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Reuse and Recycle: The Development of Adaptive Expertise, Routine Expertise, and Novelty in a Large Research Team

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Summary: Combining innovation and efficiency is ideal in many organizational settings. Adaptive expertise represents a cognitive explanation of how individuals and teams can learn to achieve simultaneous innovation and efficiency. In 2004, scientists led twin rovers on Mars in the search for historical water. The science team experienced a remarkable increase in efficiency, adapting with flexibility to unexpected events and dynamic, dwindling resources. After discussing the conceptual differences between adaptive expertise and related team learning and innovation concepts, we examine longitudinal behavioral data on novelty, routine and adaptive expertise. Sequential time series ARIMA analyses reveal that novelty fluctuated randomly, but both routine and adaptive expertise significantly increased over time. In addition, novelty, routine expertise, and adaptive expertise did not significantly predict each other directly or at a lag, suggesting that these are indeed three distinct constructs. Implications for theory and research on efficiency and innovation are discussed. Copyright © 2013 John Wiley & Sons, Ltd.

A tension exists for organizations between achieving novelty and efficiency, whether in product design, management, or scientific research. Novelty without efficiency runs the risk of being out-of-touch, unaccepted, or too slow to be of use; efficiency without novelty can be acceptable but may not evolve the domain as needed. When novelty and appropriateness come together, the product, discovery, or process may be considered creative (Amabile, 1983, 1996). Achieving both novelty and efficiency is the goal of many organizations. Innovation is a related concept. Achieving innovation requires not just a constellation of social, motivational, and environmental conditions (e.g., Amabile, 1983) but also learning how to transfer the right knowledge in the right way at the right time.

Most studies of team learning focus on routine expertise, which is the development of efficiency without innovation. This paper applies a construct combining efficiency and innovation from the cognitive individual and team learning literature—adaptive expertise—and tests it in a workplace context. This paper argues that adaptive expertise theory provides the following: (1) a new structure for distinguishing critical elements of innovation that other frameworks fail to differentiate; (2) an explanatory theory of the underlying cognitive mechanism to explain how adaptive expertise in team innovation is developed; and (3) describes a phenomenon that goes above and beyond routine expertise. It then offers an illustration by using the Mars Exploration Rover (MER) scientists, who experienced a remarkable speedup in planning time in a complex large group process in only several months, and demonstrates that our operationalization of adaptive expertise is both conceptually and statistically distinct from novelty and routine expertise.

The studied context involves a 2004 National Aeronautics Space Administration (NASA) mission of two identical rovers sent to Mars to find historical evidence for water and thus the possibility of life. This MER mission was an astonishing success in terms of both groundbreaking science and team processes. The team's performance was incredibly effective: In only a few months, the rover scientists exceeded all expectations of productive output, the group grew more expert, and the work contributed to the growth and satisfaction of the individual scientists (Squyres, 2005). Among the many successes of the mission was an unexpected, massive speedup in complex science planning. By the end of the first 90 days, the initially ambitious 8.5 hours a day of formal and informal meetings had shrunk to 2.5 to 2 hours (Tollinger, Schunn, & Vera, 2006; see Figure 1) while maintaining high levels of output and innovation.

A study of this impressive team can inform how to become simultaneously innovative and efficient. In addition, we propose that incorporating insights from the cognitive literature on adaptive expertise can inform theory and future research on team innovation and efficiency. Team adaptive expertise is relevant to managing many teams, from new product design firms to teams of scientists. In addition, this study is unusual in that it is a quantitative analysis of longitudinal behavioral data rather than a qualitative analysis or quantitative examination of only self-report surveys, allowing for important disentangling of factors.

The science team we study is quite large, comprised of over 100 members. Nonetheless, this group has the fundamental qualities of a 'real' team and thus should experience similar team processes: The members are engaged in interdependent tasks, they are an intact social entity, and they have differentiated member roles (Guzzo & Dickson, 1996; Hackman, 2012). For example, the MER science team is distinguished from the MER engineering team, which had different responsibilities and was a different social entity. Within the MER science team, different individuals held different roles, and everyone worked together to achieve interrelated science goals in the study of the history of water on Mars.

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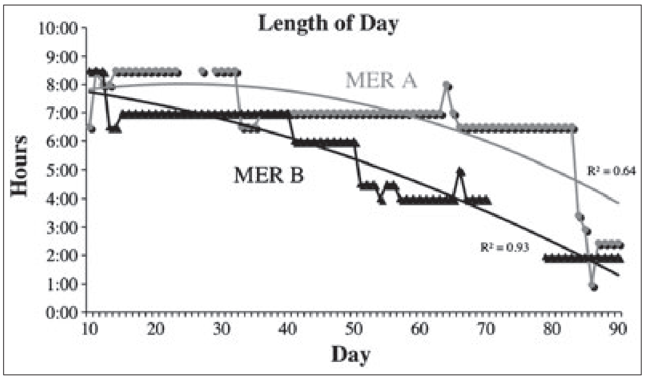

Figure 1. Speedup of schedule for science planning by Mars Rover Team (curved lines are fitted regression lines; meeting length as dictated by management is the disjoint lines)

Adaptive expertise, individual and team

A hallmark finding on learning and expertise is that with increasing practice on a task, time on a task drops and gradually approaches an asymptote (Anderson, 1982, 1993; Darr, Argote, & Epple, 1995; Logan, 1988; Newell & Rosenbloom, 1981; Newell & Simon, 1972). Much of this literature has studied expertise at the individual level (e.g., Chi, Glaser, & Farr, 1988; Ericsson & Smith, 1991), whereas other researchers have studied expertise at the team level. Team learning encompasses experimentation, refinement, knowledge sharing and generation, and a range of changes to processes and tasks (Miner, Bassoff, & Moorman, 2001; Rerup & Feldman, 2011). A great deal is already known about the development of team expertise in organizations (e.g., Argote, 1999; Darr et al., 1995; Edmondson, 2002; Edmondson, Bohmer, & Pisano, 2001; Edmondson, Dillon, & Roloff, 2007; Levitt & March, 1988; Reagans, Argote, & Brooks, 2005; Sessa & London, 2007; Tucker, Nembhard, & Edmondson, 2007; van der Vegt & Bunderson, 2005). At every level (i.e., individual, team, and organizational), the reapplication of prior solutions can lead to increasingly faster problem solving. However, it is generally insufficient to gain knowledge and simply apply it again and again increasingly quickly, given that real-world situations can change suddenly and dramatically, making past solutions, however quickly applied, much less useful.

Individual adaptive expertise

The concept of adaptive expertise was developed to explain complexities in the individual expertise literature, specifically about differences in the ability to transfer learning between different types of experts (Hatano & Inagaki, 1984, 1986). Transfer of learning is a critical element of expertise and efficiency. Without the ability to correctly apply knowledge across situations, there is little development of expertise, and in particular, no adaptive expertise. In 'routine expertise', experts are taught to focus on and become adept at efficiency—to practice tasks such that problems become easy to solve later (Schwartz, Bransford, & Sears, 2005). Efficiency here refers to an increased facility and automaticity of a task, including speedup of all task elements (e.g., Anderson, 1982; Newell & Rosenbloom, 1981). Efficiency from the cognitive literature is thus related to, but not precisely the same as, efficiency as described in other literatures (e.g., attention to detail, meeting deadlines, or keeping within budget, Miron, Erez, & Naveh, 2004). The 'routine' in routine expertise refers to the tendency for the task to become automatic, not that it is inherently easy or difficult. Routine expertise can thus include simple production tasks such as pizza assembly and delivery but also complex tasks such as surgery and medical diagnoses (e.g., Darr et al., 1995; Reagans et al., 2005; Schwartz et al., 2005). The development of routine expertise involves learning how to quickly apply domain-specific strategies and heuristics to familiar problems (Kozlowski, 1998). However, past successful experiences may also lead to cognitive entrenchment, where problem solvers inappropriately reapply past strategies to new situations (Dane, 2010; Lovett & Anderson, 1996; Luchins, 1942). Thus, routine experts may be stymied by novel and unstructured problems, potentially by misapplying heuristics or lacking the right one for the new situation (Kozlowski, 1998).

Adaptive expertise involves learning not just how to perform a procedural skill efficiently, but also to know when variations to previous approaches are necessary—*how and when* to apply their heuristics—and thus results in experts being able to handle ambiguous and novel situations (Hatano & Inagaki, 1984, 1986). In addition to the accuracy, efficiency, and automaticity that routine experts have, adaptive experts can also adapt their knowledge to new problems (Hatano & Inagaki, 1986) via knowing how and when to transfer their knowledge to novel situations; they resist cognitive fixedness (Schwartz et al., 2005). They also have metacognitive and self-regulatory skills (Kozlowski, 1998). Metacognition involves awareness and monitoring of cognitive processes, and self-regulatory skills include planning, monitoring, and adjustment of strategies (Kozlowski, 1998). The goals of efficiency and innovation are in conflict for routine experts, but they can combine effectively in adaptive experts (Schwartz et al., 2005). Adaptive expertise is generally conceptualized as an individual-level, learned ability. The concept has been applied to teams (Kozlowski, 1998), and this study examines it at that level.

At the individual level, three environmental factors have been called out as preconditions to the development of adaptive rather than routine expertise: significant variations in the practice of their skills, being in an organizational culture in which understanding the system is valued, and performing tasks with a minimum of extrinsic rewards (Hatano & Inagaki, 1984, 1986). The first two environmental factors relate directly to learning metacognitive skills. Dynamic and unpredictable environments may make it less likely that routine domain expertise will lead to cognitive entrenchment (Dane, 2010). Similarly, learning skills in different situations would also be likely to make experts aware of how and when to apply their knowledge. A small empirical study by Barnett and Koslowski (2002) supported these two factors: when given hypothetical, novel problems involved in running a restaurant, business consultants (general experts) outperformed restaurant managers (domain experts), and college students (novices). On the basis of qualitative process analyses, Barnett and Koslowski (2002) found that restaurant managers' knowledge did not transfer to novel situations because they were more likely to be bound by their specific experiences, whereas business consultants were more likely to use broad theoretical concepts (e.g., concepts like target market, and price point). As for the third environmental factor, Hatano and Inagaki (1986) suggest that in situations conducive to intrinsic motivation, experts have the freedom to experiment with different strategies and thus learn how they work. Intrinsic motivation generally tends to produce mastery learning goals (Elliot & Harackiewicz, 1994).

Team adaptive expertise

Careful analysis of existing studies suggests that adaptive expertise can be applied to the study of teams (Kozlowski, 1998). Rather than being an inappropriate application of a construct to a higher level, like individuals, adaptivity in teams appears necessary when faced with changing task demands and increased workload (Entin & Serfaty, 1999). Routine behavior in groups can have dire consequences without the awareness of when and where to apply them: for example, keeping to a flight routine in an atypical weather situation has resulted in at least one airplane crash (Gersick & Hackman, 1990). Also as suggested by the theory of adaptive expertise, team expertise has been argued to involve metacognitive and self-regulatory skills for *both* individual cognitive and team processes, such as role demands of oneself and others (Kozlowski, 1998). Other relevant team metacognitive skills include team efficacy, being aware of pacing and timing to coordinate with others, monitoring others' task loads and success, and the ability to change team roles, tasks, and networks when the situation demands it (Kozlowski, 1998).

Further, effective team training has been argued to involve not only learning one's own task, but also developing a *shared* mental model and implicit coordination (Entin & Serfaty, 1999), mutual monitoring of roles and performance, and the skills to continuously learn and adapt (Kozlowski, 1998). Mental models, or schemas, are internal representations of situations, people, actions, or objects (Johnson-Laird, 1980). *Shared* mental models are representations and relationships between constructs, including task and/or team processes (e.g., Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000) that overlap between individuals (Mohammed, Ferzandi, & Hamilton, 2010). Similarly to the concept of distributed cognition (e.g., Hutchins, 1995), shared mental models are 'dynamic, simplified, cognitive representations of reality that team members use to describe, explain, and predict events' (Burke, Stagl, Salas, Peirce, & Kendall, 2006, p. 1199). Promoting shared mental models is thought to be important for increasing team effectiveness (Kozlowski & Ilgen, 2006; Mathieu et al., 2000), particularly if those shared mental models are accurate (Edwards, Day, Arthur, & Bell, 2006). Shared mental models can be about specific tasks, but also about the teamwork itself (Lim & Klein, 2006), and thus represent a type of team metacognition.

Hatano and Inagaki's (1984, 1986) three environmental factors can also be applied to teams. Just as with individual adaptive expertise, environments conducive to the development of team adaptive expertise should be as follows: (1) provide a range of deeply different situations that enable abstracting of heuristics; (2) promote shared, accurate task, metacognitive, and self-regulatory skills that enable team members to know how and why to apply their heuristics; and (3) encourage intrinsic motivation. These three broad factors could apply just as well to small teams as large teams, so long as they are all real teams (Hackman, 2012). First, a range of new situations for teams can help them develop adaptive expertise. For example, an emergency surgery team might encounter new situations on a regular basis because of the novel constellation of factors their patients bring to the operating table. Second, as noted previously, team metacognitive skills encompass but go beyond individual metacognitive skills. In particular, shared mental models in teams are considered vital to teams in uncertain and novel situations (Orasanu & Salas, 1993)—situations that require adaptive expertise. Taking emergency surgery teams as an example, if faced with new situations—such as a move to a new facility—having shared mental models in place regarding their own task work and teamwork will aid them in their transition. Third, some groups and workplaces encourage intrinsic motivation. For example, Google encourages its employees to spend 20% of each week on individual side projects, and such side projects have become major software products for the company and for the greater good (e.g., Gmail, as well as time spent on digital tools to help Japan after the earthquake; AFP, 2011). In individualistic cultures, at least, intrinsic motivation is associated with exploration and variety seeking (see Gelfand, Erez, & Aycan, 2007 for a review). Individuals working in teams can be encouraged to have intrinsic motivation just as individuals working alone. In sum, team adaptive expertise theory provides a framework for both what team adaptive expertise is and the cognitive mechanisms by which it develops over time.

Other constructs and adaptive expertise

When applying a construct from one field (e.g., cognitive psychology) to an applied setting dominated by other disciplines (e.g., management, aerospace, and medicine), it is important to make distinctions with similar constructs (Figure 2). The adaptive expertise theory offers a framework for clearly distinguishing three constructs that are often partially conflated: novelty, routine expertise, and adaptive expertise. For example, adaptive expertise is not simply creativity (radical or incremental), novelty, or innovation. Adaptive expertise theory further makes a novel contribution to theory regarding these concepts, because it involves a mechanistic explanation of how expertise is acquired. That is, adaptive expertise involves a theory of individual and team learning (i.e., studying teams across consecutive outputs), rather than just a theory of

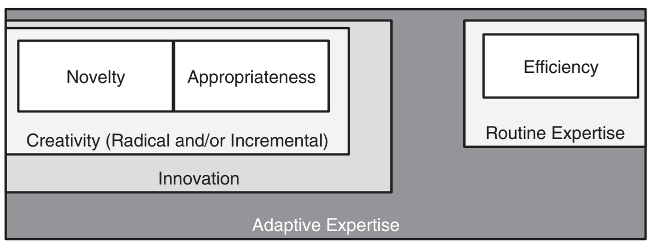

Figure 2. Concept map of other constructs and adaptive expertise

how a current creative outcome of a team came to be (i.e., studying teams producing one output).

Novelty, creativity, and innovation

Novelty involves some kind of new outcome, and may involve a random generation process (Simonton, 1999). Creativity incorporates both appropriateness and novelty (see Figure 2). Researchers have differentiated creativity as characteristics of people, environments, products or processes (Sternberg, 1999). Creative environments can affect team performance (e.g., Gilson, Mathieu, Shalley, & Ruddy, 2005), and creative people have been examined for what traits make them creative. Creative outputs can be characterized by originality (novelty), fluency (the generation of many ideas), and elaboration (the depth with which each idea is explored), among other categories (Torrance, 1988). Creative processes can include problem finding and restructuring, insight, evaluation, divergent thinking, the merging and expansion of ideas, and analogy (Ward, Smith, & Vaid, 1997). Innovation, an even broader construct, encompasses both creativity and the elements of relative rather than absolute novelty, application/ implementation, and the intentional benefit to others (West & Farr, 1990). Creativity and innovation are both considered essential for driving economic growth, job creation, and scientific progress (e.g., Ahlstrom, 2010). Creativity, novelty, and innovation are thus outcomes, traits, or lower level processes with large literatures suggesting precursors and causes (e.g., Glover, Ronning, & Reynolds, 1989; Sternberg & Lubart, 1999). Discussions of adaptive expertise often use the terms creativity and innovation interchangeably and distinguish them from efficiency rather than from each other (Schwartz et al., 2005). In this paper, we focus on 'innovation', because we interpret adaptive expertise as implying implementation and action.

Adaptive expertise includes the concept of relative novelty, as well as the concepts of creativity and innovation. However, although routine expertise encompasses efficiency alone, *adaptive* expertise additionally involves efficiency and innovation co-occurring (Figure 2; see also Schwartz et al., 2005). Adaptive expertise theory therefore is more tightly theoretically focused than theories of creativity or innovation. Adaptive expertise is also focused on efficiency and innovation as outcomes and as a result of learning. Other studies examine the combination of, for example, standardized work practices and perceived creative environments as factors influencing other outcomes, such as team performance (Gilson et al., 2005). Although clearly related to the construct of adaptive expertise, novelty, creativity, and innovation only relate to one part of adaptive expertise: Adaptive expertise also includes efficiency, and thus conceptually should remain distinct. Put another way, although adaptive expertise incorporates efficiency and innovation (and thus also novelty and appropriateness), novelty, routine expertise, and adaptive expertise are all separate constructs.

Radical and incremental creativity

Organizational theorists have recently become interested in the distinction between radical and incremental creativity (e.g., Madjar, Greenberg, & Chen, 2011). Creative ideas can deviate from existing knowledge in both radical and incremental degrees, making minor to major contributions (Mumford & Gustafson, 1988). Superficially, this distinction seems to map the routine/adaptive expertise distinction, but close examination suggests this mapping is imperfect. Radical and incremental creativity are still different types of creativity (Figure 2). Adaptive experts can make both incremental and radical changes, depending on how heuristics are combined and applied. On a conceptual level, radical versus incremental creativity is a way of categorizing an outcome, with the cognitive and team processes behind it left to further research. Thus, adaptive expertise could lead to both incremental and radical changes, likely influenced by, among other factors, the needs, opportunities, and constraints of the setting.

Other team learning literature

The majority of the team expertise and learning literature has not engaged with the construct of adaptive expertise. Many studies on the development of team and organizational expertise have focused on production efficiency without innovation (e.g., pizza production, Darr et al., 1995; and creating origami, Kane, Argote, & Levine, 2005). These studies have examined the development, transfer, creation, and retention of specific heuristics and routines that make the tasks become automatic, effortless, and/or faster.

Dividing the literature on expertise into the routine versus adaptive categories could help shed light on prior mixed findings. One area is organizational routines: as a type of team learning, organizational routines are a kind of shared procedural memory that can improve efficiency across teams and organizations (Cohen & Bacdayan, 1994). Routines are not necessarily static. In the space between ideal routines and routines as they are enacted, routines can be adapted and changed (Feldman & Pentland, 2003; Rerup & Feldman, 2011).

Further, past reviews of organizational learning have highlighted inconsistencies in the effect of experience on creative thinking: experience and routines can constrain creative thinking (Argote & Miron-Spektor, 2011), transferred knowledge can be misapplied, and/or routines can be *both* limited and useful (e.g., Levinthal & Rerup, 2006). Much of that literature has focused on what types of experiences, be they deep or diverse, will lead to creative thinking (as opposed to innovation or both innovation and efficiency; Argote & Miron-Spektor, 2011).

Some of the team learning literature has addressed adaptive expertise without referring to it as such. Adaptive teamwork is seen as required for novelty or during periods of crisis or high workload (e.g., Entin & Serfaty, 1999; Marks, Zaccaro, & Mathieu, 2000; Waller, Gupta, & Giambatista, 2004). Similarly, many researchers discuss the importance of metacognition and shared mental models in team performance, particularly with tasks that require innovation (e.g., Edwards et al., 2006; Kozlowski & Ilgen, 2006; Mathieu et al., 2000; Mohammed et al., 2010 for a review).

In the next section, we describe the MER setting and use it as a quantitative illustration of novelty, routine expertise, and adaptive expertise, showing how they can each be measured separately, exploring how they develop over time, and testing whether they are statistically independent in this growth.

The research context: Mars Exploration Rover organizational setting

The MER mission sought to find historical evidence of liquid water on Mars via the deployment of twin robotic rovers (Squyres, 2005). In January 2004, the rovers landed on opposite sides of Mars. The focus of this paper is on the 'nominal' (initially funded) mission, which was 90 Martian days[1] through April 2004. During the nominal mission, scientists were co-located at the Jet Propulsion Laboratory. This period represents roughly 720 hours of time on task (roughly 8 hours a day for 90 days): This sheer amount of expertise development is difficult to obtain in real-world data and would be even more difficult to simulate in the lab.

This paper focuses on the MER Science Team, known as the Science Operations Working Group (SOWG). The SOWG was comprised of mostly professors and technicians but also undergraduates, graduate students, and post-doctoral associates. The rovers, Spirit and Opportunity, were each matched to a science subteam. Each rover could perform several hours of scientific activities per day such as taking photographs or driving, contingent on the availability of limited resources such as solar-generated battery power. Each day, the science subteams generated a set of science activities that were processed by the engineering team and executed by the rover the next day. This process involved: understanding the daily hard constraints for the rover (e.g., power levels and data volume available), forming a sense of the type of day it would be (e.g., primarily taking large panoramic photographs versus deploying an array of sensing instruments versus driving), assessing which activities the rover successfully completed the previous day, developing each science activity request (e.g., take a 30 second image of the sky at x and y locations), and negotiating the priority of these requests among the scientists.

The MER mission is by all accounts an outstanding accomplishment from both technical and social/teamwork perspectives. The scientists faced the real possibility that the rovers could stop working at any point because of technical malfunctions (Squyres, 2005). In addition, the scientists and engineers synchronized their activities to local Mars time for each rover, leading to sleep deprivation, fatigue, and progressive desynchronization with family. Although the scientists, both individually and as a team, had impressive expertise of many types at the beginning of the mission, we propose that, individually and as a team, they gained routine and adaptive expertise in coordinating a real-time Mars science mission over the course of the first 90 Martian days.

The conceptual argument for adaptive expertise in the Mars Exploration Rover science team

During the first 90 days of the mission, each rover subteam discovered incontrovertible evidence for a Martian history of water. This discovery was accomplished by hundreds of modest but innovative ideas ranging from how to handle unexpected problems to interpreting complex, ambiguous information. The daily science discovery process is inherently innovative, as scientists had to analyze downloaded data and plan next directions for the rover on a daily basis. Large innovative shifts also occurred. For example, during the actual mission, scientists and engineers worked together to come up with a new way of using the Rock Abrasion Tool, a precise drilling instrument, to examine dust just under the surface of a rock without drilling. This new use of existing tools was not planned before the mission, necessitating refinement and the creation of new parameters through testing on Earth and practice on Mars. In addition, unlike conditions conducive to routine expertise, daily goals shifted, problems were unstructured, and the situation could change without warning (Kozlowski, 1998).

The MER setting involved all three of Hatano and Inagaki's factors. First, the SOWG experienced variety in their situation during the nominal mission. The task changed both suddenly and gradually regarding both the changing nature of the landscape and daily data, creating a state of psychological uncertainty (Schunn, 2010). Prior research examining MER meetings for the presence or absence of expressed uncertainty at the utterance level found the following: (1) the proportion of uncertainty in planning statements went down over the first 90 days as the scientists grew more familiar with the rovers' capabilities; but (2) uncertainty about science data analysis stayed at about the same levels (Tollinger et al., 2006). The day-to-day operations were challenging, particularly with regard to science: the team did not know what could be discovered as the rovers traveled. Would the next rise contain already well-characterized rocks or different rocks? Would the next crater provide incontrovertible data about the geological history of Mars? These factors combined to make working on the MER mission a highly dynamic experience.

The second factor entailed a culture that values understanding the system, leading to the development of metacognitive and self-regulatory skills. The MER mission was noteworthy among NASA missions up to that point for encouraging explicit dialogue between the engineering and science teams before the nominal mission occurred (Squyres, 2005). The Principal Investigator gave talks to the engineering team about the nature of the science questions and vice versa. There were multiple, daily whole team meetings with required representational attendance with standardized formats for subteam reporting to insure a shared understanding of the situation and plans. This cross training was a deliberate attempt to familiarize the usually disparate groups with each other's roles and background knowledge. Under these high-stakes, tightly constrained, and physically challenging circumstances, the MER mission is a remarkable illustration of successful cross-disciplinary collaboration.

Third, the MER science team was driven by intrinsic motivation. The scientists had persisted for years even before the mission began, as funding and the project plan underwent failed and/or politically charged iterations (Squyres, 2005). Although the science team had specific, predetermined, high- and mid-level goals for the mission (e.g., minimum amount of distance traveled by each rover, each instrument getting a certain amount of use), the scientists came to the project with a deep passion for

[1] Technically, they are called 'sols' but we use 'days' for simplicity. Martian days are roughly 40 minutes longer than Earth days.

understanding geology and the possibility of life on different planets (Squyres, 2005).

Increases in planning efficiency

The initial planning cycle was considered tight: similar missions had previously used a 2-day to 3-day planning cycle to generate a single day's worth of rover commands, but this mission allotted only 8.5 hours to the science planning of each day. The 8.5 hours included both unstructured time, when scientists individually and collaboratively examined new data and discussed plans for the next day, and structured, formal meetings, during which scientists determined the specific activities on the basis of resource constraints. Surprisingly, by mission day 85, the science planning process had been cut to approximately 2 to 2.5 hours on both rover missions (see Figure 1, data from official daily mission schedules). The choices to shorten the science shift, seen as discrete steps on the graph, represent decisions made by mission management, reflecting their observations that less time was needed for planning. The formal meetings became shorter and/or merged, including being shorter in terms of fewer words (Saner, 2008), but much of the speed up was due to cuts in the unstructured work time between meetings. This massive speed-up phenomenon was impressive and unexpected. Although fast decision-making executive teams exist that use relatively more information and explore more alternatives than slower teams (Eisenhardt, 1989), imagine any other high-stakes innovation domain (e.g., a startup company) that in their first three months shortened the amount of time necessary to conduct complex team collaboration and decision-making to a quarter of an originally ambitious plan.

However, some additional details about the speedup need to be presented to show that indeed increases in routine or adaptive expertise are possible, rather than simply the overall task was changed substantially over this period. Team effectiveness may increase because of favorable environmental factors (Argote, McEvily, & Reagans, 2003). The most important environmental factors to science planning on the MER mission were the resources available to the rovers to conduct their work: solar power and flash memory (onboard data storage capacity). A systematic increase could have made planning easier and allowed the scientists to come up with more activities per rover day. Available power actually decreased slowly over the course of the mission as the seasons changed on Mars (shorter days, lower sun angles for the solar-powered rover, etc.). Between the first and second halves of the first 90 days, the different rover teams endured a 31–34% decrease in power used. Available data memory fluctuated day by day. Thus, rather than an overall increase in resources that would enable the team to conduct more science, the decrease and fluctuations in resources served to make the setting more dynamic.

As a related concern, the scientists could have simplified their tasks to save time. For example, the task speedup may have occurred because the scientists chose easier daily plans. In advance of the mission, the science team developed five high-level plan types (e.g., panorama, spectroscopy, drive, etc.), and these types do vary in difficulty. Previous analyses with this dataset show that although there was some variability, easier high-level plans were *not* selected more often as the mission progressed (Tollinger et al., 2006): If anything, for one rover, more difficult plans became more common after the first third of the nominal mission.

Thus, the speedup was not due to externally or internally caused task simplifications, demonstrating that the team genuinely became more efficient at the complex planning task over time. If anything, the mission grew even more constrained and dynamic.

Hypotheses

Based on what occurred in this setting and our conceptual discussion of adaptive expertise and related factors, we have four hypotheses. The first hypothesis, as a simple sanity check, proposes that routine expertise should increase over time, given that a similar planning task is occurring every day. The second is a more critical hypothesis test, proposing that adaptive expertise should also increase over time. It is clear from both the setting and theory on expertise that this team should and did learn how to work together to innovate. For the third and contrastive hypothesis, pure novelty, as distinct from the reuse of heuristics and expertise, will not have significant trends over time. In this setting, we contend that novelty is a reaction to daily challenges and surprises, rather than steady growing or decreasing novelty over time.

We conduct Autoregressive Integrated Moving Average (ARIMA) analyses, a type of longitudinal time series analysis, to determine the precise nature of the increases over time. Most importantly, ARIMA allows us to test the independence of changes over time of different kinds of expertise. Exploratory ARIMA analyses seek the best model fit of the data. They can determine whether changes over time are simply the result of auto-regression, time-lagged effects—meaning, the value at Time 1 significantly impacts the value at Time 2—or if the increase (or decrease) over time is caused by more complex effects. For example, ARIMA also determines if, rather than the value itself at Time 1, the difference score between Times 1 and 2 significantly predicts Time 2. Beyond the prediction that routine and adaptive expertise increased in this team, we will report the specific patterns by the best fitting ARIMA models.

Hypothesis 1

Routine expertise will increase over time.

Hypothesis 2

Adaptive expertise will increase over time.

Hypothesis 3

Novelty alone will neither increase nor decrease systematically over time.

On the basis of our conceptual work previously, we consider novelty, routine expertise, and adaptive expertise to be distinct constructs. If the same random processes drove all these outcomes over time, we would expect them to be related to each other. But, we predict that routine and adaptive expertise are real, distinct, and nonrandom processes. Thus, for our fourth hypothesis, we suggest these constructs are independent, and thus changes over time should be statistically independent.

Note that an alternative hypothesis would be that novelty is negatively related to routine expertise and positively related to adaptive expertise. Novel outcomes are often traded off with routine and adaptive expertise: The focus is usually on one or the other, not on both (March, 1991).

Hypothesis 4
Novelty, routine expertise, and adaptive expertise are statistically independent.

METHODS

Data collection

We gained access to the activity plan files from the MER mission in structured, computer readable format. The variables tested reflect those variables for which we had sufficient daily data to conduct analyses. We combined our analyses across the different rover subteams to increase statistical power and because they each had the same overarching organizational structure, goals, time frame, and daily work processes. Thus, these were team-level measures.

Measures

How does one operationally distinguish between adaptive expertise, routine expertise, and novelty? Although these three represent daily outcomes, none is as simple to measure as, say, time on task. Although the length of meetings might seemingly be the best dependent variable to measure efficiency, the meeting times themselves were set by management, rather than lasting as long as they naturally needed (note the discrete breaks in Figure 1). Here, we provide an approach to measuring each. These measures, like any operational measures, are approximations of theoretical constructs. Importantly, they are logically independent, can be used in many contexts, and are easily subjected to quantitative analyses.

Our variables arise from the scientists' daily activity planning requests sent to the engineering team. These requests were a direct measure of the day-by-day work the scientists planned for the rovers and were a function of their understanding of the Martian environment, immediate and long-term scientific exploration possibilities, and the analysis of data up to that point. Each day involved multiple activities: science activities represented the specific instrument to be used and all the necessary parameters (e.g., use the Panoramic camera to take an image at X, Y, Z location with the red filter). The number of activities is inherently a measure of team success, as more activities meant more data collected. The MER mission kept all activity files on a central server such that all previous activity plans were accessible. So, our measure of *novelty* is simply the number of newly generated low-level activities logged and implemented per Martian day. For example, on Sol 14 for Rover A, there was an activity 'MTES_20_MRAD Elevation +30 degrees'. That activity/parameter combination was not carried out previously, but it was repeated again on Sol 15. To give a sense of variability in the activity parameter space, across the first two years of MER A, the 29 different activities types had a mean of 125 ($SD = 179$) unique parameters for each activity, with a maximum of 789 unique parameters for one activity.

New activities per day rather than per hour of planning are used, because during the nominal mission, the cycle of work was by the Martian day. This measure has its limitations: It does not take into account more qualitative degrees of novelty, and is thus does not distinguish between radical and incremental levels. Nevertheless, this measure provides a quantitative, generalizable operationalization of novelty: number of genuine new activities per day.

The activity planning tool also provided a mechanism by which the scientists could express routine expertise. Scientists could reuse low-level activities from previous days by using the old ones as a template. When reused, the low-level activity plans were a type of heuristic, and using them could save the scientists time. Indeed, reuse of old activities, at the team level, is parallel to the most fundamental way of measuring individual-level routine expertise: People retrieving prior solutions (Logan, 1988; Siegler & Shipley, 1995). By using a custom analysis program that exhaustively searched across prior activities, activity reuse was measured as activities with identical parameters (i.e., copypaste or retyping exactly). Thus, the sheer number of reused science activity plans per day was our operationalization of *routine expertise*. This measure is an approximation of a much broader theoretical construct. Nonetheless, the sheer number of reused plans can serve as a simple quantitative measure of routine expertise.

The main distinction between routine and adaptive expertise is that the latter incorporates innovation—the deliberate implementation of useful creativity. Reuse could be due to rote copying of the same successful activity, or it could be due to strategic choosing of different old activities. The main definition of adaptive expertise is strategic heuristic reuse. For our measure of *adaptive expertise*, we examined the variability of the age of reused activity plans. Each reused activity had information about on which Martian day it was originally created, and thus how many Martian days 'old' it was. For example, if an activity were created the day before, it would have been one day old; if it were generated 30 days before, it would be 30 days old. Not surprisingly, mean age of activities reused on a given day increased over time as the mission progressed and activities from the earlier part of the mission became 'older'. Of greater interest is the *variability* in age of reused activities in a given day. A large standard deviation of age means that activities are being used from both the earliest and more recent days of the mission. On the other hand, a small standard deviation of age might indicate that a previous day's plan was being copied, almost wholly, without integrating newer activities. Given that each day involved careful decisions about what the rover should do, a larger breadth of age implied that the scientists were constantly learning and choosing from the entire set of previously generated activities. Imagine that a small variability of age of plans occurred on one day: The likely explanation would be that very standard type of activities were occurring that had become rote and had worked in precisely the same situation previously. On the other hand, a larger breadth of age of activities implies that the solutions they are drawing from are both familiar and relatively to adapt to the changing scientific and environmental conditions. This larger breadth could not simply be a random process: a random process would have resulted in an unsuccessful outcome and would have been inefficient, whereas this team was able to produce longer enacted plans later in the mission. Recall that the MER team was able to produce their daily plans in much less time later in the mission (Figure 1). In considering whether additional breadth was due to a random process, it is important to realize that from the very beginning of the mission, each day the MER team tended to suggest twice as many activities to be implemented in the plan than could actually be fit in that plan: one rover per subteam could do much less science than many scientists wanted, and some scientists had to be resigned, on some days, to collect no data for their particular topic of interest. Over time, the greater team learned what kinds of combinations of rover activities made more efficient use of time and produced quality data for their scientific goals. To select randomly from the past would create activities that would not be relevant to the science goals of the day and would not fit efficiently with other activities being proposed. Thus, we considered the variability in the age of activities to be a measure of strategic plan reuse. Knowing how and when to apply old activities are both innovative (new combinations) and efficient (reusing rather than generating anew), and therefore a face valid operationalization of adaptive expertise. Variability in age was measured by taking the standard deviation of how many Martian days 'old' the reused activities were per day.

These variables operationalize process rather than success *per se*. Activities were too low-level to be reused based on whether they were successful: they were all successful in that they were what the scientists intended to do, and scientific success emerged from hundreds of activities across multiple days. Also, although we identify the standard deviation of age of activities as adaptive expertise, we specifically operationalize it as intentionally drawing broadly, adaptively, and strategically from existing heuristics, rather than directly measuring metacognitive skills or other aspects of the construct.

Analyses

To determine the pattern of the variables over time, a time series analysis was performed on each variable using an ARIMA model:

$$\Phi(L)\Delta^d x_t = \delta + \Theta(L)a_t$$

where $\Theta(L)$ measures auto-regression; Δ^d measures the difference score (or, 'integrated' in ARIMA); $\Theta(L)$ measures the moving average; δ is the deterministic trend (mean); x_t is the dependent variable; and a_t is the residual. The model fit was evaluated by examining the Ljung–Box test and residual autocorrelation function and partial autocorrelation function plots. ARIMA modeling is simply a statistical description of the pattern of a variable over time, with no predictor variables, and thus is not subject to overfitting. ARIMA modeling can determine whether changes over time are the simple result of autoregression, time-lagged effects such that a value at Time 2 is predicted by the value at Time 1. It can also determine whether the value at Time 2 is predicted by the error at Time 1, or, separately, by the difference between the values of Time 1 and 2. After each of the three main variables was described using ARIMA modeling, the relationship among the variables (novelty, routine expertise, and adaptive expertise) was examined using vector autoregression (VAR) model with both lag 1 and lag 2. This VAR model may fall prey to overfitting, but the ratio of data points to number of predictors is favorable so the risk for overfitting is not high.

RESULTS

Across the first 90 days of the mission, there was an average of 36 reused activities a day ($SD = 14$, Minimum = 0, Maximum = 74, $n = 132$), a mean of 19 new low-level activities planned a day ($SD = 15$, Minimum = 3, Maximum = 149, $n = 132$; Winsordized, $M = 18$, $SD = 9$), and a mean standard deviation of 10 Martian days for the age of reused activities ($SD = 6$, Minimum = 0, Maximum = 23). There were 132 days of data rather than 180 due to when data collection occurred, as well as the occasional work breaks of the scientists.

Hypothesis 1: does routine expertise significantly increase over time?

We suggested that routine expertise would significantly increase over time, and indeed, an ARIMA(0,1,1) model was the best fitting model for routine expertise as measured by reused activities such that it increased significantly (Figure 3). This model had a good fit, Ljung–Box χ^2 $(37) = 25.16$, $p = .931$, and the stationary R^2 was .32, meaning that the model explained 32% of the variance in routine expertise (reuse). Routine expertise as the number of reused activities continued to increase in sheer number from start to the mission day 50, where it stabilized. There was a significant difference in routine expertise between the two adjacent time points, $\delta = .26$, $p < .001$ (i.e., there was an average steady increase of .26 in reused activities between time points). The difference in routine expertise between the two adjacent time points was also significantly negatively predicted by the previous residual, $\theta_1 = -.75$, $p < .001$,

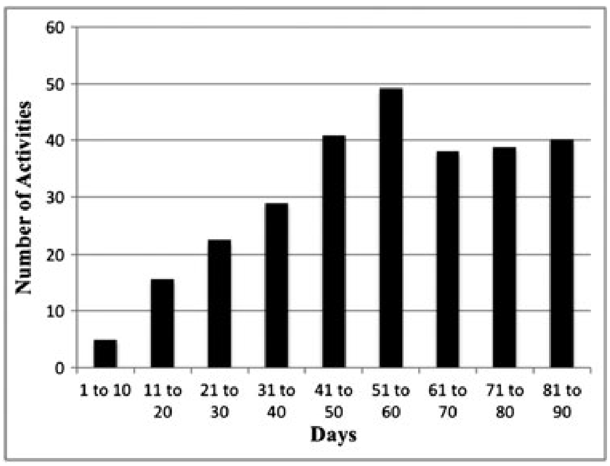

Figure 3. Number of reused low-level science activities planned per day (average in 10-day blocks)

which cannot be explained by the adjacent time points. In other words, a sudden increase in routine expertise explains a slower future growth of routine expertise in the following time points.

$$Routine_t - Routine_{t-1} = \delta + a_t + \theta_1 a_{t-1}$$

Thus, the change in routine expertise was less a matter of the sheer number of reused activities proposed the day before, but the number of reused activities at one time was significantly influenced by the increases from one day to the next (the change or difference score).

Hypothesis 2: does adaptive expertise increase significantly over time?

Similarly, we hypothesized a significant increase for adaptive expertise over time, and an ARIMA(0,1,1) model was also the best fitting model for this variable (Figure 4). The adaptive expertise values, operationalized as the standard deviation of the age of the reused activities, continued to increase from start to end of the first 90 days of the mission. This model had a good fit, Ljung–Box χ^2 $(37) = 27.64$, $p = 0.868$, with a stationary R^2 of .28, meaning that the model explained 28% of the variance. There was a significant difference in adaptive expertise between the two adjacent time points, $\delta = .28$, $p < .001$ (i.e., there was an average steady increase of .28 in adaptive expertise between time points).

$$Adaptive_t - Adaptive_{t-1} = \delta + a_t + \theta_1 a_{t-1}$$

The difference in adaptive expertise between the two adjacent time points was also significantly negatively predicted by the previous residual (what cannot be explained between the adjacent time points), $\theta_1 = -.80$, $p < .001$. In other words, a sudden increase in adaptive expertise explains a slower future growth of adaptive expertise in the following time points. Similarly to routine expertise, there was a significant effect for the difference scores: The greater the standard deviation of ages of reused plans used in comparison with the day before, the greater the standard deviation would become.

Hypothesis 3: does novelty alone increase over time?

We hypothesized that, unlike routine and adaptive expertise, novelty alone would not increase over time. We also tested the longitudinal ARIMA pattern for our measure of novelty, or the number of new activities. An ARIMA(0,0,0) model was the best fit for novelty. This model had a good fit, Ljung–Box $\chi^2(38) = 38.97$, $p = .426$, and the stationary R^2 was .00.

$$Novelty_t = \delta + a_t$$

In other words, novelty neither significantly increased nor decreased over time (Figure 5). Instead, novelty was likely a function of immediate, daily tasks and challenges.

Hypothesis 4: are novelty, routine expertise, and adaptive expertise statistically independent?

Finally, we tested whether there were significant lagged associations between the three major variables by using VAR analyses. This test is important to determine whether and how novelty, routine expertise, and adaptive expertise may be correlated, and then perhaps conceptually or empirically difficult to tease apart. There was no significant prediction of novelty (number of new activities) by lagged novelty nor routine nor adaptive expertise, $\chi^2(7) = 12.41$, $p = 0.053$, $R^2 = 0.14$ (see Table 1). Therefore, the pattern of results suggests that simply reusing activities on a previous day does not predict more new activities (novelty) on the following day, or vice versa. One might expect a cycle of more reuse of activities with more subsequent novelty, as the scientists prioritized their time accordingly, but this did not occur. Instead, novelty and both types of expertise were independent. However, there were significant predictions of adaptive expertise, $\chi^2(7) = 562.51$, $p < .001$, $R^2 = .88$, and routine expertise, $\chi^2(7) = 44.45$, $p < .001$, $R^2 = .37$ for themselves. There was a significant positive prediction of adaptive expertise (standard deviation of age of the reused activities) by itself lagged from both 1 and 2. Meanwhile, there was a significant positive prediction of routine expertise, or number of reused activities, by itself lagged 1 but not lagged 2. Thus, this analysis supported Hypotheses 1, 2, and 3, in addition to Hypothesis 4. There was no significant prediction of any of the three variables by the other variables after adjusting for the relationship with themselves over time.

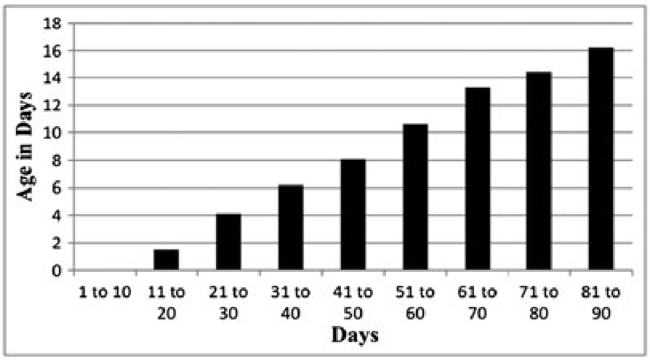

Figure 4. Standard deviation of age of reused activity plans (average in 10-day blocks)

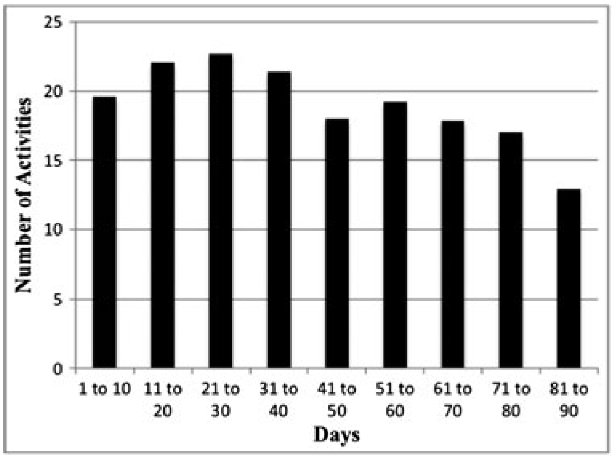

Figure 5. Number of new low-level science activities planned per day (average in 10-day blocks)

Table 1. Vector autoregression analyses of lagged relationships between novelty, routine expertise, and adaptive expertise ($t-1$ is time minus one day and $t-2$ is time minus two days)

Dependent variable	Independent variable	B	z	p	R^2
Novelty (new activities) at time t					.14
	Novelty_{t-1}	.12	1.01	.31	
	Novelty_{t-2}	.15	1.29	.20	
	$\text{Adaptive Expertise}_{t-1}$	−.44	−1.22	.22	
	$\text{Adaptive Expertise}_{t-2}$	.10	0.28	.78	
	$\text{Routine Expertise}_{t-1}$	−.02	−0.23	.82	
	$\text{Routine Expertise}_{t-2}$	.10	1.47	.14	
Adaptive expertise (standard deviation of age of reused activities) at time t					.88
	Novelty_{t-1}	.06	1.59	.11	
	Novelty_{t-2}	−.02	−0.048	.63	
	$\text{Adaptive expertise}_{t-1}$	*.61*	*5.55*	*<.001*	
	$\text{Adaptive expertise}_{t-2}$	*.35*	*3.20*	*.001*	
	$\text{Routine expertise}_{t-1}$	.03	1.31	.19	
	$\text{Routine expertise}_{t-2}$	−.00	−0.06	.95	
Routine expertise (reused activities) at time t					.37
	Novelty_{t-1}	.21	1.14	.25	
	Novelty_{t-2}	−.01	−0.03	.98	
	$\text{Adaptive expertise}_{t-1}$	.07	0.12	.91	
	$\text{Adaptive expertise}_{t-2}$	.61	1.02	.31	
	$\text{Routine expertise}_{t-1}$	*.33*	*2.90*	*.004*	
	$\text{Routine expertise}_{t-2}$	.16	1.37	.17	

Significant findings are italicized.

Summary

In sum, difference (change) scores predicted the values of both routine and adaptive expertise at specific times. This finding provides indirect evidence that we observed learning effects: it is not simply that the number of reused activities (or the standard deviation of age of those activities) influenced the next time point's values but that change from day to day spurred a greater number of (or breadth of) reused activities the next day. On the other hand, novelty on one day was not predicted by novelty on an earlier day. Both routine and adaptive expertise had significant negative effects for residuals, but these findings could be due to regression to the mean of the predicted scores. In other words, a large random increase would lead to a small random increase, and vice versa. More importantly, the three variables were distinct, with none predicting each other, after taking into account their own patterns of change over time.

DISCUSSION

This study contributes to the literature as follows: (1) by discussing the conceptual differences between adaptive expertise and similar constructs; (2) illustrating the growth of adaptive and routine expertise over time; and (3) testing an empirical and theoretical distinction between team routine expertise, team adaptive expertise, and team novelty. Over time, both team routine and adaptive expertise increased, with each leap between days predicting future levels. On the other hand, also as predicted, novelty fluctuated but did not change overall. Though the MER science team is multidisciplinary, a commonly described impediment to rapid team improvement, the strong collective identification instilled in the team (Squyres, 2005) meant that team learning could flourish (van der Vegt & Bunderson, 2005).

The MER science team was, in effect, set up to optimize the development of adaptive expertise. Scientists were able to use activities as building blocks, recombining old ones and joining them to newly created activities to accomplish feats of daily innovation. Both routine expertise and adaptive expertise were predicted by the change scores between times. Although this finding seems intuitive for this sample, it may not have occurred in all settings. For example, a specific set of reused activities could simply have been repeated time and again, leaving the overall number of reused activities constant, and increasing the mean, but not the standard deviation, of the age of those activities. Alternately, given the time constraints of the team, they could have simply chosen the most appropriate recent plans (recency effect), rather than dig through past plans. In fact, great leaps of learning, rather than prior values, predicted values for routine and adaptive expertise. In this context, the scientists could go farther than creating routines: they took heuristics of past actions and reused and recycled them, applying them as appropriate in different combinations with new low-level activities to create a new day's tasks.

We argue for the adaptiveness of their activities: The scientists were working in a hurry, and managing to fit more science discovery in every day of work. Team adaptive expertise was not simply a matter of taking a successful plan from the past and applying it endlessly; as the mission progressed, the team was able to use a broader range of both relatively older and relatively newer activities. This broader range was also not due to random selection: Indeed, by using a Monte Carlo simulation, random selection across all plans would produce a standard deviation of plan age twice as high as what was actually observed. Further, a pure sampling-based increase would not have produced the combined $t-1$ and $t-2$ ARIMA effects which we found. If adaptive and routine expertise had increased because of the simple effects of time rather than learning (e.g., the raw increase in numbers of activities led to more activities that could be reused), novelty would have likely also increased, and novelty, routine expertise, and adaptive expertise would not have been statistically independent.

Theoretical and practical implications of the findings

Future theories of team learning should take into account adaptive expertise. Currently, the development of expertise and studies of team learning either focus on routine expertise or do not make the distinction between routine and adaptive expertise. Innovation in combination with efficiency is an important aspect of expertise to study. The prior research findings for routine expertise may not apply to adaptive expertise. By understanding this important distinction, team learning theory can examine whether an adaptive versus routine expertise difference moderates the effects of long-studied variables such as leadership (e.g., Crossan, Maurer, & White, 2011), team mental models (Kozlowski, 1998; Mohammed & Dumville, 2001), intra-team communication (Entin & Serfaty, 1999; Huber & Lewis, 2010), and the use of routines (Levinthal & Rerup, 2006). Routine versus adaptive expertise on the part of organizational teams, or tasks that require routine versus adaptive expertise, may be important moderators to prior findings or help explain mixed findings in the literature. Furthermore, adaptive expertise and novelty were empirically differentiated in this study, demonstrating that not only are they theoretically distinct but that they are also different in practice. Adaptive expert teams may generate novel ideas, but the work of such teams is more complex, involving balancing evolving constraints. In organizations, managers may prefer adaptive expertise to raw novelty: Adaptive expertise is novel, but takes into account the constraints of the situation, and thus is more likely to be associated directly with team success. Much of the organizational learning literature has focused on what types of experiences lead to creative thinking (Argote & Miron-Spektor, 2011) rather than how fundamental differences in past experiences can be utilized and recombined in the service of *both* innovation and efficiency. Instead of examining differences in the simple predictors of creative versus uncreative learning, researchers could attend to these different kinds of expertise as different dependent variables and cognitive processes.

Our study applied the construct of adaptive expertise from the individual to the large team level. Turning to intermediate cases between an individual and a large team, interacting teams of much smaller size could also develop adaptive expertise, such as improvisational theater troops, academic biochemistry labs, and top management teams. In addition, future research should untangle the relationship between individual and team expertise. Indeed, when one considers *ad hoc* teams, such as pilot teams, their team adaptive expertise can be thought of as directly related to the individual experiences each pilot brings to bear. In addition, organizations do not learn quite the way teams or individuals do, but the construct of organizational ambidexterity (Gibson & Birkinshaw, 2004; Raisch, Birkinshaw, Probst, & Tushman, 2009) may be the organizational equivalent of adaptive expertise.

Although our study examines team adaptive expertise, specifically, it informs the measurement of both individual and team adaptive expertise. Similar operationalizations for novelty, routine expertise, and adaptive expertise can be used in future studies. For novelty, a parallel example could be the number of new lines of code generated by a software development team, day-by-day, whereas for routine expertise, it would be the amount of reused code pasted in and edited day-by-day. Taking the software development team example, the breadth of age and provenance of reused code could be a measure of adaptive expertise. The first two might be obvious from the existing literature. However, the literature lacks operationalization guidelines for adaptive expertise. Our study makes a contribution in that it suggests that measurements that take into account the breadth of heuristic reuse could be adopted.

By bringing the concept of adaptive expertise from the cognitive learning literature to an applied team setting, researchers are encouraged to take a nuanced look at the relationship between efficiency and innovation, as well as concrete ways in which heuristics can serve innovation. Our findings are reminiscent of a recent study showing that priming with a paradoxical frame that admitted to the difficulty of aiming for both creativity and efficiency resulted in greater creativity than either the creativity frame, the efficiency frame, or a creativity–efficiency frame that downplayed the contradiction between the two (Miron-Spektor, Gino, & Argote, 2011). The concept of adaptive expertise does not fall neatly into either radical versus incremental creativity, instead, coexisting with either. Creative ideas can range in their deviation from existing knowledge and solutions, ranging from radical to incremental, making minor to major contributions (Mumford & Gustafson, 1988). One can use adaptive expertise to make both incremental and radical changes, depending on how the heuristics are combined and applied. Strategic heuristic reuse may be one of the cognitive mechanisms underlying simultaneous innovative and efficient outcomes. Had we the data, radical versus incremental creativity could be measured by assessing the relative radicalness of different proposed plans. We say ‘proposed’ rather than ‘enacted’ plans because one of the distinguishing features between creativity and innovation is whether the idea is implemented or not. This operationalization of radical/incremental creativity would be focused on an assessment of the outcomes (proposed plans), and thus be different from the number of or breadth of enacted plans per day.

Individuals involved in routine patterns of behavior have the agency to identify problems and fix them (Feldman, 2000), thus changing and improving their work processes as they learn. Practically, organizations can extend training to include a focus on adaptive expertise as well as routine expertise. Routine expertise is insufficient in dynamic and novel situations. A backlash against MBA training is currently occurring: Bob Lutz of General Motors recently wrote a book contending, ‘we need to fire the M.B.A.s and let engineers run the show’ (Foroohar, 2011). However, Lutz seemingly sets up a false dichotomy between MBAs and engineers that confounds routine and adaptive expertise. Narrow training in engineering does not guarantee adaptive expertise: ideally, managers will have enough domain expertise to be experts but the breadth of experiences to be adaptive experts. As Barnett and Koslowski (2002) demonstrated, MBAs can outperform domain experts because of their higher level knowledge. It is unlikely that Steve Jobs excelled because he lacked an MBA, as some have claimed; he more likely excelled because he had both a broad array of domain knowledge and the knowledge of how and when to use his sharply honed heuristics (Foroohar, 2011). By using adaptive expertise, he directed his company to adapt and improve.

This study took advantage of a powerful dataset for examining group learning. In the study of team learning in real world settings (and often in experiments), the learning inside-the-head is opaque to the researcher, and only inferred by action. In adaptive expertise theory, the hypothesized mechanisms of learning (strategic heuristic reuse) are similarly implicit. In other words, we are not provided access here to which learning processes are at play; our goal is to document the outcomes of the learning processes as a first operationalization. Although this research utilizes a single setting, the concepts studied here are generalizable to a range of domains. Other settings similarly require daily innovation combined with efficiency, from product development to cross-disciplinary policy teams tasked with solving national problems. Real-world behavioral expertise data are difficult to obtain and rare but also important to study to understand the nature of team expertise over time. The data are behavioral, rather than self-report, and so do not rely on participant memory nor are they biased by lay theories of group processes (Staw, 1975). The dataset also illustrates a genuinely innovative group, working on naturalistic tasks, during a lengthy period of intense learning. Previous research examining this dataset found, similarly, a change in the prevalence of conflict over time: process micro-conflicts, but not task micro-conflicts, were more prevalent in the first 50 days compared with the subsequent 40 days of the mission (Paletz, Schunn, & Kim, 2011). Experimental studies would have difficulty testing the very real development of expertise over 720 hours that occurred here. Further, the use of three measures enables us to draw both conceptual and empirical distinctions between novelty, routine expertise, and adaptive expertise.

Conclusion

This study was a rare glimpse into team adaptive expertise. These findings suggest that future theory should incorporate the construct of adaptive expertise into investigations of team processes and points out ways that novelty, routine expertise, and adaptive expertise can be measured. Future research can unpack distal and proximal factors associated with adaptive expertise, such as organizational culture, team mental models, leadership, and reward systems.

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