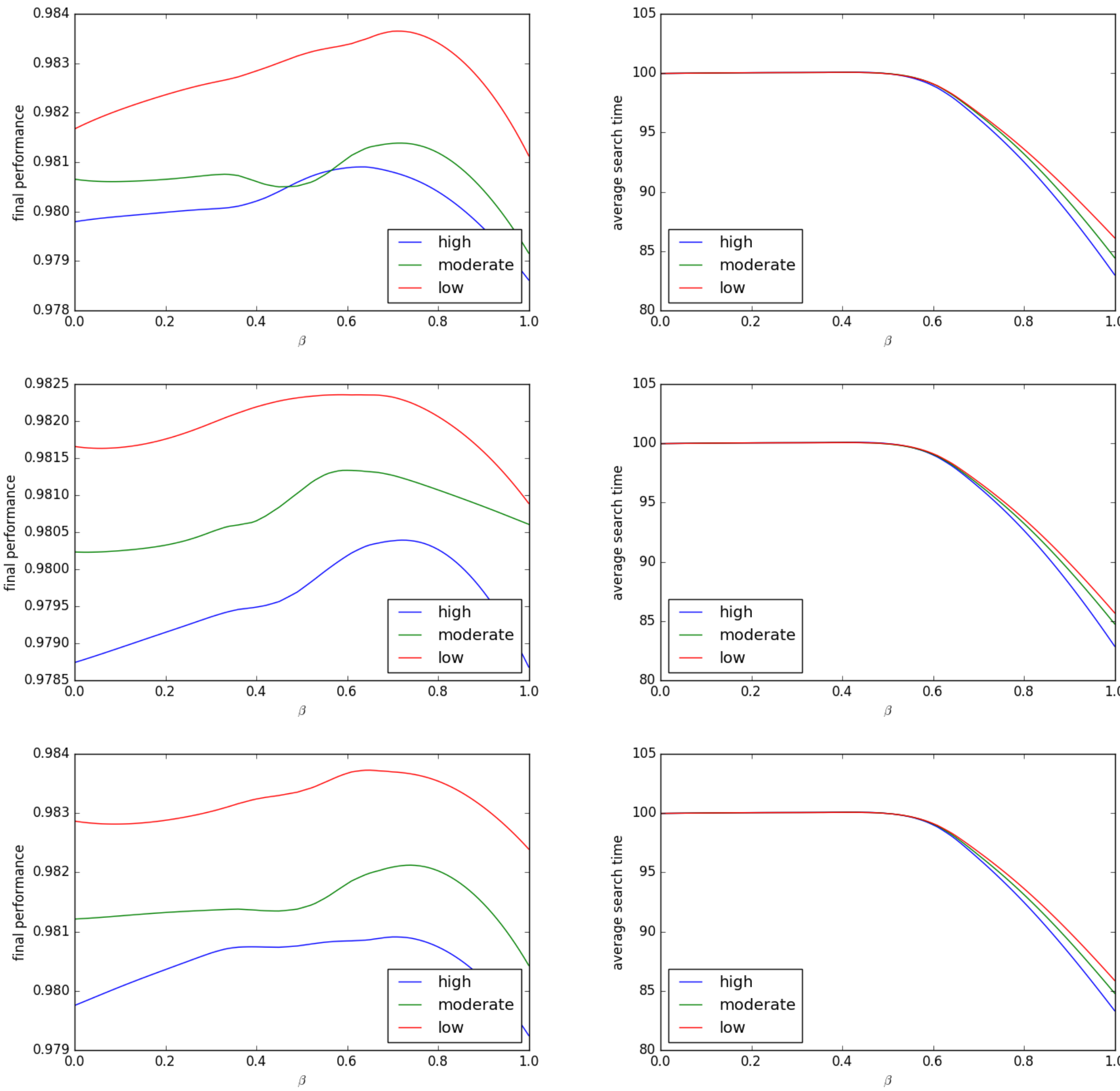


Figure 7. Learning performance effects of conservatism (β) under different levels of network hubbiness and initial knowledge variety. Network structures used in the left- and right-hand-side subplots: top, hubby networks; middle, medium-hubby networks, and bottom, non-hubby networks. The figure legends indicate high, moderate and low levels of initial knowledge variety. Low to high initial knowledge variety implies low to high degree of variation in the agents' initial beliefs about the dimensions of a problem or opportunity. Experimental control variables used in all cases: a) truthful reporting, b) equal opportunity (mixed) partner selection strategy, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

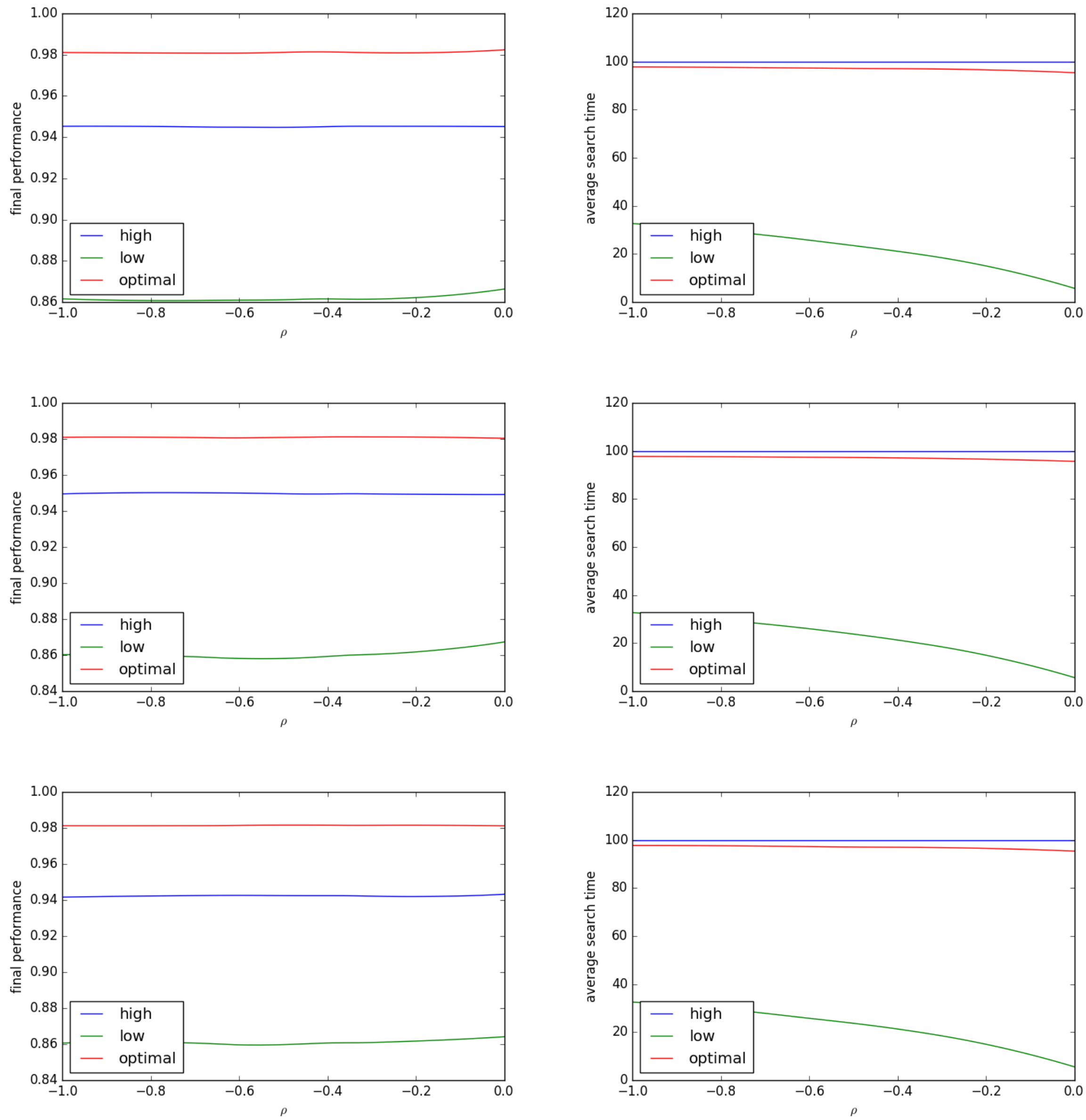


Figure 8. Learning performance effects of impatience (ρ) under different levels of network hubbiness and acceptable standard for judging the chance of attaining beliefs that perfectly correspond with reality. Network structures used in the left- and right-hand-side subplots: top, hubby networks; middle, medium-hubby networks, and bottom, non-hubby networks. The figure legends indicate high, low and optimal acceptable standards for the chance of having correct beliefs. Experimental control variables used in all cases: a) truthful reporting, b) equal opportunity (mixed) partner selection strategy, and c) moderate initial knowledge variety.

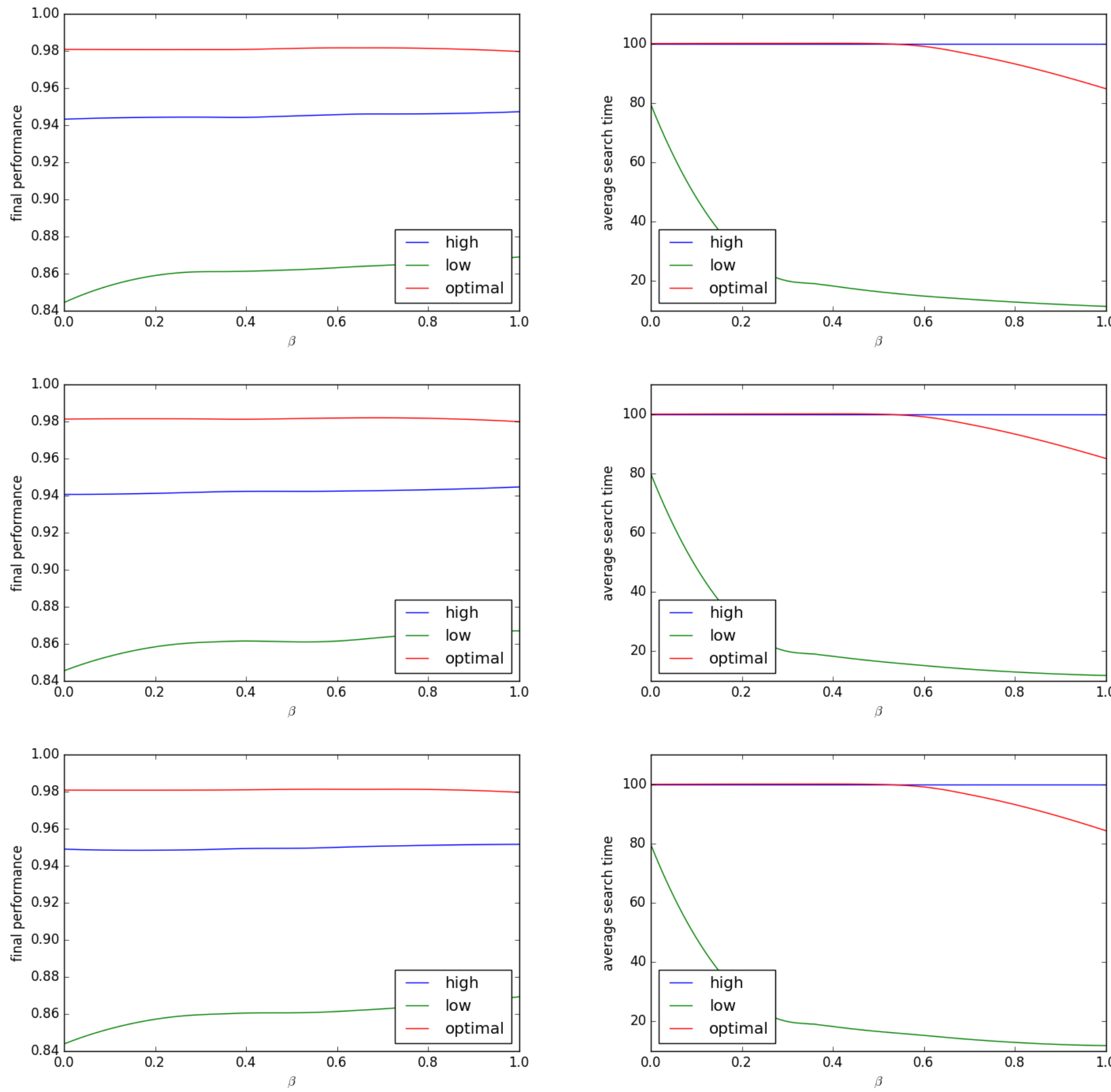


Figure 9. Learning performance effects of conservatism (β) under different levels of network hubbiness and acceptable standard for judging the chance of attaining beliefs that perfectly correspond with reality. Network structures used in the left- and right-hand-side subplots: top, hubby networks; middle, medium-hubby networks, and bottom, non-hubby networks. The figure legends indicate high, low and optimal acceptable standards for the chance of having correct beliefs. Experimental control variables used in all cases: a) truthful reporting, b) equal opportunity (mixed) partner selection strategy, and c) moderate initial knowledge variety.

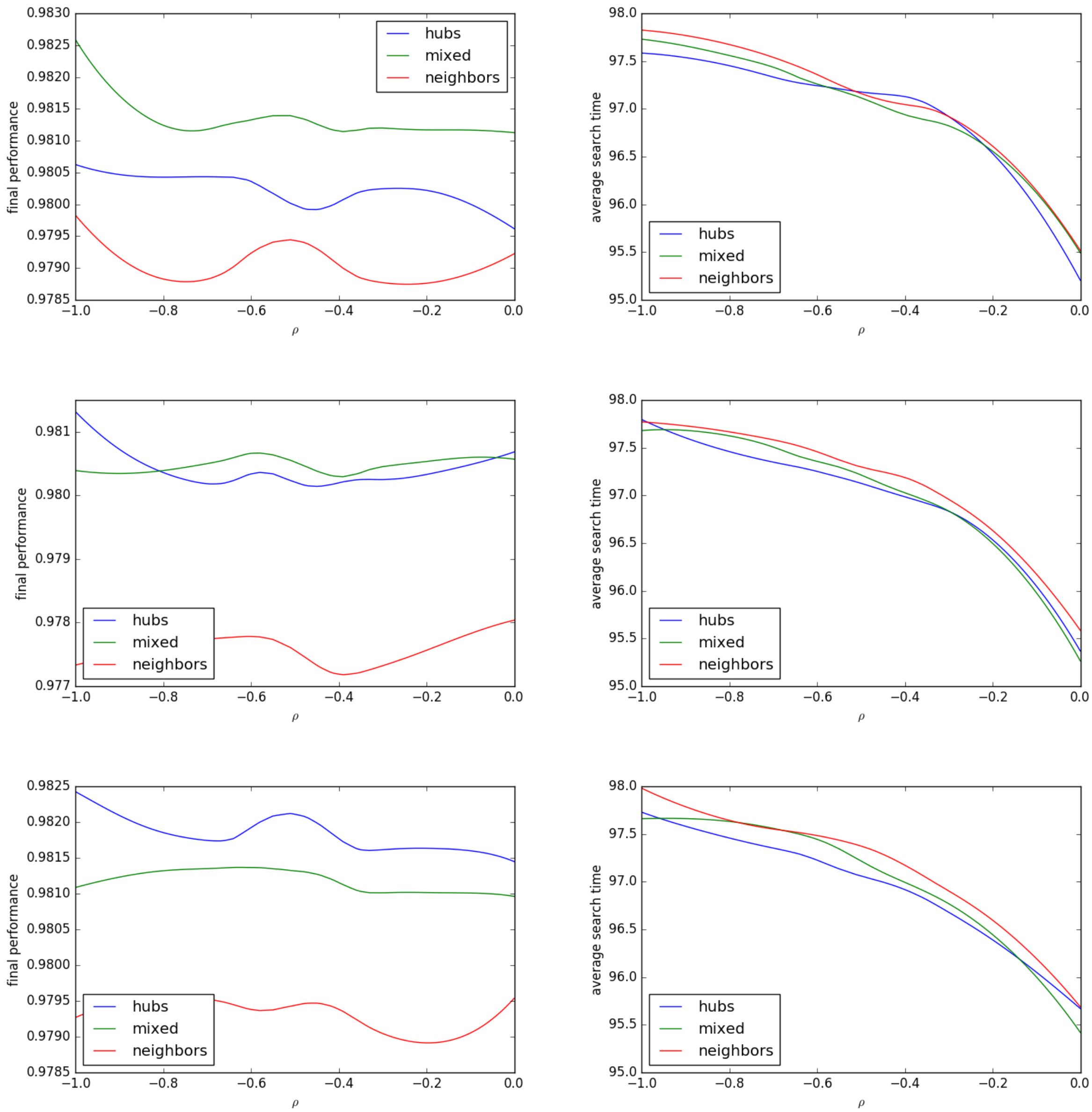


Figure 10. Learning performance effects of impatience (ρ) under different levels of network hubbiness and exchange partner selection strategies. Network structures used in the left- and right-hand-side subplots: top, hubby networks; middle, medium-hubby networks, and bottom, non-hubby networks. The abbreviated legend labels "hubs", "mixed" and "neighbors" denote hub-focused, equal opportunity (mixed), and neighbor-focused partner selection strategies, respectively. Experimental control variables used in all cases: a) truthful reporting, b) moderate initial knowledge variety, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).

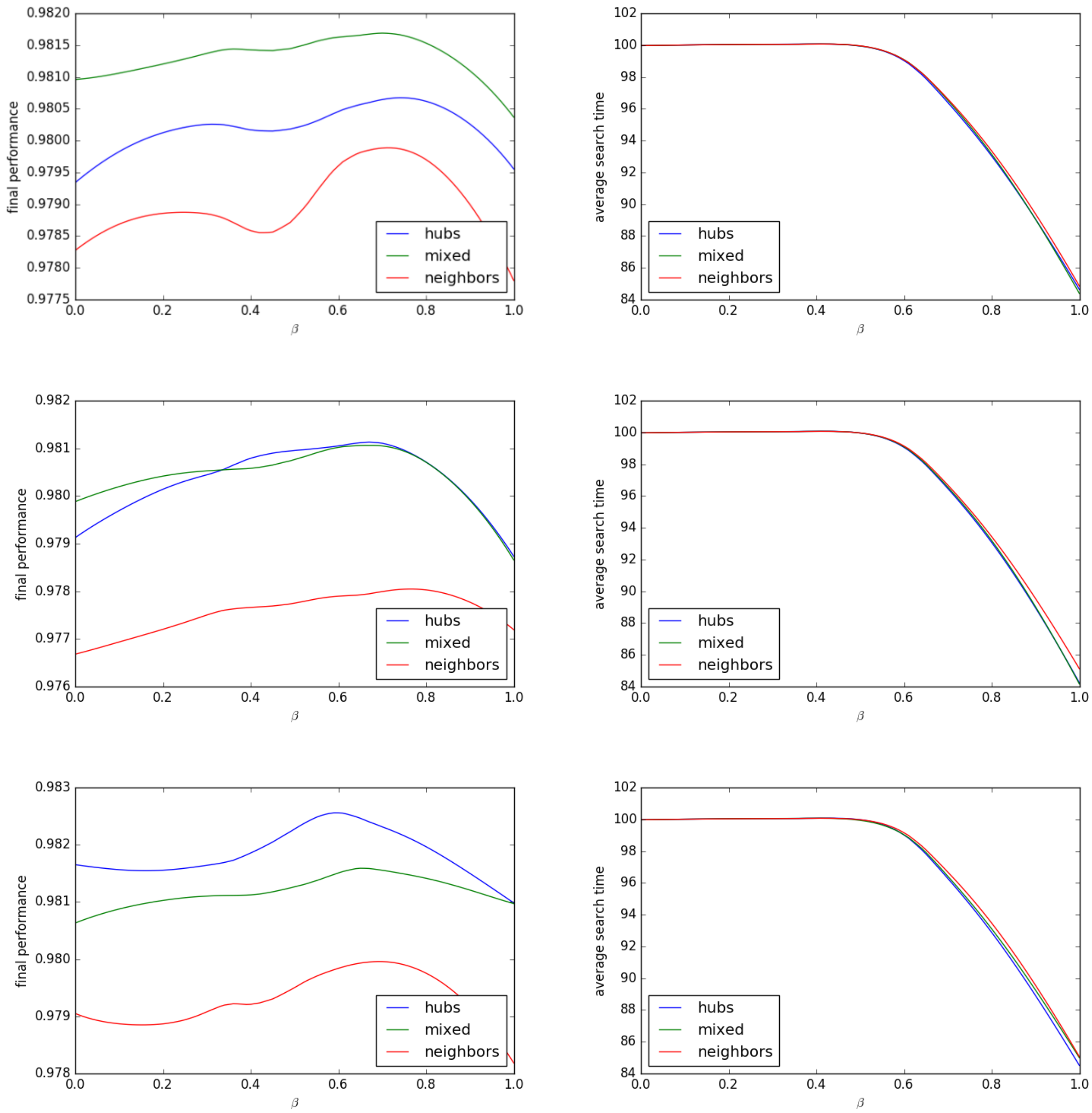


Figure 11. Learning performance effects of conservatism (β) under different levels of network hubbiness and exchange partner selection strategies. Network structures used in the left- and right-hand-side subplots: top, hubby networks; middle, medium-hubby networks, and bottom, non-hubby networks. The abbreviated legend labels "hubs", "mixed" and "neighbors" denote hub-focused, equal opportunity (mixed), and neighbor-focused partner selection strategies, respectively. Experimental control variables used in all cases: a) truthful reporting, b) moderate initial knowledge variety, and c) actual probability threshold (correct beliefs) is equal to the optimal probability threshold (correct beliefs).