Journal of Business Research xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Search behavior of individuals working in teams: A behavioral study on complex landscapes

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ARTICLE INFO

Keywords:
Teams
Behavioral interdependence
Limited knowledge
Search
NK fitness landscape
Exploration vs. exploitation

ABSTRACT

Search is a fundamental part of complex problem solving and often involves a choice between the exploration of new ideas and the exploitation of already known solutions. While literature has mainly analyzed search behavior of individuals working alone, we investigate search accomplished by individuals working in teams. We study the interplay of three theoretically grounded factors that can affect the search behavior of individuals in teams: the level of behavioral interdependence among team members, the members' limited level of knowledge about the problem, and the performance feedback they receive. We operationalize search behavior in terms of search distance, which reflects the extent of exploration in problem space. Results show that high behavioral interdependence reduces exploration, while limited knowledge promotes exploration. Furthermore, positive performance feedback leads to reduced exploration, the more so the lower behavioral interdependence and the more limited knowledge are. We discuss theoretical and practical implications of these results for team design.

1. Introduction

Search is a fundamental process involved in solving complex problems (Simon, 1957). It consists of seeking solutions to a problem by choosing between exploration of new ideas and exploitation of already known solutions. This exploration–exploitation trade-off has been extensively studied in many disciplines including management, organization, and psychology (Charnov, 1976; Hills, Todd, Lazer, Redish, & Couzin, 2015; Kim, Song, & Nerkar, 2012; Levinthal, 1997; Levinthal & March, 1981; March, 1991; Mehlhorn et al., 2015; Pirolli & Card, 1999). In particular, studies have investigated the search patterns of individual problem solvers working in isolation (Billinger, Stieglitz, & Schumacher, 2014) as well on the collective level in teams (Goldstone, Wisdom, Roberts, & Frey, 2013; Håkonsson et al., 2016; Kostopoulos & Bozionelos, 2011) and organizations (Baumann, 2015; Baumann, Schmidt, & Stieglitz, 2019; Jansen, van den Bosch, & Volberda, 2006; Levinthal & Marino, 2015; March, 1991; Puranam, Stieglitz, Osman, & Pillutla, 2015; Siggelkow & Levinthal, 2003; Siggelkow & Rivkin, 2005; Simon, 1991; Wall, 2016).

However, as teams of experts solving complex tasks have become increasingly prevalent in contemporary organizations, investigating the search behavior of individual working in teams is becoming more and more important (Wagner, Humphrey, Meyer, & Hollenbeck, 2012; Yoon & Kayes, 2016). The team context calls for proper studies because the collective effort and actions characterizing individuals working in teams tend to influence individual behavior (Håkonsson et al., 2016; Kostopoulos & Bozionelos, 2011). We address this issue by focusing on three features that can affect the search behavior of individuals working in teams: (i) the level of behavioral interdependence among team members, (ii) their limited knowledge, and (iii) the performance feedback they receive. We study how these three features influence the choice between exploration of new ideas and exploitation of already known solutions.

First, only recently literature has recognized that behavioral interdependence is crucial for team dynamics and performance (Tekleab, Karaca, Quigley, & Tsang, 2016; Wu, 2018). It is defined as the extent to which "*team members actually work together on solving a task*" (Wageman, Gardner, & Mortensen, 2012). Although teams are employed to foster collaborative behavior, this does not guarantee that team members will *actually* share knowledge and resources, be affected by others' behaviors and solutions, or even pay attention to each other. Thus, the level of behavioral interdependence, defined as the extent to which team

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https://doi.org/10.1016/j.jbusres.2019.10.045
Received 2 March 2019; Received in revised form 22 October 2019; Accepted 24 October 2019

members take into account other members' choices when making their own decisions, should be taken into account to properly analyze their behavior. In particular, we argue that the level of behavioral interdependence influences search behavior of team members. In teams with a low level of behavioral interdependence, individuals work almost independently of each other so their search behavior might be similar to that of individuals working alone. When behavioral interdependence is high, individual search patterns can be altered because of social loafing (Karau & Williams, 1993; Latané, Williams, & Harkins, 1979; Mao, Mason, Suri, & Watts, 2016) so that exploration might be reduced as behavioral interdependence increases.

Second, teams are often composed of members with different areas of expertise. In such teams, each member might have only *limited knowledge* about the overall task, being able to evaluate only some aspects of the task and not others. Agent-based simulations have shown that individuals who have expertise in some aspects of the task but not in others might need to adjust their search behavior when working with others (Carbone & Giannoccaro, 2015; De Vincenzo, Giannoccaro, Carbone, & Grigolini, 2017; Knudsen & Srikanth, 2014). However, empirical confirmations of how people search in these situations are lacking. In particular, drawing on the psychological concept of unexpected uncertainty (Mehlhorn et al., 2015), we argue that individuals with limited knowledge tend to explore more than individuals having a complete knowledge.

Third, a recent study on individual search demonstrated an important role of *performance feedback*. Positive feedback suggesting good past performance promotes exploitative behaviors, while negative feedback fosters exploration (Billinger et al., 2014; March, 1991). This behavior is also shown by teams as a whole (Håkonsson et al., 2016). We go a step further and investigate whether performance feedback affects the search behavior of individuals working in teams in the same way, and how this relationship is moderated by the team properties considered. In particular, we argue that performance feedback leads to reduced exploration, more so when behavioral interdependence is low and limited knowledge is high.

To investigate our theoretical model (Fig. 1), we use behavioral experiment as research methodology. In particular, since search is crucial to solve complex problems, we adopt the behavioral experiment proposed by Billinger et al. (2014), where the complex problem is modelled as an *NK* fitness landscape. Participants search for the highest peak on the landscape by exploring alternative positions on the space. In the experiment search behavior is operationalized in terms of search distance, i.e. how far individual moves from the current position on the landscape at each step. Thus, the higher the search distance, the more the individuals have explored (Billinger et al., 2014). In our experiment, individuals work in teams characterized by different levels of behavioral interdependence and limited knowledge. We analyze how these factors and the performance feedback they received affect their search distance.

The paper is organized as follows. We first develop our hypotheses. Then, we describe the behavioral experiment, main measures, and manipulations. Further on, we present the statistical analyses carried out to test the hypotheses and their results. We end with discussion, implications, and limitations of our study.

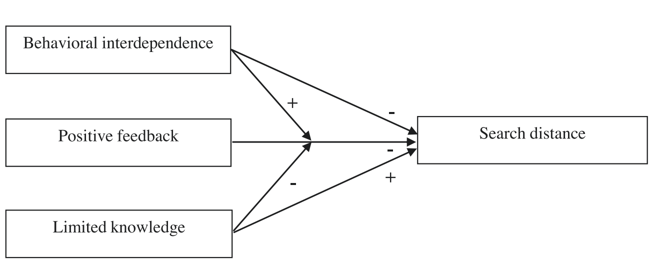

Fig. 1. Theoretical model.

2. Theory and hypotheses

Behavioral interdependence is a team property defined as the extent to which "*team members actually work together on solving a task*" (Wageman et al., 2012). It reflects the extent to which individuals rely on their team members and take into account their choices when making their own decisions. Therefore, behavioral interdependence differs from task interdependence, which is the degree to which the interaction and coordination of team members are required (but not necessarily implemented) to solve a task (Costa et al., 2017; Guzzo & Shea, 1992; Langfred, 2005; Saavedra, Earley, & Van Dyne, 1993; Wageman, 1995). It also differs from the structure of communication network, which can enable team members to communicate more or less frequently with each other (Derex & Boyd, 2016; Goldstone et al., 2013; Lazer & Friedman, 2007; Mason & Watts, 2012).

The level of behavioral interdependence of a team plays a role in members' explorative behavior. In their collective effort model, Karau and Williams (1993) suggested that individuals' willingness to exert effort in a team task depends on their expectations of the instrumentality of their efforts for obtaining valuable outcomes. It has been observed that people invest less effort in performing tasks in groups than when they do the same tasks alone. This is known as social loafing effect (Karau & Williams, 1993; Latané et al., 1979). Relying on others' knowledge about the task environment can indeed provide useful information without the need for individual exploration (Giraldeau & Caraco, 2000; Valone, 1989). Team members might perceive that they could obtain the same outcome without exploring themselves, because they can exploit the solutions explored by the others (Goldstone et al., 2013). As a consequence, they might reduce exploration. Since the higher the behavioral interdependence, the more the team members rely on the others' actions and decisions, we argue that when the level of behavioral interdependence among team members is high, they tend to explore less. We therefore offer the following hypothesis (see Fig. 1 for this and other hypotheses):

Hypothesis 1: Higher behavioral interdependence is associated with less exploration.

Teams are often composed of members who have different areas of expertise and, consequently, limited knowledge about the overall task. A medical team convened to help a cancer patient might include a cancer specialist, a nurse, a surgeon, and an anesthesiologist, each having specialist knowledge about a part of the task. A software production team might include experts in different programming languages, management, and market trends. As a consequence, each team member will often be able to evaluate only some aspects of a potential solution. For example, a marketing specialist will be able to evaluate a software product's market potential but not the efficiency of its code and vice versa for a programming expert.

Limited knowledge about some aspects of the task can induce a sense of uncertainty about what solutions are better or worse than others. While some stochasticity in levels of performance can be expected, when one lacks knowledge about an important aspect of the problem, one might feel a deeper level of uncertainty about how to achieve good performance. Mehlhorn et al. (2015) differentiated between expected and unexpected uncertainty, illustrated by an example of a machine producing widgets. A person might accept that a machine occasionally produces a faulty widget while still feeling that one understands how the machine works (expected uncertainty). In this case, one might continue using the machine. However, when a machine behaves in a fundamentally different way from expected, one might feel a deeper level of subjective uncertainty (unexpected uncertainty). This could motivate one to try other machines. More generally, a person with knowledge about all aspects of a problem can feel more certain that a solution is good even if it occasionally underperforms and might be prone to continue using the solution. In contrast, a specialist with expert knowledge about only some aspects of a problem might feel that she or he fundamentally misunderstands the problem. This more profound subjective uncertainty can lead to more exploration of other solutions (Mehlhorn et al., 2015). These individual tendencies can also be expressed when people work in teams. Simulations by Knudsen and Srikanth (2014) suggest that individuals with different expertise can show different behavior when searching together than when searching individually. Thus, we hypothesize that:

Hypothesis 2: More limited knowledge of team members about a task is related to more exploration.

Feedback about performance is used to adjust individual search behavior adaptively while solving a task. Accordingly, Billinger et al. (2014) demonstrated that individuals use feedback about their performance to adapt their search behavior. They found that search distance decreased with positive feedback: when an individual's current solution was better than the previous best solution, the extent of search would decrease; otherwise it would increase. This behavior is consistent with several models of decision making, including prospect theory. Prospect theory posits that individuals are more likely to engage in risky, exploratory behaviors after experiencing a loss and to be risk averse after obtaining gains (Kahneman & Tversky, 1979). Teams have been shown to adapt to performance feedback in a similar way (Håkonsson et al., 2016). While the effect of feedback on individuals searching in teams has not yet been studied, these prior results suggest that we can derive the following hypothesis:

Hypothesis 3: Positive feedback reduces exploration.

Feedback might also interact with behavioral interdependence. When team members work closely together and rely on each other, they might experience a high level of psychological safety (Ancona, 1990; Olivera & Straus, 2004; Stevens & Campion, 1994; Wheelwright & Clark, 1992), which is in turn conducive to taking risks because it lowers fear of punishment because of a mistake (Edmondson, 2002). This fosters the confidence to take risky behaviors in different situations, even when more caution should be adopted. As discussed above, according to the prospect theory, after experiencing a positive feedback, individuals are expected to reduce exploration because of risk aversion. However, if psychological safety is high, individuals might tend to take more risk and reduce exploration less. Therefore, as the level of behavioral interdependence with other team members rises, the negative relationship between positive feedback and exploration might be less pronounced. Therefore, we hypothesize that:

Hypothesis 4: The negative effect of positive feedback on exploration is smaller at higher levels of behavioral interdependence.

The deep subjective uncertainty about the nature of the problem can influence the effect of feedback on search. When uncertainty is very high, an individual who finds a seemingly good solution might be even more risk averse and reluctant to let it go in favor of further exploration compared to the case when uncertainty is low. It has been shown that the endowment effect, or assigning higher values to things one already possesses, is higher when there is uncertainty about future outcomes (Inder & O'Brien, 2003). Negative psychological reactions to anticipated future uncertainty can increase one's determination to keep what one already has (Liersch & McKenzie, 2011). Hence, the negative effect of positive feedback on explorative search could be even more pronounced in the circumstances of high uncertainty. Therefore, we hypothesize that:

Hypothesis 5: The negative effect of positive feedback on exploration is larger when the individual knowledge of team members is more limited.

2.1. Method setting

We conducted a behavioral experiment in the context of new product development. In particular, the experiment captured the context of designing a tablet computer by selecting 10 product attributes. Any combination of 10 product attributes (configuration) was associated with an outcome (payoff). This outcome measured the customer satisfaction.

Participants were asked to make decisions concerning the 10 product attributes so as to maximize customer satisfaction (payoff). They did not have any prior knowledge about the specific combination that is preferred by customers and had to search for the best configuration by trial and error. At each trial, participants received the payoff associated with the selected configuration, and they were informed of the configuration selected by the other team members and their payoffs. This formed the basis of their knowledge to improve customer satisfaction.

We used Billinger et al.'s (2014) approach to assign the payoffs to configurations using an *NK* fitness landscape (Kauffman & Levin, 1987). It is a well-established methodology for building complex combinatorial problems and controlling their complexity, often used in organization studies (Baumann, 2015; Baumann, Schmidt, & Stieglitz, 2019; Ethiraj & Levinthal, 2004; Giannoccaro, 2011, 2015; Giannoccaro, Massari, & Carbone, 2018; Giannoccaro, Nair, & Choi, 2018; Levinthal, 1997; Levinthal & Marino, 2015; Puranam, Stieglitz, Osman, & Pillutla, 2015; Rivkin, 2001; Rivkin & Siggelkow, 2003; Siggelkow, 2011; Siggelkow & Levinthal, 2003; Siggelkow & Rivkin, 2005; Wall, 2016). In particular, the *NK* fitness landscape is a map of configurations of decisions onto payoffs, where N stands for the number of decision variables (usually binary) and K is the average number of interactions among decisions, which tunes the complexity of the problem to solve given a fixed N. When K is high, contributions of decisions to the payoff are highly correlated, which leads to a "rugged" landscape with multiple local optima so that it is more difficult to find the highest payoff configuration on the landscape. The higher K, the more rugged the landscape.

In particular, the *NK* fitness landscape is a stochastic procedure to generate the payoff $P(\boldsymbol{d})$ of configurations. A configuration consists in a N-digit string $\boldsymbol{d} = (d_1, d_2, \ldots d_N)$, where $d_i = 0$ or 1. It is assumed that each decision gives a contribution C_i to the payoff. Averaging the contributions (C_i) over the N decisions, the payoff is computed as follows:

$$P(\boldsymbol{d}) = \frac{\sum_{i=1}^{N} C_i(d)}{N}$$

The contribution C_i that each decision d_i leads to the overall payoff, is drawn at random from a uniform [0,1] distribution. The interdependent nature of the decisions implies that the value C_i depends not only on how the decision d_i itself is resolved (0 or 1) but also on how the K interdependent decisions are resolved. For example, if the decision d_1 depends only on itself, C_1 assumes only two values, but if d_1 depends on d_2, C_1 assumes four values, depending on the possible combinations between the values of the decisions d_1 and d_2. In our experiments, N models the number of decisions on the product attributes that are needed to configure the new tablet and K captures the interdependence among the product attributes.

2.2. Description of the experiments

We developed a web-based software platform where the participants were presented with 10 product attributes and were asked to make their choice on each attribute by choosing between two available options (see Appendix A, Fig. A2). This means that there were 2^{10} or 1024 possible product configurations of the landscape. In the starting trial (trial = 0), the participants were informed of an initial combination and its payoff. Then, in subsequent trials (1–25) participants made decisions on product attributes, proposing a new configuration at each trial. A participant could change zero, some, or all attributes in a trial. There were 25 trials in which they made decisions. Each trial took a fixed time for all participants (1 min).

Participants played together with four other individuals (teammates) on the platform. They made their own decisions about product attributes. The software displayed the previously tried combinations of the individual and team members and also the respective individual payoffs of the other team members. After making a choice, participants were informed about their individual payoff on the selected combination. The link to the web-based platform is available upon request to the authors.

Every individual completed nine experimental sessions, each with one of three levels of behavioral interdependence and one of three levels of task complexity: low, medium, or high (K = 1, 4, and 8, respectively). Individuals were members of the same team for all nine sessions.

Sessions were carried out in two orders. In Order 1, sessions were presented in increasing order of complexity, starting with the simplest landscape and ending with the most complex. Within each level of complexity, participants received sessions with increasing levels of behavioral interdependence, from low to high. In Order 2, participants received experimental sessions in the reverse order (from high to low complexity, and high to low behavioral interdependence).

2.3. Participants

Participants were recruited on voluntary basis. They include 225 graduate students at the Polytechnic University of Bari (Italy), majoring in management engineering with supply chain management specialization. Among them, 125 (100) were male (female). They were from 23 to 26 years of age. Students received credit toward their final course grade for their participation in the experiments. They were first introduced to the experiments by means of an oral presentation in which the basic information about the search problem was given. For additional information see Appendix A.

Participants were randomly assigned to groups of five people. Each group was assigned to one of the two orders. All 45 groups played the experiments but those whose results were not completed or saved for technical reasons were deleted. In total we collected usable results for 30 groups (150 students with 85 male and 65 female): 10 groups for Order 1 and 20 groups for Order 2.

2.4. Measures and manipulations

2.4.1. Level of behavioral interdependence

To manipulate behavioral interdependence, participants were presented with different instructions about how much they should take into account the decisions of the other team members. In the low behavioral interdependence condition, participants were asked to "take into account the configurations chosen by the other members to a very limited degree when you propose a new configuration of the product." In the medium condition they were asked to "take into account the configurations chosen by the other members to a moderate degree when you propose a new configuration of the product," and in the high condition they were asked to "take into account the configurations chosen by the other members to a very high degree when you propose a new configuration of the product." Participants were always embedded in a fully connected network and were able to see choices and payoffs of their team members independently on the level of behavioral interdependence. To test the validity of this measure, we define the degree of similarity among decisions made by individuals at each trial t, as follows:

$$\chi(t) = \frac{1}{NM^2} \sum_{i=1}^{N} \sum_{kh=1}^{M} \sigma_k^i(t)\sigma_h^i(t)$$

where $\sigma_k^i(t)$ is the choice of the *k-th* member on the *i-th* decision, during trial t. Note that, $\sigma_k^i(t) = +1(-1)$ when the decision $d_k^i(t) = 1(0)$. We expected that the higher the level of behavioral interdependence, the higher the degree of similarity among decisions.

2.4.2. Feedback

On each trial, participants could see the payoff they received on the previous trial. Note that this is different from the work of Billinger et al. (2014), where participants were shown the payoffs for all previous trials. This choice was motivated by the findings of Håkonsson et al. (2016), who found that teams adapt to the performance achieved on the previous round. Perhaps more importantly, we wanted to avoid the visual clutter and the resulting cognitive overload because of too much information on the screen, as in our experiment participants saw not only their own payoffs but also the configurations and payoffs of their four team members.

Negative (positive) performance feedback meant that the new configuration had a lower (higher) payoff than the previous one. Feedback was defined as a binary variable where 0 (1) meant negative (positive) feedback.

2.4.3. Exploration

It was measured by the search distance computed as the Hamming distance between the current configuration chosen by the participant and the one, she or he selected at the previous trial.

2.4.4. Limited knowledge

Each participant was able to perceive payoff based on only some of the attributes (individual perceived payoff). This would correspond to an individual's specific expertise about some parts of the solution space. We designed a matrix, D, recording which attributes (decisions) could be perceived by a particular individual. These attributes (rather than all attributes) contributed to the perceived payoff of each individual. D_{ki} is a binary variable where 1 (0) means that individual k knows (does not know) the contribution C_i of attribute i to the payoff. To generate D, we drew values from a uniform probability distribution U (0,1). If a random draw $r \le 0.5$, then we set $D_{ki} = 1$, otherwise $D_{ki} = 0$. On average, the number of contributions known by individuals in the group was 0.5. Each group is assigned a different matrix D, fixed across all the experimental sessions. To measure the level of limited knowledge of an individual, we calculated the difference between the perceived and real payoff divided by the real payoff of the individual, as described next.

2.4.5. Perceived individual payoff

The payoff perceived by individual k, selecting the configuration $\boldsymbol{d}$ given his/her individual knowledge of attributes determined by matrix D was given by

$$Perc\_P_k(\boldsymbol{d}) = \sum_{i=1}^{N} D_{ki}C_i(\boldsymbol{d}) / \sum_{i=1}^{N} D_{ki}$$

2.4.6. Real individual payoff

This was the payoff that was actually associated with the configuration on the landscape and is computed based on all of its attributes:

$$Real\_P_k(\boldsymbol{d}) = \sum_{i=1}^{N} C_i(\boldsymbol{d})/N$$

Both perceived and real payoffs were normalized over the maximum payoff of the landscape, to capture the efficacy of the individuals in solving the task (i.e., finding the highest peak on the landscape). A value of 1 meant that the individual was able to reach the highest peak. Lower values meant lower efficacy.

2.5. Control variables

2.5.1. Task complexity

The level of task complexity was manipulated by means of the ruggedness of the landscape. We considered three levels of complexity corresponding to three types of landscape that were generated by using different values of K. In particular, three random influence matrices were used with $K = 1$ (low complexity), $K = 3$ (medium complexity), and $K = 8$ (high complexity). Task complexity was expected to decrease individual and group payoffs, but following Billinger et al. (2014), it was not expected to influence search distance.

2.5.2. Prior search distance

This was the search distance at the previous trial, capturing the tendency of a participant to explore or exploit (Billinger et al., 2014).

2.5.3. Trial number

This refers to the trial number in the experimental session. It was added to control for potential biases or end-game effects that might influence the results (Billinger et al., 2014).

2.5.4. Number of unsuccessful trials

This variable counted the number of trials since the last improvement in performance was achieved. It aimed to control for the frustration experienced by a decision maker, which can influence their subsequent decision making.

2.5.5. Order

This variable codes the order in which the nine experimental sessions (three levels of complexity multiplied by three levels of behavioral interdependence) were carried out. We defined the variable order as taking a value of 1 (Order 1) or 2 (Order 2).

3. Results

In this section we first present the descriptive statistics and then describe the regression analyses we carried out to test our hypotheses.

3.1. Descriptive results

Table 1 reports the means, standard deviations, and correlations of the variables included in the study.

The degree of similarity (χ) among the decisions across trials for three levels of behavioral interdependence is shown in Fig. 2. In particular, the degree of similarity in the case of low behavioral interdependence is on average 0.314 (with a standard deviation of 0.021). The corresponding value for medium behavioral interdependence is 0.524 (0.011) and for high behavioral interdependence is 0.684 (0.010). The degree of similarity in the low behavioral interdependence was significantly lower than in high ($t = -6.08$; $p < 0.00001$; *t*-test student) and medium behavioral interdependence cases ($t = -10.85$; $p < 0.00001$; *t*-test student). The degree of similarity in medium behavioral interdependence was significantly lower than the degree of similarity in high behavioral interdependence landscape ($t = -5.71$; $p < 0.00001$, t student test). These findings validated our experimental manipulations.

Fig. 3a shows the pattern of individual search behavior. We found that the participants showed higher average search distance than in a pure local search strategy (where search distance = 1). This confirms previous findings by Billinger et al. (2014) concerning the pattern of search when an individual plays alone. The search distance seems to decrease over time and with behavioral interdependence. Fig. 3b shows the pattern of perceived individual payoff. It increases over time, showing that individuals tried to increase their perceived payoff.

Table 1
Descriptive statistics and correlation matrix.

Variable	Mean	*SD*	Min	Max	Skew	Trial	Complexity	Prior search	Order of conditions	Behavioral interdependence	Unsuccessful trials	Search distance	Feedback	Limited knowledge
Trial	13	7.211	1	25	0	1								
Complexity	4.33	2.867	1	8	0.173	0	1							
Prior search	1.46	1.488	0	10	0.173	−0.23**	0.02*	1						
Order of conditions	1.67	0.4714	1	2	−0.707	0	0	−0.08**	1					
Behavioral interdependence	2.00	0.817	1	3	0	0	0	−0.05**	0	1				
Unsuccessful trials	1.69	2.681	0	23	3.179	0.25**	−0.10*	−0.32**	0.12*	0.01	1			
Search distance	1.45	1.484	0	10	1.739	−0.17**	0.02*	0.22**	−0.01**	−0.06**	−0.20**	1		
Feedback	0.40	0.491	0	1	0.395	−0.16**	0.05**	0.39**	−0.06**	−0.01*	−0.51**	0.08**	1	
Limited knowledge	0.17	0.141	3.19E-05	1.835	1.642	−0.04**	0.03**	0.05**	−0.19**	−0.02**	0.03**	0.09**	−0.07*	1

* $p < .05$.
** $p < .001$.

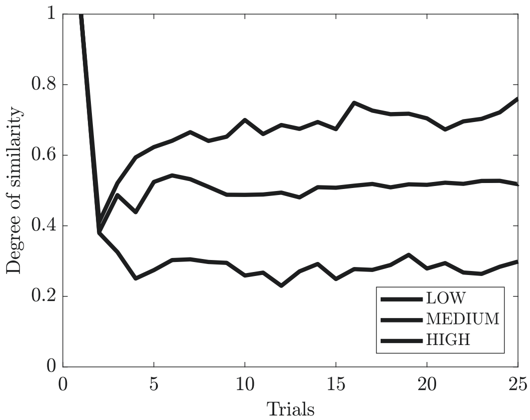

Fig. 2. Degree of similarity among decisions across trials for three levels of behavioral interdependence (low, medium and high).

3.2. Hypotheses tests

We carried out multilevel mixed-effects Poisson regression analyses to test the effects of the variables of interest on exploration (Table 2). We included random effects for teams and participants (Billinger et al., 2014). Search distance was the dependent variable. We first run the model with the control variables (Model 1). Then, we added the effect of the level of behavioral interdependence (Model 2), the effect of limited knowledge (Model 3), the effect of feedback (Model 4), the interaction effect between feedback and level of behavioral interdependence (Model 5), and the interaction effect between feedback and limited knowledge (Model 6).

Results of Model 1 mostly confirmed previous findings by Billinger et al. (2014). Complexity did not significantly influence search distance, trial number negatively influenced search distance ($\beta = -0.009$, $p < .001$), and prior search distance significantly promoted exploration ($\beta = 0.085$, $p < .001$). In contrast to Billinger et al. (2014), we found that the number of unsuccessful trials negatively and significantly influenced team member search distance ($\beta = -0.015$, $p < .001$). When the individuals experienced a long series of trials with decreasing payoffs, they tended to be more conservative and risk averse, so that their search distance was reduced. Finally, we found a negative and significant effect of the order of experimental sessions ($\beta = -0.267$, $p < .001$).

Results of Model 2 confirmed Hypothesis 1. We found that the level of behavioral interdependence had a negative and significant effect on search distance ($\beta = -0.077$, $p < .001$).

Model 3 tested Hypothesis 2. Results confirmed the positive effect of limited knowledge of team members on search distance. We found that limited knowledge had a positive and significant effect on search distance ($\beta = 0.316$, $p < .001$).

In Model 4 we included the effect of positive feedback to test Hypothesis 3. We confirmed that positive feedback had a negative effect on search distance ($\beta = -0.328$, $p < .001$). This suggests that individuals searching in teams showed similar patterns to those of individuals searching alone (as in Billinger et al., 2014). They tended to decrease their search distance when they were able to improve payoff compared to previous trials and increase the search distance when they received negative feedback.

We also confirmed Hypothesis 4 using Model 5. We found that the level of behavioral interdependence had a positive effect on the relationship between feedback and search distance ($\beta = 0.032$, $p < .001$). This suggests that when people rely more on other team members, they are prone to taking more risks and exploring more.

Results of Model 6 confirmed Hypothesis 5. There was a negative moderating effect of limited knowledge on the relationship between positive feedback and search distance ($\beta = -0.279$, $p < .001$). In the case of high uncertainty because of limited knowledge, individuals' tendency to explore less after positive feedback was more pronounced.

4. Discussion and conclusions

This paper contributed novel findings on search behavior. While past studies have mainly analyzed search behavior of individuals working alone, we investigated search accomplished by individuals working in teams. We examined the role of three main features: behavioral interdependence, limited knowledge, and performance feedback.

Following a recommendation by Wageman et al. (2012), we studied teams whose members had different levels of behavioral interdependence, that is, the extent to which they relied on each other to solve a task. This feature is important as it captures the influence of the team context on search behavior. Our findings demonstrate that behavioral interdependence influenced individual search behavior, even though team members were always embedded in a fully connected network. In particular, we show that higher behavioral interdependence promotes exploitative individual behavior, possibly

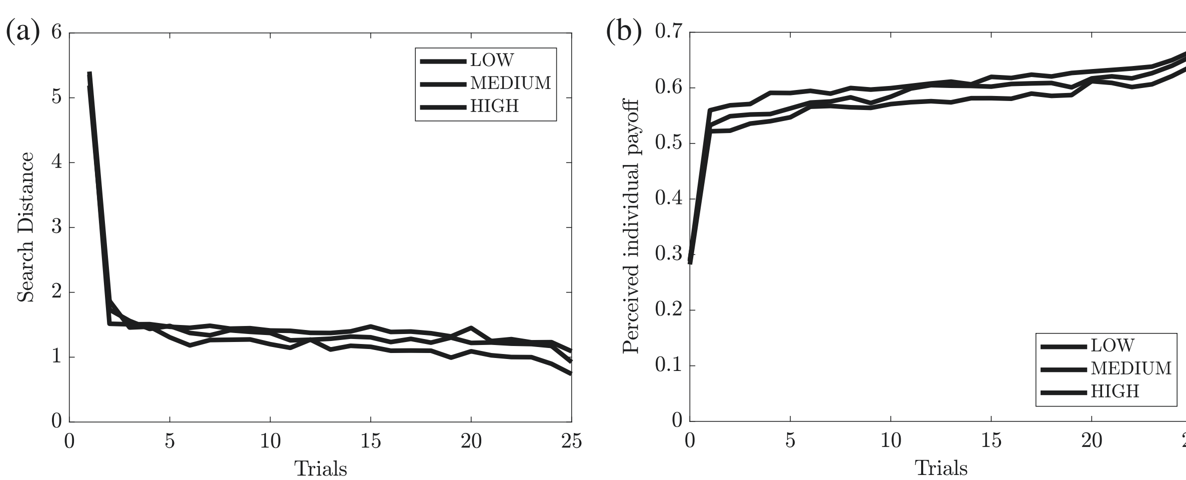

Fig. 3. Search distance (a) and perceived individual payoff (b) across trials for three levels of behavioral interdependence (low, medium, and high).

Table 2
Results of the regression analyses with search distance as dependent variable.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.609**	0.769**	0.683**	0.834**	0.859**	0.841**
	(0.1477)	(0.1497)	(0.1496)	(0.1420)	(0.1420)	(0.1418)
Trial	−0.009**	−0.009**	−0.009**	−0.008**	−0.008**	−0.008**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Complexity	0.003	0.003	0.002	0.002	0.002	0.002
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Prior Search	0.085**	0.082**	0.081**	0.104**	0.104**	0.104**
	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0033)
Unsuccessful trials	−0.015**	−0.014**	−0.016**	−0.061**	0.104**	−0.061**
	(0.0028)	(0.0028)	(0.0028)	(0.0036)	(0.0033)	(0.0036)
Order of conditions	−0.267**	−0.268**	−0.249*	−0.240*	−0.241*	−0.239*
	(0.085)	(0.0857)	(0.0855)	(0.0808)	(0.0808)	(0.0806)
Behavioral interdependence		−0.077**	−0.077**	−0.074**	−0.087**	−0.086**
		(0.0061)	(0.0061)	(0.0061)	(0.0078)	(0.0078)
Limited knowledge			0.316**	0.210**	0.208**	0.295**
			(0.0390)	(0.0393)	(0.0393)	(0.0454)
Feedback				−0.328**	−0.390**	−0.341**
				(0.1416)	(0.0271)	(0.0301)
Feedback × Behavioral Interdependence					0.032*	0.031*
					(0.0124)	(0.0124)
Feedback × Limited Knowledge						−0.279**
						(0.0743)
Number of observations	33,750	33,750	33,750	33,750	33,750	33,750
Wald χ^2	1340.89**	1491.75**	1554.63**	2197.34**	2206.93**	2223.36**
Log likelihood	− 44,837.17	− 44,757.93	− 44,725.67	− 44,392.35	− 44,388.97	− 44,381.90

Standard errors in parentheses.
* $p < .01$.
** $p < .001$.

because of the social loafing effect.

Teams are often composed of individuals characterized by diverse levels of expertise, which limits their knowledge of different aspects of the task. We therefore endowed our team members with limited knowledge of contributions of different attributes of their solutions to the overall payoff. We found that this limited knowledge affected individual search behavior. It promoted exploration because of the increased uncertainty about how to achieve a good payoff. Both of these findings represent a novel contribution to the literature.

We also investigated the role of performance feedback in team member search and the moderating effect of behavioral interdependence and individual limited knowledge. Our results confirm previous findings of the literature: individuals searching in teams, similarly to individuals searching alone and teams as a whole, adapt their search behavior to performance feedback. In particular, they exploited when they received a positive feedback and explored in the case of a negative outcome (Billinger et al., 2014; Håkonsson et al., 2016). Furthermore, we found that both behavioral interdependence and limited knowledge influenced the adaptive behavior of team members in response to performance feedback. High behavioral interdependence, perhaps by promoting interpersonal trust (Costa et al., 2017; De Jong & Dirks, 2012), might have reduced individual risk aversion, so that the explorative behavior persisted even when individuals received positive feedback about their performance. Conversely, the more limited the individual knowledge, the more pronounced the exploitative behavior in response to positive feedback, perhaps because uncertainty increases risk aversion.

From a theoretical point of view, we have extended research on team search behavior by focusing on individuals as the unit of analysis, while previous studies mostly adopted teams as the unit of analysis (Goldstone et al., 2013; Håkonsson et al., 2016; Kostopoulos & Bozionelos, 2011). An advantage of our approach is that it allowed us to study team dynamics as a bottom-up process emerging from the individual behaviors and their interactions. In this way we can understand micro-level processes underlying team behavior rather than solely observing the macro-level behavior. This approach is in line with the view that a team is a complex adaptive system (Hackman, 2012; Uitdewilligen, Rico, & Waller, 2018).

Furthermore, we have integrated organizational search literature with psychological theories concerning group and individual behavior. In this study, individuals might have perceived that they could learn from configurations explored by others rather than exploring themselves. This social loafing effect has been analyzed in organizational contexts (George & Jones, 2011; Mao et al., 2016), social (Karau & Williams, 1993; Latané et al., 1979), and cognitive psychology (Goldstone et al., 2013). We also found support for the effect of unexpected uncertainty described by Mehlhorn et al. (2015). Individuals who had more limited knowledge showed more explorative behavior, possibly because they experienced more unexpected uncertainty. We further confirmed the interpretative power of prospect theory to predict adaptive behavior in response to feedback of individuals working in teams, and to clarify moderating effects of behavioral interdependence and limited knowledge.

Our study has practical implications for designing teams to promote exploration or exploitation. When exploration is more important, our findings would suggest reducing behavioral interdependence among team members. For instance, low behavioral interdependence can be associated with virtual teams. The use of information and communication technologies to communicate and interact limit the efficacy of social interactions so that team members are less prone to rely one each other. In contrast, face-to-face teams, where social interactions are more influential, could be used to foster exploitation. These issues could be studied in further empirical studies.

From a managerial perspective, it is also fundamental that managers of the teams be aware of the significance of behavioral interdependence and its influence on search behavior and performance. Our results suggest that they should pay attention not only to teams' task interdependence and network structure but also to how much individuals actually rely on one another.

Our findings also suggest that the level of expertise of team members affects exploration. Designing cross-functional teams with complementary expertise would promote exploration, while teams composed of generalist members, having similar and overlapping knowledge, would increase exploitation.

Our research has several limitations. First, to manipulate levels of task complexity, we used a stylized task constructed using an *NK* landscape. Even though this approach is frequently used in organization science to model organization problems (see Ganco & Hoetker, 2009, for a review), it has been only recently proposed by Billinger et al. (2014) and Goldstone, de Leeuw, and Landy (2015) as an effective tool for studying individual search behavior empirically. We tried to reduce the abstract nature of this task by using a cover story where participants needed to identify the most promising combination of product attributes to increase customer satisfaction.

We also implicitly assumed that every search distance is equally costly to the decision maker. However, higher search distances might be more expensive because of higher number of changes that the individual should accomplish to modify the current configuration. Since the search distance maintained, on average, quite low values during the experiments, we are confident that neglecting this aspect did not affect the findings of our study. Further research will address this issue.

A further limitation concerns the way social interactions occur among team members. To properly manipulate behavioral interdependence, we permitted team members to communicate only indirectly with each other: they could see on the screen the decisions and payoffs of the other team members. This helped the internal validity of our results by reducing the effect of any other variables on the differences between experimental conditions. At the same time, this reduced external validity of our findings for real-world settings where interaction is often richer and includes various social and emotional aspects. Therefore, further research could be devoted to replicating our findings in more realistic settings, both in the lab (e.g., Mao et al., 2016) and in real-world organizations.

A related question is how to measure changes in behavioral interdependence over time, in order to anticipate a decrease in performance if team members become too interdependent. This is, however, beyond the scope of this paper and is a matter for further research.

Ethics statement

This study was approved by the Research Office of the Department of Mechanics, Mathematics and Management, at the Polytechnic University of Bari in Italy. Written informed consent was obtained from all participants before beginning the experiments.

Acknowledgments

This work was partially supported by National Science Foundation grants 1745154 and 1757211.

Appendix A

All subjects were introduced to the experiments through an oral presentation in which they were instructed, by means of visual descriptions, on how to login to the web-based software platform and how to perform the experiments. During the oral presentation, the cover story shown in Fig. A1 was also presented. All the clarification questions regarded how to deal with the graphical user interface (see Fig. A2) were clarified by performing a single dry run. Then, the students participated in the experiment.

COVER STORY

You are a team member and your role is to design a new tablet by defining the value of its ten attributes. You are asked to make your decisions to propose the products' configuration

The aim of your team is to design the tablet to maximize the customer's satisfaction, named product's payoff

The decisions are binary and interdependent. Your choice (0 or 1) on a certain decision (e.g. 2nd, 3rd and so on) leads the payoff to increase or decrease, depending on the decision's itself and its interdependent decisions' value

You, as well as the other members in your team, have incomplete knowledge: you can estimate how, only some attributes, contribute to the product's payoff. This estimate is an incomplete measure of the product's payoff, namely your perceived payoff

However, the knowledge is uniformly distributed in your team: on average, the other members know what you don't. Hence, it's necessary to interact with other members otherwise the product's payoff won't be maximized. To interact means you, while proposing your configuration, take into account the decisions of the other members according to the level of behavioral interdependence. When the behavioral interdependence is low, medium and high respectively, you are asked to take into account the configurations chosen by the other members to a very limited, moderate and high degree

Each experimental session has 25 rounds, each lasting 1 minute. At the end of each round you will see your perceived payoff, the decisions and the perceived payoffs of the other members

Fig. A1. Cover story.

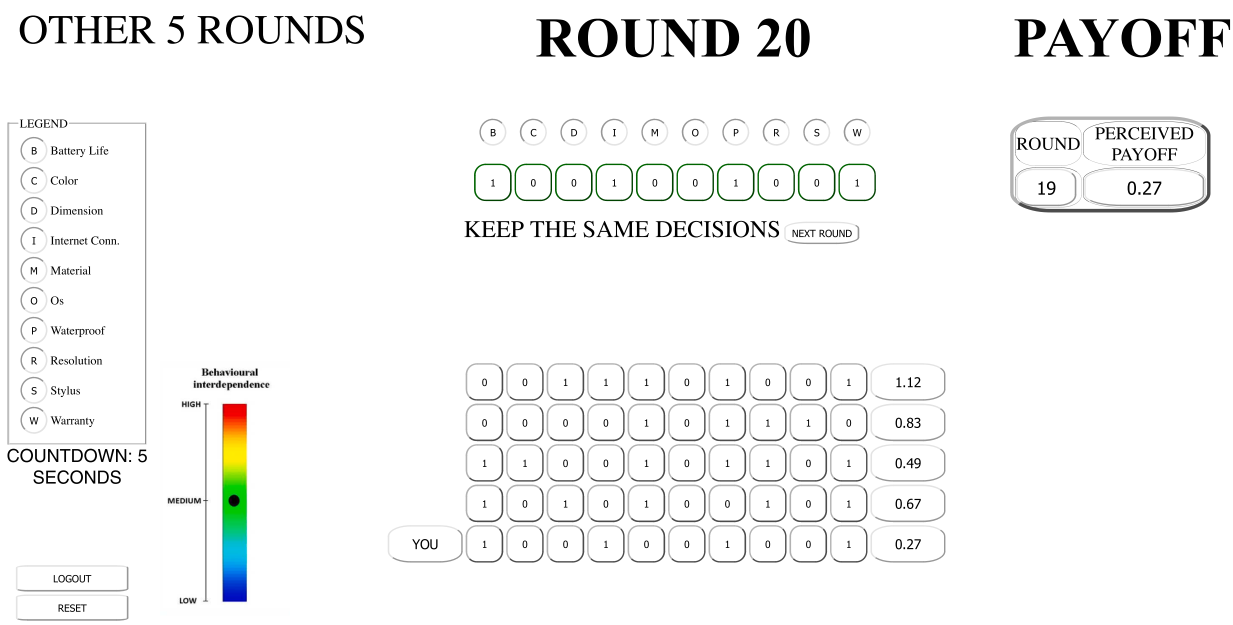

Fig. A2. Graphical user interface.

References

Ancona, D. G. (1990). Outward bound: Strategic for team survival in an organization. *Academy of Management Journal, 33*, 334–365.

Baumann, O. (2015). Models of complex adaptive systems in strategy and organization research. *Mind & Society, 14*(2), 169–183.

Baumann, O., Schmidt, J., & Stieglitz, N. (2019). Effective search in rugged performance landscapes: A review and outlook. *Journal of Management, 45*(1), 285–318.

Billinger, S., Stieglitz, N., & Schumacher, T. R. (2014). Search on rugged landscapes: An experimental study. *Organization Science, 25*, 93–108.

Carbone, G., & Giannoccaro, I. (2015). Model of human collective decision-making in complex environments. *The European Physical Journal B, 88*. https://doi.org/10.1140/epjb/e2015-60609-0.

Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology, 9*, 129–136.

Costa, M., Alves, S. P., Francisco, A., Almeida, J., Alfaia, C. M., Martins, S. V., ... Bessa, R. J. B. (2017). The reduction of starch in finishing diets supplemented with oil does not prevent the accumulation of trans-10 18:1 in lamb meat. *Journal of Animal Science, 95*, 3745–3761.

De Jong, B. A., & Dirks, K. T. (2012). Beyond shared perceptions of trust and monitoring in teams: Implications of asymmetry and dissensus. *Journal of Applied Psychology, 97*, 391–406.

De Vincenzo, I., Giannoccaro, I., Carbone, G., & Grigolini, P. (2017). Criticality triggers the emergence of collective intelligence in groups. *Physical Review E, 96*. https://doi.org/10.1103/PhysRevE.96.022309.

Derex, M., & Boyd, R. (2016). Partial connectivity increases cultural accumulation within groups. *Proceedings of the National Academy of Sciences of the United States of America, 113*, 2982–2987.

Edmondson, A. C. (2002). The local and variegated nature of learning in organizations: A group- level perspective. *Organization science, 13*(2), 128–146.

Ethiraj, S. K., & Levinthal, D. (2004). Modularity and innovation in complex systems. *Management Science, 50*, 159–173.

Ganco, M., & Hoetker, G. (2009). NK modeling methodology in the strategy literature: Bounded search on a rugged landscape. In D. D. Bergh, & D. J. Ketchen (Vol. Eds.), *Research methodology in strategy and management: Vol. 5*, (pp. 237–268). Bingley, UK: Emerald Group.

George, J. M., & Jones, G. R. (2011). *Understanding and managing organizational behavior* (6th Ed.). London, UK: Pearson.

Giannoccaro, I. (2011). Assessing the influence of the organization in the supply chain management using NK simulation. *International Journal of Production Economics, 131*, 263–272.

Giannoccaro, I. (2015). Adaptive supply chains in industrial districts: A complexity science approach focused on learning. *International Journal of Production Economics, 170*, 576–589.

Giannoccaro, I., Massari, G. F., & Carbone, G. (2018). Team resilience in complex and turbulent environments: The effect of size and density of social interactions. *Complexity, 2018*. https://doi.org/10.1155/2018/1923216.

Giannoccaro, I., Nair, A., & Choi, T. (2018). The impact of control and complexity on supply network performance: An empirically informed investigation using NK simulation analysis. *Decision Sciences, 49*(4).

Giraldeau, L. A., & Caraco, T. (2000). *Social foraging theory.* Princeton, NJ: Princeton University Press.

Goldstone, R. L., de Leeuw, J. R., & Landy, D. H. (2015). Fitting perception in and to cognition. *Cognition, 135*, 24–29.

Goldstone, R. L., Wisdom, T. N., Roberts, M. E., & Frey, S. (2013). Learning along with others. In B. H. Ross (Vol. Ed.), *Psychology of learning and motivation: Vol. 58*, (pp. 1–45). Waltham, MA: Academic Press.

Guzzo, R. A., & Shea, G. P. (1992). Group performance and intergroup relations in organizations. In M. D. Dunnette, & L. M. Hough (Eds.). *Handbook of industrial and organizational psychology* (pp. 269–313). Palo Alto, CA: Consulting Psychologists Press.

Hackman, J. R. (2012). From causes to conditions in group research. *Journal of Organizational Behavior, 33*, 428–444.

Håkonsson, D., Eskildsen, J. K., Argote, L., Mønster, D., Burton, R. M., & Obel, B. (2016). Exploration versus exploitation: Emotions and performance as antecedents and consequences of team decisions. *Strategic Management Journal, 37*, 985–1001.

Hills, T. T., Todd, P. M., Lazer, D., Redish, A. D., & Couzin, I. D. the Cognitive Search Research Group. (2015). Exploration versus exploitation in space, mind, and society. *Trends in Cognitive Science, 19*, 46–54. https://doi.org/10.1016/j.tics.2014.10.004.

Inder, B., & O'Brien, T. (2003). The endowment effect and the role of uncertainty. *Bulletin of Economic Research, 55*, 289–301.

Jansen, J. J. P., van den Bosch, F. A. J., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management Science, 52*, 1661–1674.

Kahneman, D., & Tversky, A. (1979). On the interpretation of intuitive probability: A reply to Jonathan Cohen. *Cognition, 7*, 409–411.

Karau, S. J., & Williams, K. D. (1993). Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality and Social Psychology, 65*, 681–706.

Kauffman, S. A., & Levin, S. (1987). Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology, 128*, 11–45.

Kim, C., Song, J., & Nerkar, A. (2012). Learning and innovation: Exploitation and exploration trade-offs. *Journal of Business Research, 65*(8), 1189–1194.

Knudsen, T., & Srikanth, K. (2014). Coordinated exploration: Organizing joint search by multiple specialists to overcome mutual confusion and joint myopia. *Administrative Science Quarterly, 59*, 409–441.

Kostopoulos, K. C., & Bozionelos, N. (2011). Team exploratory and exploitative learning: Psychological safety, task conflict, and team performance. *Group and Organization Management, 36*, 385–415.

Langfred, C. W. (2005). Autonomy and performance in teams: The multilevel moderating effect of task interdependence. *Journal of Management, 31*, 513–529.

Latané, B., Williams, K., & Harkins, S. (1979). Many hands make light the work: The causes and consequences of social loafing. *Journal of Personality and Social Psychology, 37*, 822–832.

Lazer, D., & Friedman, A. (2007). The network structure of exploration and exploitation. *Administrative Science Quarterly, 52*, 667–694.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science, 43*, 934–950.

Levinthal, D., & March, J. G. (1981). A model of adaptive organizational search. *Journal of Economic Behavior and Organization, 2*, 307–333.

Levinthal, D. A., & Marino, A. (2015). Three facets of organizational adaptation: Selection, variety, and plasticity. *Organization Science, 26*(3), 743–755.

Liersch, M. J., & McKenzie, C. R. M. (2011). In defaults we trust. In R. Ahluwalia, T. L. Chartrand, & R. K. Ratner (Vol. Eds.), *Advances in consumer research: Vol. 39*, (pp. 182–183). Duluth, MN: Association for Consumer Research.

Mao, A., Mason, W., Suri, S., & Watts, D. J. (2016). An experimental study of team size and performance on a complex task. *PLoS ONE, 11*. https://doi.org/10.1371/journal.pone.0153048.
March, J. G. (1991). How decisions happen in organizations. *Human-Computer Interaction, 6*, 95–117.
Mason, W., & Watts, D. J. (2012). Collaborative learning in networks. *Proceedings of the National Academy of Sciences of the United States of America, 109*, 764–769.
Mehlhorn, K., Newell, B. R., Todd, P. M., Lee, M. D., Morgan, K., Braithwaite, V. A., ... Gonzalez, C. (2015). Unpacking the exploration–exploitation tradeoff: A synthesis of human and animal literatures. *Decision, 2*, 191–215.
Olivera, F., & Straus, S. G. (2004). Group-to-individual transfer of learning: Cognitive and social factors. *Small Group Research, 35*, 440–465.
Pirolli, P., & Card, S. (1999). Information foraging. *Psychological Review, 106*, 643–675.
Puranam, P., Stieglitz, N., Osman, M., & Pillutla, M. M. (2015). Modelling bounded rationality in organizations: Progress and prospects. *The Academy of Management Annals, 9*(1), 337–392.
Rivkin, J. W. (2001). Reproducing knowledge: Replication without imitation at moderate complexity. *Management Science, 12*, 274–293.
Rivkin, J. W., & Siggelkow, N. (2003). Balancing search and stability: Interdependencies among elements of organizational design. *Management Science, 49*, 290–311.
Saavedra, R., Earley, P. C., & Van Dyne, L. (1993). Complex interdependence in task-performing groups. *Journal of Applied Psychology, 78*, 61–72.
Siggelkow, N. (2011). Firms as systems of interdependent choices. *Journal of Management Studies. 48*, 1126–1140.
Siggelkow, N., & Levinthal, D. A. (2003). Temporarily divide to conquer: Centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. *Organization Science, 14*, 650–669.
Siggelkow, N., & Rivkin, J. W. (2005). Speed and search: Designing organizations for turbulence and complexity. *Organization Science, 16*, 101–122.
Simon, H. A. (1957). *Models of Man: Social and Rational.* New York: John Wiley and Sibs.
Simon, H. A. (1991). Organizations and markets. *Journal of Economic Perspectives, 5*, 25–44.
Stevens, M. J., & Campion, M. A. (1994). The knowledge, skill, and ability requirements for teamwork: Implications for human resource management. *Journal of Management, 20*, 503–530.
Tekleab, A. G., Karaca, A., Quigley, N. R., & Tsang, E. W. (2016). Re-examining the functional diversity–performance relationship: The roles of behavioral integration, team cohesion, and team learning. *Journal of Business Research, 69*(9), 3500–3507.
Uitdewilligen, S., Rico, R., & Waller, M. J. (2018). Fluid and stable: Dynamics of team action patterns and adaptive outcomes. *Journal of Organizational Behavior, 39*, 1113–1128.
Valone, T. J. (1989). Group foraging, public information, and patch estimation. *Oikos, 56*, 357–363. https://doi.org/10.2307/3565621.
Wageman, R. (1995). Interdependence and group effectiveness. *Administrative Science Quarterly, 40*, 145–180.
Wageman, R., Gardner, H., & Mortensen, M. (2012). The changing ecology of teams: New directions for teams research. *Journal of Organizational Behavior, 33*, 301–315.
Wagner, J. A., III, Humphrey, S. E., Meyer, C. J., & Hollenbeck, J. R. (2012). Individualism–collectivism and team member performance: Another look. *Journal of Organizational Behavior, 33*, 946–963.
Wall, F. (2016). Organizational dynamics in adaptive distributed search processes: Effects on performance and the role of complexity. *Frontiers of Information Technology & Electronic Engineering, 17*(4), 283–295.
Wheelwright, S. C., & Clark, K. B. (1992). Competing through development capability in a manufacturing-based organization. *Business Horizons, 35*, 29–43.
Wu, Y. (2018). Behavioural interdependence in project team collaboration: Study of engineering students 'collaborative behaviours in high levels of interdependent task settings. *Dissertations - ALL,* 883.
Yoon, J., & Kayes, D. C. (2016). Employees' self-efficacy and perception of individual learning in teams: The cross-level moderating role of team-learning behavior. *Journal of Organizational Behavior, 37*, 1044–1060.