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The effect of expertise on collaborative problem solving

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Why do some groups succeed where others fail? We hypothesise that collaborative success is achieved when the relationship between the dyad's prior expertise and the complexity of the task creates a situation that affords constructive and interactive processes between group members. We call this state the *zone of proximal facilitation* in which the dyad's prior knowledge and experience enables them to benefit from both knowledge-based problem-solving processes (e.g., elaboration, explanation, and error correction) and collaborative skills (e.g., creating common ground, maintaining joint attention to the task). To test this hypothesis we conducted an experiment in which participants with different levels of aviation expertise, experts (flight instructors), novices (student pilots), and non-pilots, read flight problem scenarios of varying complexity and had to identify the problem and generate a solution with either another participant of the same level of expertise or alone. The non-pilots showed collaborative inhibition on problem identification in which dyads performed worse than their predicted potential for both simple and complex scenarios, whereas the novices and experts did not. On solution generation the non-pilot and novice dyads performed at their

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predicted potential with no collaborative inhibition on either simple or complex scenarios. In contrast, expert dyads showed collaborative gains, with dyads performing above their predicted potential, but only for the complex scenarios. On simple scenarios the expert dyads showed collaborative inhibition and performed worse than their predicted potential. We discuss the implications of these results for theories of collaborative problem solving.

Keywords: Collaborative inhibition; Collaborative success; Decision-making; Expertise; Problem-solving.

Why do some groups exhibit exceptional performance whereas others fail? This question has been the topic of much debate in both practical and scientific discourses over the last century (Anaconda & Bresman, 2007; Barron, 2003; Sawyer, 2007; Steiner, 1972). Examples of collaborative success can be found in most human endeavours, including science (e.g., Watson and Crick's discovery of the structure of DNA), business (e.g., Sergey Brin and Larry Page's creation of Google), and the arts (e.g., Joel and Ethan Coen's critically acclaimed films). Often these successes have been attributed to the collaborative interaction of the individuals involved. The resulting collaborative product is typically considered more than the sum of the individual contributions. In contrast, much laboratory research has shown that individuals in collaborative situations often fail to perform as well as individuals working alone, a finding commonly referred to as *collaborative inhibition* (Basden, Basden, Bryner, & Thomas, 1997) or *process loss* (Steiner, 1966, 1972). These findings show that, although the dyads and groups often perform better than the average individual (group-level advantages), they also typically perform worse than nominal groups (the sum of the individual contributions).

How do we reconcile the examples of collaborative success found outside the laboratory with the collaborative inhibition findings from psychology experiments? One critical factor that appears to differentiate these popular examples from the laboratory findings is the relationship between the participants' prior knowledge and experience in the domain and its relevance to the target task. Much of the laboratory work has investigated collaborative problem solving with non-experts (most often, undergraduate psychology students solving novel tasks). This experimental situation lies in stark contrast to the anecdotal examples mentioned above, where collaborative success is accomplished by *experts*—people with extensive training/experience in the domain when performing domain-relevant tasks. This contrast raises an important question: *How does the relationship between prior knowledge and skills in the domain impact collaborative success?*

To examine this question we conducted an experiment in which participants with different levels of aviation expertise, experts (flight instructors), novices (student pilots), and non-pilots, solved domain-relevant

problems of varying complexity with either another participant of the same level of expertise or alone. We hypothesised that participants with more knowledge and experience in a domain would show more collaborative success than those with less experience. Furthermore, we postulated that a set of task conditions must be satisfied to enable collaborative success. Specifically, the task must be of sufficient difficulty,¹ so that participants have to *interact* to solve the problem. If the task can be solved easily by any of the individual members of the group, then collaborative success will not be observed. The task must also not be so complex as to be outside the dyad's ability to make progress towards a solution. In this paper we test the hypothesis that collaborative success depends on the relation between the dyad's prior knowledge and experience (learner factors) and the structure/complexity of the target task (situative factors).

The primary focus of our work is to better understand the factors that impact both collaborative success and failure. An understanding of these factors has both practical implications for improving collaboration in education and industry settings, and theoretical implications for integrating cognitive and social theories of collaboration. Practically speaking, knowing what elements improve collaborative success enables one to scaffold, foster, and create environments that afford those elements. Similarly, knowing what factors contribute to collaborative failure enables one to minimise, mitigate, and avoid those elements. Theoretically, we are interested in the intersection between cognitive, social, and distributed theories of cognition and draw upon them to explain collaborative success and failures in problem solving.

In the next two sections we review prior work on collaborative success and failure in the laboratory and discuss the implications of expertise for collaboration. We then describe our experiment testing the effect of expertise on collaboration, followed by a discussion of the results with implications for theories of collaborative problem solving.

PRIOR RESEARCH ON COLLABORATIVE SUCCESS AND FAILURE

Collaborative problem solving refers to situations in which two or more participants solve a problem together while working towards the same goal. The impact of collaboration on problem solving can be measured at both the group and individual level (i.e., by treating each level as a different unit of analysis; Okada & Simon, 1997). Research has shown that, at the group

¹ We define difficulty in terms of the distance between one's prior knowledge and experience and the target task. We adopt Chen and Klahr's (2008) theoretical framework for defining three relevant dimensions of transfer including: contextual similarity, task similarity, and temporal interval. Sufficient difficulty is beyond near transfer on each of these dimensions.

level of analysis, groups can perform better than the average individual (for reviews see Hastie, 1983; Hill, 1982; Kerr & Tindale, 2004). These advantages are often explained in terms of groups being more likely than individuals to recognise and reject incorrect solutions, recognise and accept correct solutions, and engage in more effective problem-solving strategies. However, the cognitive mechanisms and the types of interactive processes underlying these advantages are poorly understood.

Research comparing participants at the individual level has revealed a different pattern of results showing that individuals working in groups perform worse than individuals working alone (e.g., Bouchard & Hare, 1970; Weldon & Bellinger, 1997). This *process loss* has been attributed to a number of cognitive and social factors including: cognitive load (Dillenbourg, 1999), lack of coordination (Steiner, 1972), disruption and production blocking of individual contributions (Diehl & Stroebe, 1987), diffusion of responsibility (Latane, Williams, & Harkins, 1979), and fear of evaluation (Mullen, 1983, 1987), among others. Many attempts have been made to identify the factors that mediate or eliminate process loss and even achieve collaborative gains.

A few examples of collaborative gains exist in the literature. Research on group induction has shown that participants working together in a group can perform better than the best individuals working alone (Laughlin, Bonner, & Miner, 2002; Laughlin, Zander, Kneivel, & Tan, 2003). In these studies groups showed better performance than the best individuals when solving letters-to-numbers problems where the goal is to induce a set of rules for coding 10 letters to 10 numbers. Groups discovered the rules in fewer trials using more effective strategies than individuals working alone. It was hypothesised that participants working in groups performed better because the following four pre-conditions were met: (1) all participants had the basic knowledge required to solve the problems (in this case arithmetic, algebra, and logic), (2) some subset of participants could generate the solution, (3) the participants who did not generate the solution could recognise and understand it when it was proposed by other group members, and (4) that these members could also demonstrate the effectiveness of the proposed solution (Laughlin et al., 2003).

Similarly, Okada and Simon's (1997) research on scientific discovery has shown that participants working in dyads were more likely than nominal groups (pooled performance of participants working alone) to discover biological mechanisms of molecular genetics by conducting experiments in a computer simulated micro-world. Analysis of process outcomes showed that the dyads were more likely than the participants working alone to generate explanations. However, these explanations only improved the dyads' performance if they also conducted critical experiments that provided evidence that enabled them to induce the mechanism. These results were

interpreted as consistent with the learning advantage students experience when explaining new text or examples (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, de Leeuw, Chiu, & LaVancher, 1994).

Another set of studies that showed collaborative gains were investigations of students' generation of abstract representations when solving novel problems (Schwartz, 1995; Shirouzu, Miyake, & Masukawa, 2002). Schwartz (1995) had middle school students work in dyads or alone while solving a variety of different problem-solving tasks (e.g., a gears problem, a biological transmissions problem, and a visualisation of organisms and habitats problem). Each problem embodied three task demands that were hypothesised to facilitate collaborative success in generating abstract problem representations including: (1) requiring multiple perspectives, (2) mutual knowledge, i.e., that the task required constructing common ground, and (3) task-relevant information structures. Participants in dyads generated four times as many abstractions as individuals and twice as many abstractions as their predicted potential for the gear problems. This result was replicated in the second and third experiment with participants in dyads generating more abstract visualisations than their predicted potential for the biological transmissions and habitats problems.

This result was explained as an outcome of the task demands in which participants needed to create a common ground in order to work on the problem. The development of common ground was facilitated by participants' attempts to reconcile their multiple perspectives of the underlying problem structure that in turn facilitated the construction of an abstract representation of the problem. This result is consistent with research showing that the development of common ground and joint management of attention is critical to collaborative success (Barron, 2003; Clark, 1996; Clark & Wilkes-Gibbs, 1986). A similar set of results was found by Shirouzu et al. (2002) showing that dyads were more likely than nominal pairs to generate an abstract representation in two types of paper-folding (origami) tasks. The authors explained the collaborative advantage as due to dyads generating multiple solution strategies (with differing degrees of abstraction), which were then reflected upon and further abstracted.

A study by Wiley and Jolly (2003) found similar results showing collaboration benefits when participants in a dyad had different types of prior knowledge as compared to when they had the same type of prior knowledge. They examined performance on a creative problem-solving task in which prior knowledge of baseball would lead participants to fixate on an incorrect solution (Wiley, 1998). They found that dyads that consisted of one participant with much baseball knowledge and one participant with little baseball knowledge (mixed-knowledge dyads) showed larger collaborative gains than dyads in which both participants had either high or low baseball knowledge. This result is intriguing and may be due in part to

mixed dyads having an opportunity to interact and reconcile their different response biases based on their prior knowledge, with the low-knowledge participants helping the high-knowledge participants break their fixation.

In sum, the work reviewed here hypothesised that particular task features facilitated the construction of common ground and cognitive processes that supported successful collaboration. Schwartz (1995) hypothesised that three task features were critical for collaborative abstraction, including multiple perspectives, developing common ground, and embedded structural features. In the work on group induction participants were hypothesised to share basic knowledge of the target domain and to be able to recognise, demonstrate, and evaluate correct solutions (Laughlin et al., 2003). The Wiley and Jolly (2003) work showed that the particular combination of the individual's relevant (or irrelevant) prior knowledge plays an integral role in facilitating (or inhibiting) collaborative success on a specific task. In the current work we build on this research to test the idea that collaborative success depends critically on the relation between the participants' prior domain knowledge, collaborative skill, and the task affordances. To test this hypothesis we examine the impact of expertise on collaboration.

IMPLICATIONS OF EXPERTISE FOR COLLABORATION

Expertise is likely to promote successful collaboration for several reasons. Experts are hypothesised to have overlapping knowledge of their domain (Coughlin & Patel, 1987). We define knowledge broadly to include both declarative and procedural knowledge components. Consistent with other perspectives in cognitive science we define declarative knowledge as “knowing that” or having knowledge about the world (e.g., facts, strategies, and principles) and procedural knowledge as “knowing how” or having knowledge that supports performing actions in the world (Anderson & Lebiere, 1998; Koedinger, Corbett, Perfetti, & the PSLC, 2010). Procedural knowledge is hypothesised to be goal specific and tailored for use in very specific contexts (Anderson & Lebiere, 1998; Singley & Anderson, 1989).

These fundamental concepts and procedures provide a coherent body of knowledge from which experts can reason. This is consistent with Laughlin et al.'s (2003) pre-condition for collaborative success stipulating that participants should share the same basic knowledge underlying the task. Declarative knowledge (i.e., facts, principles, and common examples) can enable participants to detect and correct errors (Schriver, Morrow, Wickens, & Talleur, 2008) as well as recognise, explain, and evaluate possible solutions. Prior work on error correction has shown that this is a critical mechanism of successful individual (Nokes, 2009; Ohlsson, 1996) as well as group problem solving (Laughlin et al., 2003). Prior research has also shown that participants' ability to generate explanations is correlated

with problem-solving success in collaborative settings (Webb, Troper, & Fall, 1995).

Expert knowledge is also likely to be *organised* in similar ways, perhaps as hierarchical schemas (Chi, Feltovich, & Glaser, 1981; Nokes, Schunn, & Chi, 2010). *Problem-solving schemas* are knowledge structures that consist of prototypical aspects of the problem type including declarative information about the features, facts, principles, and strategies associated with the problem. Schemas may also include procedural operators for how to solve a problem type. Prior research has shown that experts from the same domain who engage in similar goal-directed activities tend to organise their knowledge in similar ways as measured by categorisation tasks (Lynch, Coley, & Medin, 2000).

The similarity in knowledge organisation between experts in a given domain should facilitate collaborative success for two reasons. First, it should facilitate rapid problem identification. Experts have been shown to spend more time on features designated as critical to the problem (Morrow et al., 2009; Shanteau, 1992) and to rapidly encode features of problems based on goal-relevant representations. This suggests that two experts are likely to encode problems in similar ways and should be able to quickly identify the most useful problem representation. Second, similar knowledge structures should promote collaborative success by increasing the possibility of elaboration during collaborative tasks. If domain knowledge is similarly organised between collaborators, it may be the case that information produced by one expert may effectively cue another expert to produce additional information on the topic (cf. Andersson & Ronnberg, 1995). Experts should possess overlapping, similar knowledge, so the potential for cross cueing and elaboration is high.

Social communicative factors as well as domain knowledge are likely to support collaboration (Clark, 1996; Rummel & Spada, 2005). To the extent that collaborative work is integral to the domain of expertise, collaborative skills such as sharing information and constructing a common ground will be an important facet of that expertise. In the current work we investigate expert pilots, who are trained to work with crew members and to effectively communicate important information to the Air Traffic Controllers using specific collaborative strategies (Morrow, Rodvold, & Lee, 1994).

To summarise, experts' knowledge allows them to contribute more than non-experts and increase the chance of quick problem detection, cross-cueing, elaboration, explanation, and error correction. However, once possible solutions/cues/strategies are generated, the extent to which that information contributes to collaborative success may depend on whether partners acknowledge the contribution, so that critical information is maintained in common ground. Therefore collaborative skills related to joint attention may be necessary for collaborative success (Barron, 2003;

Clark, 1996). Indeed, prior research examining how to scaffold effective collaborative communications and facilitate the construction of common ground has found that providing students with either an example of a successful collaboration to study or a collaborative script that specifies what roles participants should take improves collaborative problem solving performance compared to conditions without scripts or examples (Rummel & Spada, 2005).

Given the ubiquity of situations in which experts collaborate and the importance of identifying factors that lead to collaborative success, it is surprising that relatively few studies have investigated the impact of expertise on collaborative problem solving. Although there is a vast literature on team processes and distributed decision making, this work is typically limited to a special kind of group in which individuals have different roles and responsibilities associated with a common team task (for a review see Kozlowski & Ilgen, 2006). There are also observational data on collaboration among experts with different knowledge (e.g., medical doctors and computer scientists working on a joint task; Patel, Allen, Arocha, & Shortliffe, 1998; see also Patel, Cytryn, Shortliffe, & Safran, 2000). However, neither the team process research nor the observational studies explicitly address the role of underlying cognitive mechanisms. In the next section we describe the theoretical framework for the effect of expertise on problem solving.

COLLABORATIVE SUCCESS: ZONE OF PROXIMAL FACILITATION

The current work builds on work in the tradition of social learning theorists such as Vygotsky (1978), Palinscar and Brown (1984), Greeno (1998), and Rogoff (1998) by examining what factors contribute to successful problem solving and learning in collaborative settings. Key to Vygotsky's seminal work was the observation that the child–adult relation creates a *zone of proximal development* or ZPD. The ZPD is determined by the difference in the ability of the child to accomplish a task with the help of a more competent individual (parent or peer) and the ability to accomplish the task by him or herself. Vygotsky hypothesised that entering the ZPD was a critical precondition for learning and performance. The ZPD concept critically focuses on the relation between the prior knowledge of the individual, the prior knowledge of the more competent other, and the task content.

A study conducted by VanLehn et al. (2008) provides a recent examination of how the ZPD concept plays out in the domain of learning from computer tutors. Across seven experiments VanLehn and colleagues examined how different amounts of preparation in physics interacted with different types of tutoring and instruction. They found that when novices

studied material that was written for intermediates they learned more from more-interactive forms of tutorial dialogue than from less-interactive forms. In contrast, when their prior experience matched the complexity of the materials (novices studying materials intended for novices), they learned similar amounts from more- and less-interactive dialogues. These results suggest that interaction facilitates learning when there is sufficient distance from one's prior knowledge and experience on the target task. In the current work we build on the ZPD concept to examine how expertise affects successful collaboration when participants solve domain-relevant problems of varying complexity.

We are interested in the interaction between the dyad's past experience (i.e., each individual's prior knowledge and collaborative skill) and the structure and complexity of the target task. We hypothesise that the relation between learner factors (prior knowledge and skills) and situative factors (environment and task) is critical to collaborative success. Adapting Vygotsky's notion of zone of proximal development, we hypothesise that individuals working towards the same goals create a zone of collaborative facilitation depending on the parameters of the group's prior knowledge/skills and the characteristics and structure of the target task.

Predictions

We hypothesise that two factors are necessary for collaborative success. First, participants must have some prior knowledge or skills in the target domain. In addition, experience collaborating with others in the domain will further contribute to collaborative success. Second, the task must be of sufficient "distance" from the dyad's prior knowledge and experience, such that it does not simply trigger an automatic response (e.g., fact retrieval and application), but instead requires deliberate problem solving vis-à-vis applying domain knowledge and skills to a new, but domain-relevant, task. If the task is too similar to the dyad's prior knowledge, they will not show collaborative success because individual experts can perform at high levels (e.g., Klein, 1998). If the task requires active problem solving and transfer of prior knowledge to the current situation, the dyad should show collaborative success. If the task is too far outside the purview of the group's knowledge and skills they will also fail. See Figure 1 for an illustration of these hypotheses.

We predict that experts collaborating will achieve high-level performance showing collaborative success on complex tasks. We also predict an expertise by task complexity interaction. Specifically, we expect that experts will show collaborative facilitation on complex tasks and will show no collaborative benefits or even collaborative inhibition on simple tasks. Experts should show collaborative facilitation on complex tasks because

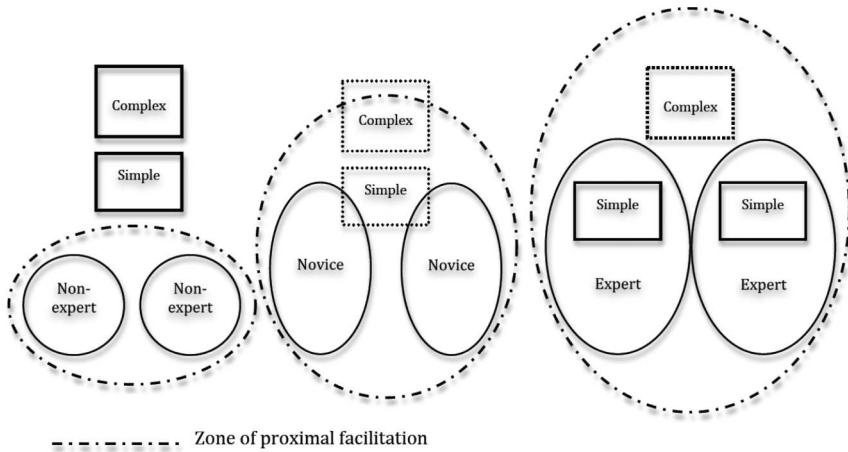


Figure 1. Illustration of the zone of proximal facilitation.

neither expert could solve the problem both immediately and accurately individually, and thus could benefit by interacting and using their knowledge and skills collaboratively. In contrast, experts may show no benefits or inhibition on simple tasks because each individual can presumably solve each task independently, therefore attempting to collaborate may lead to a focus on non-relevant features or non-productive additional processing due to implicit task demands for collaboration, i.e., coming up with a joint solution. For novices we predict an elimination of collaborative inhibition for both simple and complex scenarios. These participants should benefit from having some similar knowledge and skills to reduce typical collaborative inhibition effects. For non-experts we expect collaborative inhibition on both simple and complex tasks because these participants have little domain-relevant knowledge or skills to benefit from when solving these problems.

These predictions are consistent with Chi's (2009) active-constructive-interactive framework which postulates that dyads who show collaborative success will also engage in more constructive and interactive behaviours than those who do not. Chi (2009) defines *constructive* behaviours as those that produce new outputs (e.g., explaining or elaborating) and *interactive* behaviours as those that require dialogue or discussion (e.g., revising errors from feedback from a partner). For each type of behaviour, Chi postulates a set of corresponding cognitive processes. For example, constructive behaviours facilitate generative processes (e.g., inferring new knowledge), and interactive behaviours facilitate jointly generative processes (e.g., processes that incorporate a partner's contributions).

METHOD

Participants

Participants included the same 32 expert pilots, 32 novice pilots, and 32 non-pilots who participated in the memory study reported by Meade, Nokes, and Morrow (2009). For each level of expertise 16 participants were randomly assigned to work individually and 16 were assigned to work in pairs, creating eight dyads for each condition. However, one expert dyad was dropped from the analysis because they neglected to follow the collaboration instructions during the problem-solving phase of the experiment (i.e., they did not verbally collaborate at all for one of the test problems and for the remaining problems had very few utterances, with the large majority of those coming from a single participant). This left seven expert dyads for this condition.

Expert pilots were flight instructors at the Institute of Aviation at the University of Illinois Urbana-Champaign, novice pilots were undergraduate, entry-level aviation students, and non-pilots were undergraduate UIUC students with no prior aviation experience. As reported by Meade et al., 2009, and evident in Table 1, expert pilots had significantly more flight hours and higher scores on the piloting skills questionnaire (which measured knowledge of aviation concepts relevant to the problem-solving task) than did novice pilots and non-pilots ($ts > 3.6$, $ps < .05$), and novices had more flight hours and higher scores on the piloting skills questionnaire than did non-pilots ($ts > 2.1$, $ps < .05$).

TABLE 1
Demographics showing aviation experience, age, education, and scores on
standardised ability measures

	<i>Non-pilots</i>	<i>Novices</i>	<i>Experts</i>
Flight hours	0 (0)	45.6 (122.28)	884.8 (1243.90)
Piloting skills*	8.5 (2.36)	11.6 (2.68)	15.5 (4.95)
Age	21.1 (1.78)	19.0 (1.51)	23.5 (5.31)
Education	15.4 (1.90)	12.8 (1.14)	15.4 (1.82)
Shipley**	30.2 (4.32)	29.6 (4.17)	31.1 (4.0)
Digit comparison***	77.7 (12.28)	70.4 (12.60)	72.2 (8.94)
Pattern comparison***	61.7 (12.87)	61.9 (7.83)	60.9 (6.73)

*From Morrow, D. G., Menard, W. E., Stine-Morrow, E. A. L., Teller, T., & Bryant, D. (2001). The influence of task factors and expertise on age differences in pilot communication. *Psychology and Aging*, 16, 31–46.

**Shipley, W. C. (1946). *Institute of living scale*. Los Angeles Western Psychological Services.

***Salthouse, T. A., & Babcock, R. (1991). Decomposing adult age differences in working memory. *Developmental Psychology*, 27, 763–776.

Expert pilots ($M=23.5$ years) were also older than novice pilots ($M=19.0$ years) and non-pilots ($M=21.1$ years), $t_s > 2.35$, $p_s > .05$; and expert pilots and non-pilots both had more education ($M=15.4$ years for both groups) than did novices ($M=12.8$ years), $t_s > 6.6$, $p_s < .05$. Finally, expert and novice pilots both performed worse than non-pilots on the Digit Comparison task (measure of speed of mental processing; Salthouse & Babcock, 1991), $t_s > 2.0$, $p_s < .05$, but there was no difference between groups for scores on the Shipley Vocabulary task (a measure of verbal ability; Shipley, 1946) or the Pattern Comparison task (measure of speed of mental processing; Salthouse & Babcock, 1991), $F_s < 1.0$. The pattern of findings suggests that the expert group had more knowledge and experience relevant to the problem-solving task than the novice group, which in turn had more knowledge and experience than the non-pilot group. However, the more expert groups did not have an advantage in domain-general cognitive abilities relevant to problem solving.

Design

The experiment consisted of a $3 \times 2 \times 2$ mixed design. Expertise level (expert pilots, novice pilots, or non-pilots) and collaboration level (individual or dyad) were manipulated between participants; problem complexity (simple or complex) was manipulated within participants. The primary dependent variables were the number of problems correctly identified and the number of problems correctly solved. Separating problem identification from solution generation is consistent with multi-stage problem solving theories that postulate a search through both a hypothesis generation space as well as a hypothesis testing space (Klahr & Dunbar, 1988; Klahr, Fay, & Dunbar, 1993). A successful solution in the current task is the product of a number of interdependent problem-solving processes that involves successfully identifying the primary problem in the scenario as well as generating an appropriate solution for that problem. This distinction is also consistent with the research in expertise distinguishing between the skills and knowledge required for problem identification and those required for reasoning (for a review see Chi, 2006).

Materials

Problem-solving scenarios previously shown to elicit differences in novice and expert memory and decision making were selected from Morrow et al. (2009). All scenarios described a flight situation in which a problem arises and each scenario had a simple and a complex version (see Table 2 for an example scenario). For each scenario critical set-up information was provided regarding the type of plane, the airports (departure, destination,

TABLE 2
Simple and complex versions of a scenario

Set-up (same for simple and complex)

DEPARTURE AIRPORT: Charlotte-Douglas INTL
 DESTINATION AIRPORT: Raleigh-Durham INTL
 CURRENT POSITION: Inside final approach fix Runway 5R
 AIRCRAFT ALTITUDE: About 1435' above field elevation
 TIME OF DAY: 4 PM EST
 ALTITUDE TEMPERATURE: 42 degrees F
 WIND CONDITIONS: 030 degrees 5 kts
 DESTINATION AIRPORT CONDS: 400' overcast 1 mi vis
 DESTINATION RUNWAY: 5R is 7000' with standard ILS; Dry
 ALTERNATE: (landing) Washington National
 AIRCRAFT: Wing-mounted, twin-engine, turbo jet; ILS, autopilot with approach coupler

Simple

Complex

You are being vectored for an approach to Runway 5R. First Officer is pilot flying. You are handling communications, monitoring, and giving altitude calls. First Officer has mentioned he really wants to get home to Washington. It is his wife's birthday and he has promised her a nice dinner out. ***Tower advises that visibility has increased to 7 miles with passing of the thunderstorm.*** First Officer also said that with this weather he would have asked for runway 5L because it is 10000' long and has ILS DME. You chose 5R since it is a shorter taxi to your terminal. Just then, you encounter wake turbulence from a heavy jet that is on vectors to 5L, which causes autopilot to trip. Localiser is intercepted by First Officer. Autopilot will not re-engage. First Officer's glide slope needle shows IN-OP flag. ***You lower flaps to approach setting and check electronic circuit breaker panel.***

You are being vectored for an approach to Runway 5R. First Officer is pilot flying. You are handling communications, monitoring, and giving altitude calls. First Officer has mentioned he really wants to get home to Washington. It is his wife's birthday and he has promised her a nice dinner out. ***Tower advises that they can see visibility decreasing with a thunderstorm approaching from the north end of the airport.*** First Officer also said that with this weather he would have asked for runway 5L because it is 10000' long and has ILS DME. You chose 5R since it is a shorter taxi to your terminal. Just then, you encounter wake turbulence from a heavy jet that is on vectors to 5L, which causes autopilot to trip. Localiser is intercepted by First Officer. Autopilot will not re-engage. First officer's glide slope needle shows IN-OP flag. ***Attempting to set approach flaps you get asymmetrical flap warning.***

alternate, runway information), and the features of the current situation (e.g., position, altitude, temperature, wind, time of day, etc.).

The participants' task was to identify the problem, generate possible solutions, and then choose the best one. Each scenario had a primary problem as well as one or more secondary, or minor problems. For example, the primary problem in the simple scenario in Table 2 is that the first

officer's glide slope is inoperable. The secondary problems for that version of the scenario included autopilot failure, weather, and the runway length. In contrast, the primary problem in the complex version was asymmetrical flaps. The secondary problems were the same as the simple scenario plus glide scope inoperability and controllability of the plane. The complex scenarios had more secondary problems than the simple scenarios. Because many of the scenarios explicitly described the problems in the text, such as the last sentence of the complex scenario in Table 2 "asymmetrical flap warning", we expected even the non-experts to be able to identify some problems based on the cues given in the scenario. However, we did not expect them to have a deep understanding as to why these were problems or how to correct them. Furthermore, collaboration in determining the problem may lead non-experts to second guess their initial thoughts and lead to poor performance on problem identification.

Each scenario had one correct solution as determined by a consensus of expert commercial airline pilots (see Morrow et al., 2009 for details). Most solutions fell into one of three categories: emergency landing, trouble shooting the plane, or to continue the flight plan as intended. For the emergency landing solutions participants would have to describe how and where it was to be done. For example, in the simple version of the scenario in Table 2 the solution is for the captain to take control and fly the approach, and in the complex version it is to "go around" and troubleshoot the plane. The problems described in the complex versions were rated by commercial airline pilots as being more multifaceted and having less-obvious solutions than the problems outlined in the simple versions, and therefore requiring more integration of and inference from domain knowledge (see Morrow et al., 2009 for details). Because the categories of the scenario solutions are consistent with non-expert naïve prior knowledge about what to do in a flight emergency (e.g., make an "emergency landing" or "troubleshoot" the plane) we expected non-experts would be able to make some limited progress in generating solutions for these scenarios.

Each scenario was accompanied by a problem solution sheet, where the participant or dyad recorded their answers to three questions: (1) What is the problem? (2) What are your options? and (3) What is the best option and why? Each question was open-ended and it was the participant/dyad's task to determine the best solution for each part.

Procedure

Participants first completed a memory task in which they read and recalled the flight scenarios (reported in Meade et al., 2009) and then completed a problem-solving task involving these scenarios as follows. First they were presented with the aviation scenarios a second time and asked to read

through each one at their own pace and to imagine the flight scenario was actually occurring. They were informed they would be asked to come up with solutions to the problems outlined in the scenario. Specifically, participants were provided with a response sheet that required them to first identify the problem outlined in the scenario and then discuss possible options for solving the problem. Finally they were asked to indicate which of the possible options offered the best solution to the problem.

Participants were instructed to talk aloud throughout this response period and all sessions were tape-recorded. They completed the response sheet either alone or in collaboration with another participant of the same expertise level depending on the condition. Participants in the collaborative condition were given no specific instructions on how to resolve errors or negotiate speaking turns. They were allowed 10 minutes to solve each scenario, although most participants finished in less than the time allotted. Once participants completed the problem-solving task for a given scenario, the procedure was repeated until all four scenarios had been presented. Each participant or dyad was presented two simple and two complex scenarios and the order was counterbalanced across all participants and conditions. One additional scenario was presented at the beginning of the session as a practice trial. Finally, participants completed the standardised measures reported in Table 1, were debriefed, and compensated at the rate of \$8 per hour. The entire problem-solving session took approximately 50 minutes.

RESULTS

We assess participants' problem-solving performance by examining their accuracy in problem identification and solution accuracy. Problem identification (correct or incorrect) and generating the correct solution (success or failure) are dichotomous measures, so we use non-parametric statistics comparing frequencies across the conditions. We also compare dyad performance to the predicted theoretical dyad performance using statistical methods based on Lorge and Solomon (1955) and Schwartz (1995). Alpha was set to .05 for all main effects, interactions, and planned comparisons (Keppel, 1991). Effect sizes (Cramer's V and Cohen's d) were calculated for main effects, interactions, and planned comparisons. Cohen (1988; see also Olejnik & Algina, 2000) has suggested that effects be regarded as small when $d < .20$, as medium when $.20 < d < .80$ and as large when $d > .80$.

Problem identification

This measure assessed whether participants could successfully determine what the problem was for each scenario. Participants' problem identification

performance was assessed as either correct (the primary problem) or incorrect (any other problem). Since each individual or dyad solved two simple and two complex problems we examined the frequency of correctly identified problems for each scenario. Table 3 presents the number of individuals or dyads from each condition to correctly identify zero, one, or two problems for each scenario type. We also report the probability of correctly identifying a given problem for each condition. Based on the performance of each individual condition we calculated the theoretical dyad performance described in detail below. This estimate enables us to compare the performance of the observed dyads to the predicted potential of the theoretical dyad.

Observed dyads versus individuals. We begin by comparing dyad performance to individual performance for each condition. We conducted separate chi-square analyses to investigate the effect of expertise and collaboration on identifying problems in both simple and complex scenarios. For simple scenarios there was a medium effect of expertise, $\chi^2(4, N=71)=9.61, p < .05, V = .26$. Follow-up comparisons showed that experts were better than both the novices and non-pilots in problem identification, $\chi^2(2, N=47)=5.43, p < .05, V = .34$ and $\chi^2(2, N=47)=8.19, p < .05, V = .41$ respectively, and there was no difference found between

TABLE 3
Problem identification

Expertise	N	Scenario type							
		Simple				Complex			
		0	1	2	Probability	0	1	2	Probability
<i>Non-pilots</i>									
Individual	16	0	6	10	.81	0	2	14	.94
Observed dyad	8	1	4	3	.63*	1	2	5	.75*
Theoretical dyad					.97				.99
<i>Novice</i>									
Individual	16	0	8	8	.75	1	7	8	.72
Observed dyad	8	0	1	7	.94	0	1	7	.94
Theoretical dyad					.92				.92
<i>Expert</i>									
Individual	16	0	2	14	.94	0	3	13	.91
Observed dyad	7	0	0	7	1	0	1	6	.93
Theoretical dyad					.99				.99

Number of individuals and dyads who correctly identified 0, 1, or 2 problems and the estimated probability of correctly identifying a given problem for individuals, dyads, and theoretical dyads.

novices and non-pilots, $\chi^2(2, N=48) = 1.19$, *ns*. Chi-square analyses also revealed no overall effect of collaboration when comparing dyads to individuals for the simple scenarios, $\chi^2(2, N=70) = 2.91$, *ns*. This shows that for simple scenarios there was no added benefit to working together when compared to working individually when identifying the problem.

Unlike the simple scenarios there was no overall effect of expertise for the complex scenarios, $\chi^2(4, N=71) = 3.57$, *ns*. Inspection of the frequencies in Table 3 reveals that all three groups had relatively high performance in problem identification on complex scenarios. In addition there was no overall effect of collaboration, $\chi^2(2, N=72) = .83$, *ns*, showing that there was no added benefit in problem identification for participants working together versus working individually on complex scenarios. Next, we compare the dyad performance in each condition to the predictions of the theoretical dyad.

Observed dyads versus theoretical dyads. To calculate the predicted performance of the theoretical dyad we adapted a technique from Lorge and Solomon (1955) and Schwartz (1995) that calculates the predicted probability based on combined measures of individual performance. The theoretical dyad performance is the sum of probabilities that either one of the individuals or both together could identify the problem. For example, if the average probability of an individual correctly identifying a given problem is .20 then the predicted performance of the theoretical dyad is the sum of the following three possibilities: the probability that individual 1 finds the problem and individual 2 does not (.20 * .80 = .16), the probability that individual 1 does not find the problem but individual 2 does (.80 * .20 = .16), and the probability that both individuals alone would have found the problem (.20 * .20 = .04). These three probabilities are summed to get the predicted probability of the theoretical dyad (.16 + .16 + .04 = .36). In this case the theoretical dyad is expected to identify the problem 36% of the time. This has been called a “truth-wins” or “rational” probability model because it assumes that if only one of the two individuals identifies the problem the other individual will immediately recognise and accept the other’s response as correct or “the truth”. The predicted theoretical dyad performance for each condition is presented in Table 3.

To test the predicted performance against the observed performance the theoretical dyad is treated as the population mean and the observed dyad as a sample and a one-tailed *z*-test was conducted for each level of expertise (Schwartz, 1995). The results showed that only the non-pilots had significantly worse performance than the theoretical dyad predictions for both simple and complex scenarios ($z = -2.71$, $p < .05$ and $z = -4.07$, $p < .05$ respectively). The expert and novices showed no differences from the nominal predicted performance ($zs < 1$).

These results are consistent with the interpretation that non-pilots perform less well when working with another person of the same expertise level than when working alone. This replicates the classic collaborative inhibition effect typically found for non-experts. One possible reason for this effect is that non-pilots working together do not construct an accurate representation of the problem. Non-pilots are unlikely to differentiate the important subtle aspects of the problem and, although both partners may be able to generate a possible problem, they lack the prior domain knowledge to properly evaluate each other's proposals and determine which is most important to the current circumstances. When they work alone they may simply rely on the most salient surface-level problem that is highlighted in the scenario. Although this is a plausible explanation we do advise some caution in interpreting this result, as the non-pilots' overall performance was better on the more complex problems than on the simple problems, which is a counterintuitive finding and is not consistent with our *a priori* predictions of problem complexity.

In contrast to the non-pilots, the novices and experts did not show collaborative inhibition. We hypothesise that this result comes from having relevant domain knowledge and constructing a shared mental model of the problem scenario vis-à-vis creating common ground. Although the novices and experts did not show collaborative inhibition they also did not show collaborative facilitation for problem identification. This null finding may reflect a ceiling effect for the experts as both the individual and dyad conditions had near perfect problem identification performance. Next we analyse participants' solutions across the two problem scenarios.

Problem solutions

This measure assessed whether participants could successfully determine the correct solution for each scenario. A coding rubric based on expert commercial pilot consensus was used to score participants' solutions (see Morrow et al., 2009, for details). Solutions were scored as either correct or incorrect and no partial credit was given. Since each individual or dyad solved two simple and two complex scenarios we examined the frequency of correctly solved problems for each scenario type. Table 4 presents the number of individuals or dyads from each condition to correctly solve zero, one, or two problems for each scenario type. Similar to problem identification we report the probability for correctly solving a problem for individuals, dyads, and the predicted performance of theoretical dyads.

Observed dyads versus individuals. We conducted separate chi-square analyses to investigate the effect of expertise and collaboration on solving problems in both simple and complex scenarios. For simple scenarios there

was a medium effect of expertise, $\chi^2(4, N=71)=23.30, p < .05, V = .40$. Follow-up comparisons showed that experts were better than both the novices and the non-pilots in solution generation, $\chi^2(2, N=47)=13.12, p < .05, V = .53$ and $\chi^2(2, N=47)=16.70, p < .05, V = .60$ respectively, and there was no difference found between novices and non-pilots, $\chi^2(2, N=48)=1.41, ns$. Chi-square analyses also revealed no overall effect of collaboration when comparing dyads to individuals for the simple scenarios, $\chi^2(2, N=70)=4.49, p = .10$. This shows that for simple scenarios there was no added benefit to working together when compared to working individually when solving the problem. However, we note that this result should be interpreted with some caution as there is a trend for dyads to perform better than individuals for both non-pilots and novices, and that low N may be reducing power to detect statistically significant effects here.

Similar to the simple scenarios there was a medium effect of expertise for the complex scenarios, $\chi^2(4, N=72)=22.11, p < .05, V = .55$. Follow-up comparisons showed that experts solved more problems than the novices, $\chi^2(2, N=48)=5.96, p = .05, V = .35$ and novices solved more problems than non-pilots, $\chi^2(2, N=47)=7.18, p < .05, V = .39$. In addition, there was a large effect of collaboration, $\chi^2(2, N=72)=7.99, p < .05, V = .33$, showing that participants working together solved more problems correctly than those working individually on complex scenarios.

TABLE 4
Problem solving

Expertise	N	Scenario type							
		Simple				Complex			
		0	1	2	Probability	0	1	2	Probability
<i>Non-pilots</i>									
Individual	16	10	6	0	.19	12	4	0	.13
Observed dyad	8	2	5	1	.44	4	4	0	.25
Theoretical dyad					.34				.24
<i>Novice</i>									
Individual	16	7	9	0	.28	0	6	2	.32
Observed dyad	8	1	6	1	.50	1	4	3	.63
Theoretical dyad					.48				.53
<i>Expert</i>									
Individual	16	1	8	7	.69	3	8	5	.56
Observed dyad	7	0	4	3	.71*	0	1	6	.93*
Theoretical dyad					.90				.81

Number of individuals and dyads who solved 0, 1, or 2 problems and the estimated probability of solving a given problem for individuals, dyads, and theoretical dyads.

These results show that prior expertise in the domain had a large impact on successful problem solving. We hypothesise that this advantage was due to expert domain knowledge and in the dyads' case, collaborative skill as well. The collaborative effect is consistent with the hypothesis that participants engage in more constructive problem-solving activities when working with a partner than when working alone. Next we compare the dyad performance in each condition to the predictions of the theoretical dyad.

Observed dyads versus theoretical dyads. The predicted theoretical dyad performance is based on the sum of the probabilities that either one or both of the individuals in a dyad solves the problem. The predicted theoretical dyad performance for each condition is presented in Table 4. Similar to problem finding, the theoretical dyad is treated as the population mean and the observed dyad as a sample, and a one-tailed z -test was conducted for each condition (Schwartz, 1995). The results showed that the experts performed significantly less well than the theoretical dyad on simple scenarios ($z = -1.99, p < .05$) whereas they performed significantly better than the theoretical dyad complex scenarios ($z = 1.79, p < .05$). This shows that the experts exhibited collaborative inhibition on simple scenarios and collaborative facilitation on complex scenarios. The novices and non-pilots showed no differences from the theoretical dyads predicted performance for either simple or complex scenarios ($z_s < 1$). This shows no collaborative inhibition or facilitation for either group.

The expert results are consistent with the interpretation that successful collaboration is determined by the relation between the groups' prior knowledge and experience (learner factors) and the difficulty/affordances of task (situative factors). The complex scenarios showed collaborative facilitation because they were the "optimal" distance from the expert dyad's prior knowledge. That is, these scenarios were close enough that the participants could use and build on their prior knowledge and skill in the domain to generate a solution, but were distant enough that they did not have a specific solution in memory and could benefit from collaborative interaction. In contrast, experts showed collaborative inhibition on simple scenarios, suggesting that these problems led to non-productive interactions.

The novices showed no evidence of collaborative inhibition, which is consistent with the hypothesis that they benefited from having some shared knowledge in the domain and performed up to their predicted potential on both the simple and complex scenarios. They are hypothesised to have engaged in some constructive and interactive processes thus eliminating collaborative inhibition. In contrast to our predictions, the non-pilots showed no collaborative inhibition on solution generation when compared

to their predicted potential. Although this group showed collaborative inhibition effects on problem finding they did not show analogous decrements on solution generation. This null finding may be partially due to floor effects, especially on the complex scenarios.

DISCUSSION

We tested a hypothesis of collaborative facilitation that is based on the idea that successful collaboration depends on creating a sufficient distance between the dyad's prior knowledge and skill in the domain and the task solution. This distance affords interactive and constructive processes and requires the creation of common ground to successfully solve the problem. Consistent with prior work, we hypothesised that collaboration requires sufficient cognitive resources (working memory capacity/attention skills), and that less-successful groups may suffer disproportionately from the cognitive cost of working together, thereby overwhelming any possible benefit of collaboration. We hypothesised that this cost can be reduced by increasing the dyad's prior knowledge and collaborative skill in the domain. We predicted that if the participants had more expertise in the domain, the cognitive cost might be reduced and provide dyads the opportunity to engage in constructive and interactive processes.

To test these hypotheses we had expert flight instructors, novice aviation students, and non-pilots solve simple and complex aviation problem-solving tasks, either individually or with a partner of the same level of expertise. The non-pilots were less successful in identifying problems when working in dyads than when working individually, whereas novices and experts showed no costs for collaborating. Experts were at ceiling and showed high performance on problem identification regardless of working alone or with another partner. The results for the non-pilots replicate the typical findings in the literature showing collaborative inhibition for non-experts working on a novel task (e.g., Kerr & Tindale, 2004; Mullen, Johnson, & Salas, 1991). In contrast, the novices and experts performed at their predicted potential. The individuals working in dyads were able to pool their knowledge/skills without showing any decrements from interacting. These results are consistent with our hypothesis that sharing knowledge in the domain leads to successful collaboration (no cost) but having no relevant prior domain knowledge led to unsuccessful collaborations as compared to the predicted performance. But did expertise impact participants' ability to successfully solve the problems once they were identified?

As expected, we found large expertise effects for problem-solving accuracy with experts performing better than novices and novices performing better than non-pilots. Furthermore, the experts showed

collaborative facilitation with the expert dyads performing better than their predicted potential on the complex scenarios. This result is consistent with the hypothesis that experts show interactive or synergistic benefits from working together but only on domain-related tasks that are a challenge. For simpler tasks that they can presumably solve on their own, they did not show such benefits. In fact, experts surprisingly showed collaborative inhibition on the simple scenarios. This result suggests that collaboration on tasks that experts are presumably competent to solve on their own is at times detrimental. In contrast the novices showed no sign of collaborative inhibition on solution generation for either simple or complex scenarios. This is consistent with the hypothesis that prior knowledge and experience helped them to avoid “process loss” during collaboration. Having some relevant knowledge may have helped them offset the detriments typically observed in non-experts when solving novel problems. Finally, in contrast to our predictions, the non-experts also showed no collaborative inhibition on solution generation. We have no explanation for this surprising finding. However, we do note that solution generation may have suffered from floor effects, especially on the complex scenarios.

Taken together, the problem-solving results suggest that collaborative success is a complex interaction of the prior knowledge and experience of the individuals working together, and the relation of their combined knowledge to the task (complexity level and task structure). The results support the hypothesis that individual learner and task structure combine to create a zone of proximal facilitation in which participants can go beyond what they could do individually. An important direction for future work is to further examine the cognitive and social processes underlying this successful collaboration.

Another important direction for future work would be to examine the impact of problem-solving resources on collaboration. One limitation of the current work is that all participants were given problem-solving worksheets to write down their answers when identifying the scenario problem, options, and final solution. The purpose of the sheet was to provide a measure of the different stages of the problem-solving process. However, it is interesting to consider the potential impact of the presence of the sheet on collaborative behaviour. The worksheet might have helped participants “off load” information, thus reducing cognitive load, and perhaps helped them keep better track of information than simply just discussing each scenario and coming to a verbal answer. This possibility may help to explain the lack of collaborative inhibition for the non-pilot group on solution generation. Future work should further examine the impact of various resources on supporting or inhibiting collaborative performance. Next we consider the implications of these results for theories of collaborative problem solving.

Implications for theory

The proposed hypothesis may help us understand the findings in the literature showing relatively more collaborative success in some situations than others. The critical factor in the current framework is the relationship between the individual's prior knowledge, their shared knowledge (knowledge overlap and organisation), and its relationship to the target task. In work that has examined non-experts solving novel tasks, it is likely that the cognitive costs of collaborating outweigh any possible benefits of working together (e.g., elaboration and explaining). This is likely due to cognitive load (Dillenbourg, 1999), coordination processes (Steiner, 1972), retrieval disruption (Basden et al., 1997), production blocking (Diehl & Stroebe, 1987), and in some situations social factors such as social loafing (Latane et al., 1979), and self-attention/evaluation (Mullen, 1983, 1987).

In contrast, when participants share much prior knowledge and/or experience in the domain we see collaborative success, showing that individuals perform better working with another person of the same level of expertise than they would working individually when solving a challenging problem. This result is consistent with the pre-condition hypothesised by Laughlin et al. (2003) focusing on participants having shared knowledge for collaborative success. It is also consistent with the implications of the expertise literature showing that expertise reduces cognitive load and facilitates rapid, reliable knowledge retrieval even in the face of interruption (Ericsson & Kintsch, 1995). Experts should also perform better collaboratively because they can quickly identify problems and focus on the most critical features of the task, providing an opportunity for constructive and interactive processes to create a common ground for a task that is sufficiently challenging.

This work attempts to bring together multiple perspectives on what factors contribute to collaborative success by examining both learner factors (prior knowledge and experience in the domain) and situative factors (task complexity). Our work builds on the prior work of social theorists such as Vygotsky (1978), Palinscar and Brown (1984), Greeno (1998), and Rogoff (1998; Rogoff, Goodman Turkkanis, & Bartlett, 2001) who focus on the dyad/group-level interactions as critical to understanding successful learning and performance. These theorists focus on the dyad/group as the unit of interest and the interactions between partners as critical. Core to this perspective is that knowledge is always "in-relation-to" other knowledge, people, objects, and situations.

However, we aim to link this situative perspective to a cognitive view by examining participants' prior knowledge (i.e., knowledge decomposition, Anderson & Lebiere, 1998; Koedinger et al., 2010) and how that knowledge changes with experience in the domain (Ericsson, Charness, Feltovich, &

Hoffman, 2006; Nokes et al., 2010). We interpret the results as consistent with Chi's (2009) active-constructive-interactive framework. Specifically, we hypothesise that constructive and interactive processes may be triggered in different situations depending on the dyad's prior knowledge and the characteristics of the target task. Different tasks are likely to afford different activities depending on one's prior knowledge, its relation to the other participant's knowledge, and its relation to the target task. For example, although a simple task may trigger interactive processes from novices because they share some mutual knowledge; for experts it may only trigger individual-level constructive or active processes or early termination of interactive processes because the individual experts could solve the problem easily on their own.

To make progress in understanding collaborative problem solving, social theories must be anchored to cognitive approaches to get traction on the underlying knowledge representations and problem-solving mechanisms, and cognitive theories must move beyond individual cognitive analyses and consider interaction patterns as critical, irreducible, and fundamental to learning and performance of dyads and groups. This view positions one to understand collaboration as a complex system of interacting participants. Each participant has a set of internal cognitive representations and processes at the individual-level of analysis that are governed by the input from the environment and the other participants and the structure and complexity of the task. Simultaneously, interactive behaviours are taking place at the group-level of analysis, which are governed by complex social processes between participants, such as developing common ground, and are dependent on the group's knowledge, task constraints, and goals. Processes at both levels must be taken into account to explain the variance contributing to collaborative success. Future work may take a dynamic systems approach to modelling these complex interactions by defining the knowledge and learning processes for each individual as well as a set of interaction rules for each participant that drive the group-level behaviours.

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