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Bringing in the Experts

How Team Composition and Collaborative Planning Jointly Shape Analytic Effectiveness

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This study investigates the separate and joint effects of the inclusion of experts and collaborative planning on the performance of analytic teams. Teams either did or did not include members with expert-level task-relevant cognitive abilities, and either did or did not receive an intervention that fostered collaborative planning. Results support the authors' hypothesis that analytic performance requires both task-appropriate expertise and collaborative planning to identify strategies for optimally using that expertise. Indeed, high expertise in the absence of collaborative planning actually decreased team performance. Teams engaging in collaborative planning were more likely to effectively integrate their information on key aspects of the analytic problem, which significantly enhanced their analytic performance. Furthermore, information integration mediated the effects of the interaction of expertise and collaboration on performance. The implications of the findings for the optimal use of team member skills and the development of team performance strategies are discussed.

Keywords: *team performance; experts; collaboration; information integration*

Many prominent organizational failures are rooted in flawed analysis of data that are used to guide action. Flawed medical diagnoses, misinterpretation of financial indicators, and biased interpretations of intelligence data can result in ill-advised actions that have unfortunate consequences. In many of these situations, team members from different specialties are asked to work together to integrate multiple sources of information and draw conclusions. In this article, we explore the conditions under which teams whose members are specialists can collaborate effectively to analyze incomplete or unreliable data and use those data to generate trustworthy conclusions about unknown states of affairs.

Analytic work invariably involves both cognitive and social processes. At core, analysis is a *cognitive* activity. Although analysts often draw on both technological aids and input from others, it ultimately is the human brain that organizes and interprets data to generate an assessment of an event that has happened, is happening, or is likely to happen. But analytic work also is inherently a *social* process. The lone analyst working in isolation to extract the meaning from a set of data is the exception rather than the rule. Instead, analysts typically draw heavily on the expertise, experience, and insights of their colleagues in developing and testing their conclusions (Hackman & O'Connor, 2004).

Previous research on the cognitive and social aspects of the analytic process has been carried out as if the two factors are independent. This research explores the possibility that a robust understanding of the factors that shape analytic performance can be obtained only by examining the interaction of member expertise and collaborative planning on analytic performance.

Not Expertise Alone

Considerable evidence documents that cognitive abilities shape team performance. The general intelligence of members, for example, has been shown to predict a number of team effectiveness criteria (LePine, 2005; Neuman, Wagner, & Christiansen, 1999), as well as team learning (Ellis et al., 2003). The relationship between cognitive ability and performance is particularly strong for tasks that are unfamiliar (Devine, 1999). Composing teams to include content experts therefore should raise the quality of the

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team's product by expanding and deepening the level of knowledge and skill available to the team.

Experts are individuals who possess an appreciably higher level of knowledge or skill than the average person (Ericsson & Lehmann, 1996; Patel, Groen, & Arocha, 1990). An individual's expertise can be the result of training and experience or may be a function of his or her cognitive or physical abilities (Ericsson, 2005; Volmer, 2006). Because a person's *cognitive* abilities are particularly germane to analytic work, we focus on them in this research. Specifically, we take advantage of recent advances in cognitive neuroscience that offer the possibility of using brain-based measures to assess members' cognitive abilities (Cabeza & Nyberg, 2000; Kosslyn, 1994; Kozhevnikov, Kosslyn, & Shephard, 2005). Analytic teams that include members with strong task-relevant abilities have greater potential to perform well than teams composed entirely of average-ability members.

Integrating experts into a team can create social dynamics that compromise team performance. Research on team diversity shows that bringing together teams of members from different social categories can create significant difficulties in collaborative work (Bunderson & Sutcliffe, 2002; Caruso & Woolley, in press; Dahlin, Weingart, & Hinds, 2005; Jehn, Northcraft, & Neale, 1999; Thomas-Hunt, Ogden, & Neale, 2003). Even in the absence of social categories, designating particular team members experts can evoke status dynamics that override benefits that can be obtained from the higher overall ability of the team: High-status experts may be disinclined to take seriously the views of others, and lower status members may be tempted to give more credence to higher status members than is warranted by their actual expertise (Beersma et al., 2003; Hackman & Morris, 1983; Littlepage, Robison, & Reddington, 1997). Merely including high-expertise members in teams that perform analytic work, therefore, may be insufficient to foster team performance effectiveness. Members also must be aware of the full complement of their teammates' abilities and, important to note, must have the opportunity to develop a performance strategy that enables them to optimally use those capabilities.

These dysfunctions can be overcome when members of well-designed teams collaborate to formulate and implement a performance strategy that is uniquely suited to task and situational requirements (Hackman, Brousseau, & Weiss, 1976; Okhuysen, 2001; Okhuysen & Eisenhardt, 2002; Woolley, 1998). Explicit coordination processes are necessary for tasks that are highly interdependent (Wittenbaum, Vaughan, & Stasser, 1998), but competent team collaboration about work strategy rarely occurs spontaneously (Gurtner, Tschan, Semmer, & Nagele, 2007; Hackman & Wageman, 2005). Therefore, an intervention usually is required to induce members to engage in explicit discussions about how they will carry out their collaborative work and, important to note, how they will capture and use well the contributions of individual members who have special task expertise. We hypothesize, therefore, that both ability composition and an intervention to help members engage in collaborative planning are required for effective performance. Specifically,

Hypothesis 1: The interaction of team ability composition and collaborative planning more strongly predicts team performance than does team composition alone.

Not Collaboration Alone

Analytic work involves multiple steps, about which considerable research has been done: recognition of the situation in need of assessment (Bazerman, 2006; Chugh & Bazerman, 2007; Moreland & Levine, 1992), definition of the problem (Fiore & Schooler, 2004), creation or selection of the information to be considered (Heuer, 1999), pooling of knowledge and coordination of members' inputs (Faraj & Sproull, 2000), and decision making about analytic conclusions (Davis, 1996; Kerr & Tindale, 2004). The research literature on team analytic performance is pessimistic about how well teams accomplish these functions. For example, teams tend to combine information ineffectively, omitting pieces of critical information (Henry, 1995); they focus too much on shared information (Stasser, Stewart, & Wittenbaum, 1995); and they do not coordinate expertise well, often giving specific members' contributions more or less weight than is warranted by their actual abilities (Bottger & Yetton, 1988; Hackman & Morris, 1983; Hackman & Wageman, 2005).

Even well-designed and competently administered strategy-planning interventions cannot compensate for the absence of task-critical member capabilities, however. Only teams whose membership includes individuals with ample task-relevant expertise will be helped by them, as is illustrated by a recent study in which dyads were required to navigate a virtual maze and identify repeated instances of complex objects (Woolley et al., 2007). The task required two specific abilities: skill at navigation (spatial ability) and skill at storing images of complex forms (object memory ability). Both of these abilities reflect the operation of distinct neural systems (Kozhevnikov et al., 2005). One member of each team was assigned to navigate and one to *tag* repetitions of forms. Teams were composed of members who were either strong or weak on each of the two abilities and, after completing work on the first maze, were given the opportunity to converse about how they were working together. These conversations about work strategy enhanced team performance only when members had been assigned to roles that were incongruent with their abilities (i.e., the person with high spatial ability was assigned to memorize shapes, or the person with high object ability was assigned to the navigation task). Conversation did not help when role assignments were consistent with members' abilities—and actually impaired performance when both members were high on the same ability. Therefore,

> *Hypothesis 2*: The interaction of team ability composition and collaborative planning more strongly predicts team performance than does collaborative planning alone.

Team Information Integration

A critical challenge for teams performing analytic work is to find ways to extract, organize, and integrate all information that can inform the team's assessment that is known to some, but not all, team members. Research evidence affirms that coordinating member knowledge and expertise is critical to success for knowledge tasks (Faraj & Sproull, 2000), but teams frequently fail to do this effectively (Bunderson, 2003; Cronin & Weingart, 2007), particularly if they lack members with the intrapersonal diversity, or breadth of personal skills and experience, to help bridge among others with more narrow expertise (Bunderson & Sutcliffe, 2002). Absent an effective strategy for dealing with this challenge, team members may either become so overwhelmed with data that they cannot make sense of what the data mean (e.g., Mintzberg, Raisinghani, & Theoret, 1976; Yen, Fan, Sun, Hanratty, & Dumer, 2006), or they may fail to detect links or associations among independent facts that could provoke original ideas or stimulate fresh thinking (Okhuysen & Eisenhardt, 2002).

To overcome these problems, an analytic team requires some systematic means of structuring its search for data and for evaluating the evidence the team unearths. In analytic work, certain variables usually can be assessed sooner and more reliably than others and then used to structure follow-on searches for other evidence. A murder investigation team, for example, needs to identify the weapon used, the perpetrator, and the motive. In many cases, the weapon can be determined more readily than the other elements, both because there are fewer possibilities and because information obtained about it is likely to be reasonably trustworthy. Because certain people and certain motives will fit better with some weapons than with others, identification of the weapon can inform and constrain subsequent data gathering about possible perpetrators and motives. This iterative process can continue until a coherent story emerges, at which point additional analytic strategies, such as testing alternative hypotheses and trying out structured analogies, can be used to protect against confirmation biases and to explore the merits of various alternative story lines.

The same logic holds for analytic teams. Analytic teams that engage in effective collaborative planning should devise better performance strategies and exhibit better information integration, which in turn improves performance. Specifically,

> *Hypothesis 3*: Information integration mediates the effects of the interaction of expertise and collaborative planning on team analytic performance.

Figure 1 depicts the hypothesized relationships among the variables investigated in this study and their impact on performance.

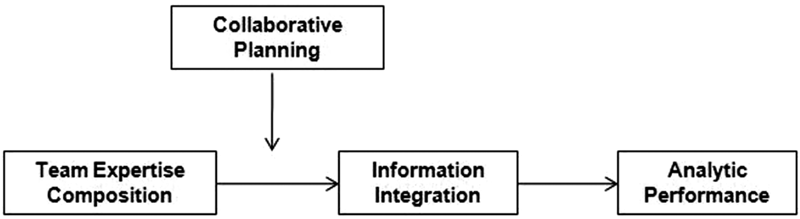
Method

We tested the research hypotheses in an experimental study of four-person teams that performed a partial analog intelligence analysis task. The task required members to assess and integrate diverse kinds of data to determine what suspected terrorists were planning. Two factors were experimentally manipulated: (a) team composition (experts vs. no experts) and (b) collaborative planning intervention (presence vs. absence of guidance about ways to use member resources well). Performance measures included both the objective accuracy of each team's analysis and independent assessments of the quality of their reasoning.

Participants

A sample of 1,692 Boston-area students and residents were recruited on an Internet bulletin board for preliminary screening of cognitive abilities and were given a $10 gift certificate from an online retailer as compensation. Of these participants, 164 (41 four-person groups) were selected to take

Figure 1
Model of Hypothesized Relationships Among Expertise, Collaborative Planning, Information Integration, and Performance



part in the experiment, based on their scores on the screening tests (described in more detail below). Those selected for the experiment were paid an additional $25 for participating. Sixty-three percent of the participants were women; participant age ranged from 18 to 59 (M = 27, SD = 8.7), and all were college students or graduates.

Task

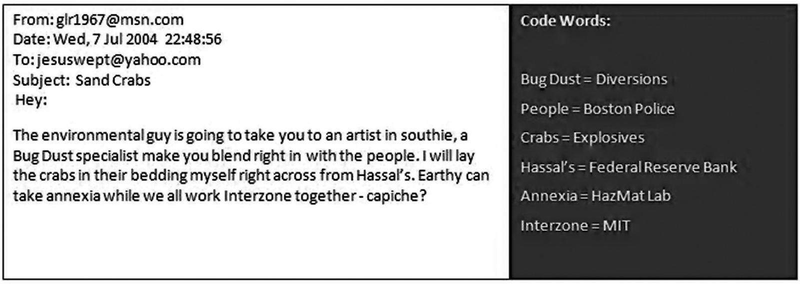
The task required four-person teams to solve a terrorist plot by correctly identifying within 45 min three guilty individuals from a pool of 10 suspects, one target building from five potential locations, and the terrorists' planned activities. Four types of evidence were provided, as described below. The evidence was available to the teams on four eMac computers placed together in the room, each of which was loaded with brief biographical sketches of all the suspects and one of the four types of evidence.

The task was structured so that obtaining the correct answer required both accurate analysis of each set of evidence and integration across the four different kinds of evidence. Both the setup of the experimental room and the large quantity of available evidence encouraged groups to spend some time working on their individual computers to analyze a single type of evidence before coming together to discuss and draw conclusions about what they had learned.

Materials

Four types of evidence were supplied to help the teams determine the terrorists' plans: (a) degraded security camera photos, (b) surveillance

Figure 2a
Sample of Encrypted E-Mail


From: glr1967@msn.com
Date: Wed, 7 Jul 2004 22:48:56
To: jesuswept@yahoo.com
Subject: Sand Crabs
Hey:

The environmental guy is going to take you to an artist in southie, a Bug Dust specialist make you blend right in with the people. I will lay the crabs in their bedding myself right across from Hassal's. Earthy can take annexia while we all work Interzone together - capiche?

Code Words:

Bug Dust = Diversions
People = Boston Police
Crabs = Explosives
Hassal's = Federal Reserve Bank
Annexia = HazMat Lab
Interzone = MIT

video footage without audio, (c) a codeword-based e-mail set, and (d) reconnaissance photos and building plans. Figure 2 contains examples of each type of evidence.

The degraded security camera photos were supplied from each of the five suspected plot locations. Photos of 5 of the 10 suspects were mixed in with 10 distracter photos from each location, and participants were instructed to determine which of the 10 suspects appeared at each of the five locations, with the implication that the guilty suspects would have all visited the targeted building. Surveillance video footage of each suspect leaving a hazardous materials laboratory where critical chemicals were stolen provided additional information for participants to use to determine who seemed nervous as they departed. Codeword-based e-mails exchanged between the suspects were supplied to provide details of the plot itself. Finally, reconnaissance photos, found on a personal digital assistant (PDA) suspects purportedly had lost, could be matched up to building plans to reveal the probable location of the plot.

Two of the four types of evidence, the e-mail evidence and the security camera photo evidence, were designed to require specific cognitive abilities for successful analysis. Analysis of the e-mails was constrained by limiting participants to a single viewing of numerous code words used in the e-mails. Furthermore, they were not permitted to write down the codes. These restrictions increased the degree to which strong verbal memory was required to analyze the e-mail evidence. Analysis of the security camera photos was made difficult by degrading the quality of the photos and increasing their graininess. This increased the degree to which face-recognition ability was required to analyze the security camera data. Pretest data affirmed that

Figure 2b
Sample Degraded Security Camera Photos

participants' verbal memory (assessed by a paired-associates memory test, described below) and their ability to recognize faces were significantly correlated with their ability to correctly analyze the e-mail and security camera photo evidence ($r = .48$, $p < .001$ and $r = .47$, $p = .013$, respectively). The video surveillance footage and building plan layouts did not require special abilities and were shown in a pretest to be challenging but achievable by most participants.

Measures of Cognitive Abilities

The two cognitive abilities used in selecting experts—verbal memory (VM) and face recognition (FR) ability—were assessed using a paired-associates memory task and the Cambridge Face Memory Test (CFMT; Duchaine & Nakayama, 2006), respectively.

VM. The paired-associates task required respondents to remember the pairings of nouns from a list of 25 pairs. The test was constructed using Paivio, Yuille, and Madigan's (1968) norms for concreteness and imagery of nouns. One hundred nouns were tested, each of which had a concreteness rating less than 2.5 on a scale from 1 (most abstract) to 7 (most concrete).

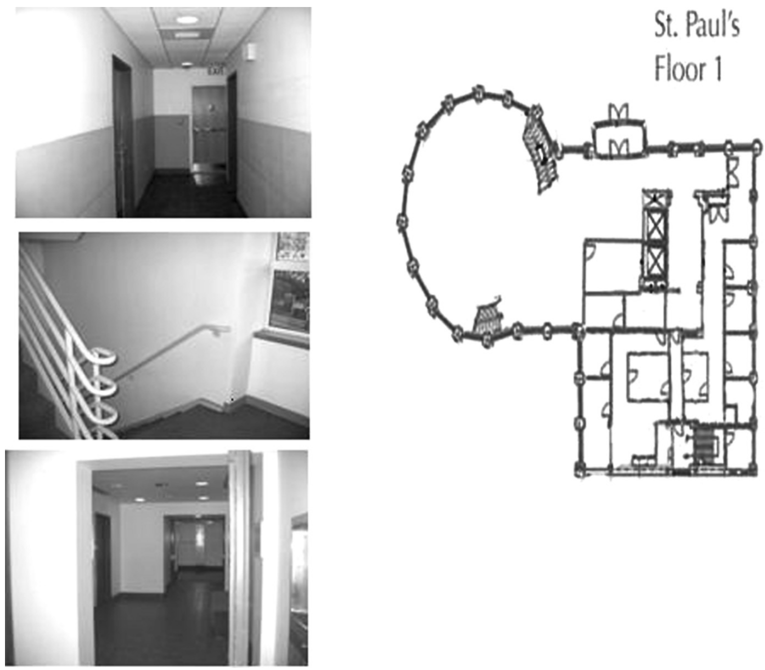
Figure 2c
Screen Shot of Security Camera Footage of Suspect

All nouns tested had frequency ratings higher than 3 per million. We used these words to create two 25-item lists of pairs, and also used latent semantic analysis matrices to minimize the semantic relatedness of cues and targets in each list (Howard & Kahana, 2002). The average latent semantic association in List 1 was .078; for List 2 it was .086.

The paired-associates lists were pretested online by 127 participants. Performance on the two lists was significantly correlated ($r = .67$, $p < .001$). List 1, which was slightly more difficult than List 2 ($M = .49$, $SD = .22$; and $M = .58$, $SD = .26$, respectively), was chosen for use in screening participants.

FR. The CFMT requires respondents to examine a set of target faces and then to recognize the targets among sets of distracter faces of increasing graininess. Although the present implementation of the test was adapted for online use using Psyscope-FL, all stimuli and timings were identical to those used by Duchaine and Nakayama (2006). The scores of the 127 pretest participants ($M = .77$, $SD = .14$) were comparable to those previously obtained by Duchaine and Nakayama.

Figure 2d
Sample Photographs and Blueprints Used to Determine Route Through Building



Screening and selection. We developed eligibility criteria for participation in the experimental study based on the performance of the 127 pretest participants and applied them to the 1,692 individuals who were screened. *Excellent performance* was set at the 90th percentile (FR score > .93, VM score > .76); *good performance* was set as between the 66th and the 33rd percentiles (.71 < FR score < .85, .32 < VM score < .52); and *fair performance* was set as below the 33rd percentile (FR score < .71, VM score < .32). Performance falling between the 66th and 90th percentiles was considered *null*, and those participants were not invited to the laboratory for the team portion of the study.

Respondents were eligible for the experimental portion of the study as nonexperts if they received either a fair or good score on both tasks. Participants falling between the 66th and 90th percentiles were considered null and excluded in order to maximize the ability distinction between experts and nonexperts. Those who received an excellent score on one task and a fair or good score on the other task were considered experts in the domain in which they received the excellent score. Of the 1,692 people completing the screening, 112 (6.6%) qualified as FR experts, 120 (7%) as VM experts, and 789 (47%) as nonexperts. Among the remaining 671 respondents, 37 (2%) received excellent scores on both tasks, and the rest (37%) had a score on either or both tasks that fell between good and excellent and were not invited to participate in the experiment.

Experimental Conditions and Procedure

The experiment was conducted using a 2 × 2 design, with expertise composition (special ability or average ability) crossed by collaborative planning (planning intervention or no planning intervention). We manipulated team expertise composition by constructing either (a) special ability teams consisting of one VM expert, one FR expert, and two nonexperts, or (b) average-ability teams consisting of four nonexperts.

Collaborative planning was manipulated by either (a) requiring teams to discuss explicitly who would be responsible for which type of evidence, and to plan how they would integrate the various types of evidence to determine who the terrorists were and what they were planning, or (b) allowing members to launch immediately into their work on the task. Specifically, teams receiving the collaborative planning intervention were given a worksheet that delineated the steps of the planning exercise, and the investigator started a 10-min QuickTime presentation that guided the teams through those steps. The exercise required members to collectively review the types of evidence they were provided, relate the evidence to components of the problem solution (e.g., suspects, location, or plot), review member abilities and their relationship to the types of analyses that were involved, and then plan their approach to their analysis. Completion of the exercise occurred during the team's work time; thus, these teams had 10 min less than others to spend on the task itself.

Forty-one teams were assigned to the four experimental conditions as follows: 20 teams received the collaborative planning intervention (10 special ability, 10 average ability), and 21 teams received no intervention (10 special ability, 11 average ability).

Once all team members had arrived at the laboratory, they were shown a 6-min QuickTime presentation describing the terrorist scenario, the evidence that was available, and suggestions about how they might use their time (specifically, 30 min for organization and individual evidence analysis followed by 15 min for discussion and integration). The investigator then gave each member of the team his or her personal-ability report based on the online screening. Participants learned whether they were fair, good, or excellent for each of the two key abilities—word-pair memory and FR ability. Teams were encouraged to share their scores with each other in determining how to divide up their work, at which time the expert members (when present) were revealed. All teams correctly assigned expert members to the appropriate roles.

Teams were given time warnings when 15 min and 5 min remained. When time had elapsed, the investigator collected the answer sheet from the team and gave them a postsession questionnaire to complete. They then were debriefed, thanked, and dismissed.

Outcome Measures

Performance. Each team was given a single score for its final solution to the plot. This score combined a suspect score, a building score, and a plot score. The suspect score was the number of suspects the team correctly identified as terrorists. The building score was whether the team correctly identified the building that was the suspects' target. Teams were given full credit for selecting the target building and half credit for selecting the building that suspects visited and discussed in the e-mails but were using as a decoy for the real target. The plot score was a weighted total of the correct plot elements the team identified. Pretests indicated that the plot elements varied in difficulty due to the number of times they were mentioned in the e-mail and the number of code words needing translation in discerning their details. In analysis, these plot elements were weighted for the difficulty of their determination as follows. Three easy-to-detect elements were assigned a weight of 1.0, three moderately difficult plot elements were assigned a weight of 2.0, three hard-to-detect plot elements were assigned a weight of 3.0, and four commonly but incorrectly identified plot elements were given a weight of –.75. Two judges independently read and scored the plot descriptions for each team; the interrater reliability of the judges' ratings was .98. The few discrepancies in their evaluations were discussed and resolved. The suspect, building, and plot scores were then z scored and summed to form the overall correctness score.

*Information integration***.** The information integration score assessed whether a team's answer was internally consistent. Teams were given credit

Table 1
Mean Performance Scores by Condition

Condition		Performance	Information Integration
No experts/no planning	M	-0.02_{b}	4.91_{a}
	SD	2.37	2.43
No experts/planning	M	0.04_{b}	$5.20_{a,b}$
	SD	2.13	1.93
Experts/no planning	M	-0.80_{a}	4.40_{a}
	SD	2.03	1.26
Experts/planning	M	1.04_{c}	6.60_{b}
	SD	2.47	2.12
Total	M	0.00	5.14
	SD	2.18	2.06

Note: Means in the same column that do not share subscripts differ at $p < .05$, one-tailed.

for integration by selecting suspects that had appeared in the security camera photos at the building the team selected as the target, regardless of whether the suspects or target selected were part of the correct solution. Similarly, they were given credit for the number of plot elements they listed that were consistent with their selected building target. Because these elements of the solution were typically determined by different team members, integration of these solutions indicates integration of the work of the team. The suspect and plot-consistency scores standardized and combined to form the information integration measure.

Results

Hypothesis 1 states that the interaction of team expertise composition and collaborative planning would jointly control more variance in performance than expertise composition alone. Table 1 displays standard deviations and comparisons of means by condition, and Table 2 displays the results of regression analyses. The results support Hypothesis 1. The difference between the effect sizes for team composition and those for the interaction of composition and collaborative planning on performance is statistically significant ($\beta = -.57$ for team composition vs. $\beta = .87$ for the interaction); $t(38) = 11.68$, $p < .0001$, $d = 3.79$.

Hypothesis 2, which predicts that the interaction of team expertise composition and the collaborative planning would control more variance

Table 2
Results of Regression Analyses for Team Performance

	Team Performance			
	Step 1		Step 2	
	β	*t*	β	*t*
Expertise composition	–.38	–0.77	–.10	–0.28
Collaboration	–.57	–1.15	–.15	–0.40
Expertise × Collaboration	.87	1.78*	.14	0.27
Information integration			.72	5.69***
R^2	.08		.52	
F	1.12		9.64	
ΔR^2			.44***	

*$p < .10$. ***$p < .01$.

in performance than collaborative planning alone, was also supported. The effects of collaborative planning and the effects of the interaction of expertise and planning are significantly different (β = –.38 for collaborative planning vs. β = .87 for the interaction); $t(38) = 10.84$, $p < .0001$, $d = 3.52$.

Finally, there is support for the third hypothesis, which predicts that information integration will mediate the effects of the interaction of expertise and planning on performance. As discussed above, the interaction of composition and collaborative planning significantly predicts performance. Information integration also significantly predicts performance (β = .72), and when the two together are used to predict performance, the effect of the interaction of composition and collaborative planning decreases significantly (β = .14). A Sobel test indicates that the change in β is significant with the addition of the mediator ($Z = 2.05$, $p = .04$), confirming the presence of a mediated effect. Examination of team social interaction further suggests how teams went about effectively integrating information. Teams that structured their search by solving the plot location first (the lowest variability, highest reliability element) performed significantly better than those that did not, $t(38) = 3.35$, $p = .002$, and those receiving a collaborative planning intervention were significantly more likely to structure their search in this way: 40% of intervention (confidence interval [CI]: 19%, 64%) versus 14% of nonintervention (CI: 3%, 36%), $\chi^2(df = 1, n = 41) = 3.45$, $p = .03$, one-tailed.

Conclusion and Discussion

These findings suggest that team analytic work is accomplished most effectively when teams include task-relevant experts *and* the team explicitly explores strategies for coordinating and integrating members' work.

Prior work has examined the importance of team composition. We know that functional diversity is important, and that teams with relevant functional diversity generally outperform teams that lack such diversity (Dahlin et al., 2005; Thomas-Hunt et al., 2003). We also know that teams of specialists can fail to share information effectively when they lack individuals with sufficient personal breadth to translate between members (Bunderson & Sutcliffe, 2002). Because it is not always possible to include members with the necessary intrapersonal diversity, we must also consider ways that teams can help themselves to create the right bridges, through collaborative planning. However, existing research has shown that such planning rarely happens in the absence of a leadership or instructional intervention (Hackman et al., 1976; Wittenbaum et al., 1998). The present findings affirm that conclusion and further suggest that such interventions are especially important for teams including expert members. Teams including experts that did not receive the collaborative planning intervention performed worse than other teams, raising the perverse possibility that the presence of expert members may actually decrease team effectiveness if members are not helped to use the experts' special talents. Because analytic teams almost always consist of members who bring a diversity of expertise and experience to the work, further research on the factors that can increase such teams' ability to recognize and use well these resources is needed.

One of the benefits of collaborative planning, we found, was that it resulted in members more effectively integrating information. For many analytic tasks, resolution of uncertainty about certain questions early in the analytic process radically constrains the scope of what must be dealt with subsequently—and thereby reduces considerably analysts' data processing load. If, for example, antiterrorism analysts can determine the specific geographical area in which a terrorist activity is being planned, then they can focus mainly on data relevant to that area and not spread their analytic resources across all possible areas. Structuring analysis in this way is particularly valuable for analyses conducted by teams, because team analytic tasks almost always are broader in scope than those assigned to individuals, and therefore pose a greater risk that analysts will be overwhelmed by the sheer quantity of the information to be processed. We found that teams that conducted a structured search through the available evidence, which in almost all cases were those that had received the collaborative planning intervention, did indeed perform better than those that gave the same priority to all aspects of the overall task in the early stages of their work. This finding is significant for the current task, as the piece of information that the analyses needed to be structured around and subordinated to was held by a nonexpert member of the team. We found that expert teams not receiving a collaborative planning intervention helping them to weight member inputs appropriately were less likely to integrate their information effectively in this kind of situation.

In summary, there appear to be two important benefits of the collaborative planning intervention. The first benefit of the intervention is to increase members' awareness of their teammates' task-relevant expertise and experience, and thereby to increase the team's chances of fully using members' contributions. The second benefit is to increase the degree to which all members, as a consequence of working through the steps in the intervention together, come to appropriately structure their work and weight their expertise such that all members can contribute to the team's collective task. Further research on these secondary effects of strategy-planning interventions could both increase basic understanding of work team processes and be of considerable practical use in guiding those who create and lead task-performing teams.

Notes

1. The lists were shown for 6 s first in a learning phase, followed by a 10-min distracter task, followed by the four alternative multiple-choice recognition trials for the words. List 1 was always completed first so that any interference would not vary across participants. Word pairs were shown in a random order that was fixed across participants. Each target word appeared four times—once as the correct choice and three times as a distracter. Thus, the task was very difficult; chance performance was 25%.

2. The weight for incorrect elements was devised so that it perfectly balanced with the score that teams could receive for the three easiest plot elements, which made it possible to distinguish between teams that were indiscriminately writing down everything they could think of from those who were carefully filtering all of the information.

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