Chapter 4
Innovation in Team Interaction: New Methods for Assessing Collaboration Between Brains and Bodies Using a Multi-level Framework

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Abstract As research on teams becomes increasingly sophisticated, scientists face challenges related to understanding collaboration at multiple levels of analysis, beyond that of the individual or the group alone. Grounded in Hackman's work on interaction and levels of analysis, this chapter explores theory development for understanding team collaboration from multiple perspectives. We argue that to enhance and improve the study of collaboration and to increase explanatory power, the development of theory must focus not only on the major issues at each level, micro, meso, macro, but also issues that cross these levels of analysis in team interaction. This method of cross-level analysis provides insight on some of the causal factors related to better understanding collaboration effectiveness. Furthermore, this chapter explores the need to leverage complementarity within and between disciplines to enhance our understanding of team interaction and to provide a more holistic method for assessing collaboration in a variety of complex domains.

Keywords Collaboration · Team interaction · Problem solving · Team science · Cross-level analysis · Micro · Meso · Macro

4.1 Teams and Technology: New Methods for Assessing Interaction and Collaboration Between Brains and Bodies

Over 400 years ago, a Dutch tinkerer named Zacharias Janssen, who worked in the fledgling spectacle industry, created a new tool. By engineering a set of lenses in a particular configuration, light could be manipulated such that objects could be

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A.A. von Davier et al. (eds.), *Innovative Assessment of Collaboration*,
Methodology of Educational Measurement and Assessment,
DOI 10.1007/978-3-319-33261-1_4

magnified many more times than before (Masters, 2008). Although not immediately recognized as such, this tool would revolutionize much of science. Within a few decades, Marcello Malpighi, an enterprising physician and biologist in Bologna, used this new technology to identify the capillaries posited in an earlier theory of the circulation of blood. Soon, the scientists of the day began their own modifications to this new tool, called a microscope, making it more powerful and more usable (Masters, 2008). But improving this technology was not the goal; it was merely the means to a newly realized end, that is, the ability to investigate tissue components that could not be seen with the human eye. For what they had perceived as a hidden world, was now visible thanks to this powerful new instrument—a tool that would help them discover the many and varied layers of this world. They could now explore biological intricacies and interconnections across various levels. At the micro-level of analysis, cellular components were now visible. At the meso-level, interactions between these cellular components and how they interact with one another were illuminated. Finally, at the macro-level, the complex systems, functioning as a result of multiple cellular interactions across levels, could be understood. By peeling away layers of organisms, subjecting them to forms of analysis never before possible, and studying inter-connections within and across these layers, they were able to observe and understand the beauty and the complexity of biological systems.

This brief tour of science history is merely an illustration, albeit a powerful one, of how a technology can revolutionize our understanding of the world around us. We are seeing a similar revolution in the study of collaboration. For, in research on groups and teams, we are having introduced to us, not just one, but many new tools and technologies helping us instrument and/or observe the world of interaction in ways never before possible. Importantly, though, we are observing interaction not just within, but also across, multiple levels, From this, we now have the opportunity to integrate levels of interaction in a meaningful way, and study collaboration in a variety of domains.

Within a volume emphasizing the importance of developing effective measures of collaboration via consideration of assessment approaches from a variety of disciplines, we submit that scientists must have an appropriate conceptual scaffold for understanding multiple forms and levels of analysis. This requires methods for diagnosing causal factors associated with collaboration effectiveness. In particular, by moving our analysis either one level up, or one level down, we can emphasize differing factors associated with teamwork. First introduced by Hackman (2003), the idea of shifting focus from an isolated level to a higher or lower level can lead to new insights into causal mechanisms that shape team process and performance. More importantly, bracketing a phenomenon of interest, via a level above and a level below, can increase the precision of explanation in that the "explanatory power of bracketing lies in crossing levels of analysis, not blurring them" (Hackman, 2003, p. 919). We build upon this to suggest that the simultaneous consideration of micro, meso, and macro-levels of collaboration, in addition to bracketing phenomena, can provide a rich explanatory framework for assessment.

From this, a truly multi-level theoretical perspective, that can specify constructs cutting across levels is within our reach (see Dansereau & Yamarino, 2002; Fiore et al., 2012).

4.2 The Context for Collaborative Assessment

In this chapter, we illustrate how multiple levels of analyses are moving us in important new directions for assessing collaboration. This provides grounding for a discussion of how integration of measures can be of value in the assessment of collaborative problem solving. We structure this summary by the level of analysis being used—micro, meso and macro-levels. First, we discuss recent research within these levels, on the study of collaboration. We then provide examples of how to integrate these to understand cross-level phenomena. Finally, we describe how such methods of assessment can be used to enrich our understanding of collaborative problem solving. We do this with the specific example of scientific problem solving as engaged by teams. In sum, we show that developments across disciplines are creating new methods for assessing interactions at the level of the brain, body, behavior, and network. Our goal is to help collaborative problem solving assessment researchers make sense of the varied studies emerging by more systematically considering the level of analysis in which collaboration is being studied so as to consider how to supplement more traditional forms of problem solving assessment.

4.2.1 Looking at Levels

Traditionally, team research focuses on a limited set of measures, and usually only at a single level of analysis. Although such approaches produce robust results, unidisciplinary assessment methods, and/or measures that too narrowly focus on one form of collaboration, or one level of analysis, can limit our understanding of the true richness of collaboration. As such, they do not adequately capture the complexity inherent in teamwork. Following calls for multi-level analyses (Dansereau & Yamarino, 2002; Hackman, 2003), we suggest that the assessment of collaboration match the complexity of team interaction by examining multiple levels and through a multi-method and multidisciplinary approach. In this way, we can address limitations in the literature on collaboration assessment.

Toward this end, we discuss multiple levels of analysis for analyzing concepts associated with collaboration and the developments being made in these areas. At the micro-level, we are interested in understanding the neurobiological and physiological *underpinnings* of social cognitive processes. Expanding outward, we move to the meso-level, encompassing *mediating* artifacts as well as movements and non-verbal behaviors between bodies. Finally, we reach the macro-level of analysis, which involves interactions *within and across* teams of teams and networks.

When we better understand concepts and methods for studying collaboration within levels, we can then move towards one of the more profound challenges in research on teams. This is creating and synthesizing theories and methods that can cross levels of analysis (cf. Hackman, 2003). With this, we can better understand the specific dynamics emerging in collaboration. To achieve this we must evolve team research into a truly interdisciplinary enterprise. Using this integrative approach, then, our goal is to help the field recognize the broader implications of interaction between bodies and brains and how this can be leveraged for more effective assessment of collaboration at all levels of analysis. For the purposes of this chapter, we discuss innovative assessments of collaboration and then relate these to collaborative problem solving as an specific form of collaboration.

4.2.2 Level One: Micro Level

As methods of assessment in neuroscience became more sophisticated and more robust, research has transitioned from a purely individual cognitive focus to understanding the biological mechanisms that drive social cognitive processes. The emerging area of social neuroscience solidified around these developments and brought about an important perspective on social cognitive mechanisms. Research at this more micro-level focuses on investigating the relationship between biological states, neurological properties, and collaboration.

Electroencephalogram (EEG) has matured into one of the important tools for research in the cognitive and neural sciences. EEG relies on electrodes attached to the scalp to detect electrical activity in the brain. Particular patterns of electrical impulses are used to assess varied forms of neural activity (e.g., attentional focus). Because of decreases in cost, and increases in reliability, EEGs are now one of the new ways for assessing neural activity in collaborative contexts.

To illustrate methods of collaboration assessment at this micro-level, EEG has been used to measure neural synchrony. This describes complementary or similar electrical impulses that emerge during collaborations. For example, in the context of coordination in body movement during a cooperative interaction, EEG was used in conjunction with motion tracking to study physiological changes in interacting pairs (Yun, Watanabe, & Shimojo, 2012). More specifically, phase synchrony was used to study inter-brain connectivity, the synchrony between the neurological responses of a dyad. Through this instrumentation, implicit interpersonal interactions were observable at a very fine-grain level based upon body movement synchronization. This study found that training in a cooperative task increased synchrony, “between cortical regions across the two brains [to suggest] that such inter-brain synchrony is a neural correlate of implicit interpersonal interaction” (Yun et al., 2012, p. 3). This illustrates how embodied approaches to assessing interaction can utilize methods developed within neuroscience. In particular, methods specifically assessing body movements, linked to neural assessment, can help us understand the relationship between interacting bodies and brains (cf. Valera, Thompson, & Rosch, 1991).

Synchrony in EEG activation has also been used during the complex coordinative process of guitar duets. This research expected brain areas associated with executive control and metacognition (the pre-frontal cortex, PFC) to be involved given the need to monitor teammates in the duet. This can be seen as a form of mental state attribution arising within the team while playing together. In this study, they examined coordination within guitar duets by recording EEG from each player in 12 duets (see Sanger et al., 2012). They assigned team roles for the duet by making one player a leader and the other a follower. Within-brain and between-brain coherence in time-frequency signals were then assessed. This study showed how synchronous oscillations in the duet varied dependent upon leader-follower assignments. Further, they found within-brain "phase locking" and between-brain "phase coherence" was heightened in the PFC when there were high demands placed on musical coordination. This can be interpreted as neural markers of interpersonal action coordination arising when there exists higher demands for monitoring teammates.

Body mirroring in collaboration, is another emerging area of research that continues to evolve. Research in this area examines joint action and biological function in the context of collaborative environments. Studies have demonstrated the influence of musical structure in choral singing on cardiovascular function by measuring the heart rate variability (HVR) and respiratory sinus arrhythmia (RSA) rates (Vickoff et al., 2013). This suggests that singing "as a group" can cause individual biological responses to synchronize.

Neuroendocrinology research is helping us understand how the neuropeptide oxytocin influences trust and cooperation in groups and can alter behaviors across groups (De Dreu, Shalvi, Greer, Van Kleef, & Handgraaf, 2012). Using a modification of the classic Prisoner's Dilemma game, this experiment studied the traditional patterns of interaction that can arise during game-play (e.g., reward or punishment). They found that oxytocin, when administered via nasal inhalation, influenced the desire to protect vulnerable group members. In other words, even when not personally threatened, oxytocin uptake produces prosocial behaviors, in this case, the desire to protect group members perceived as vulnerable (De Dreu et al., 2012). Such findings can help us understand micro-level methods to assess trust and motivation in terms of defensive capabilities that arise during collaboration.

Further, research has shown how neuropeptides change when team members engage in cooperative and collaborative behaviors. Levels of oxytocin were found to be related to group-serving tendencies during an incentivized poker game (Ten Velden et al., 2014). While De Dreu et al. (2012) outlined the effects of oxytocin towards vulnerable group members, Ten Velden et al. (2014) showed that participants decreased competitive behaviors when playing poker with an in-group member. Additionally, results indicated that participants receiving a dose of oxytocin were more likely to demonstrate cooperative behaviors when compared to the placebo group. This research suggests that, although oxytocin may not indiscriminately increase the prevalence of benevolence in humans, it may play a role in increasing cooperative behavior within groups.

These studies provide new insights on micro-level assessments by documenting that neurophysiological changes can be connected to interaction. This provides further support for using neuroscience in combination with traditional methods to measure collaborative interactions. As research advances in the study of the neurobiological underpinnings of behavior, we can use these to understand how they are related to traditional measures for studying collaboration. As we describe in more detail later, from this, then, we can consider how these related to the assessment of collaborative problem solving behaviors (e.g., heart rate variability and information sharing; oxytocin levels and back-up behaviors). As such, this can provide a more comprehensive picture and a richer understanding of interaction through assessments of neurological and biological markers of collaborative behavior.

4.2.3 Level Two: Meso Level

As we move beyond the neural level, we transition to what we label "meso-level" research, defined here as research focused on measuring interactions between bodies. This encompasses developments in the study of non-verbal behavior to offer rich insights from the observation of interactions. This also includes interactions, not just between team members, but also between members and artifacts in the world. These forms of external cognition are manipulated in service of shared information processing during collaborative problem solving (see Fiore & Schooler, 2004; Fiore et al., 2010). For example, research in human-computer interaction has blended psychological and computational approaches to examine how technologies are scaffolding group process and how artifacts and material objects mediate complex collaborative cognition.

At this meso-level, researchers have studied collaborative constructs such as shared awareness and common ground. For example, using a digital puzzle task that varied factors such as item complexity and visual feedback, research showed how shared visual spaces influence collaborative effectiveness (Gergle et al., 2013). This examined interactions in a problem solving task via study of "helpers," participants describing a puzzle configuration, and "workers," the participants actually assembling the puzzle. They found that visual spaces designed to scaffold the interaction, through the use of screens optimized for the task based on the role of the member in the dyad, influenced performance by altering conversational grounding and shared task awareness. This illustrates an important path for assessing cognition and communication in the context of material objects and how these relate to collaboration effectiveness.

Enhanced displays represent another important development for assessing how artifacts mediate interactions and cognition between interacting bodies. For example, in visual analytics, researchers have studied collaboration processes emerging during a complex task requiring distillation and comprehension of large amounts of information (Isenberg et al., 2012). Here, via study of mediated interaction through tabletop displays, researchers assessed collaboration patterns that arise when teams virtually manipulated hundreds of digital documents to solve problems requiring the integration of a vast amount of text. This provides insights for assessing the relationship between loosely and tightly coupled interactions "around" tasks, artifacts, and displays as team members collaborate to, for example, distill and synthesize information.

Developments within the field of "environmentally aware computing" are also allowing us to understand patterns of interaction related to any number of team outcomes. For example, by integrating the use of sociometric badges (i.e., wearable devices that collect social data such as proximity to, and amount of interaction with, others), with traditional surveys, research is studying the influence of collaboration and creativity (Tripathi & Burleson, 2012). This research assessed individual creativity but examined it in the context of team meetings via sociometric badges and the amount of interaction team members experienced. By studying interaction in situ, they developed a predictive model of creativity in teams in their organizational context. This study illustrates a powerful way to infuse new technology (sociometric badges) into traditional studies so as to improve assessment and gain a better understanding of collaboration embedded in context (see also Khan, this volume, Chap. 11).

Sensor technology is also providing new ways of assessing group performance in the actual context of interaction. Infrared optical systems and passive markers are now being used for kinematic data capture during group interaction (D'Ausilio et al., 2012). Here, non-verbal behavior was studied to examine movement patterns related to leadership in orchestras. This research was able to produce detailed computational analysis of the causal relations between a conductor's wand and violinists' elbow movement. From this, they were able to uncover trends in leadership that were then related to the aesthetic quality of music. This provides an unobtrusive method for assessing a complex form of interaction, that, when paired with appropriate analytic techniques, help us better understand traditional concepts like leader-follower behaviors as discussed in the collaboration literature.

In short, these studies illustrate how technologies are helping us study, at a finer-grain, and in new ways, the behavioral aspects of social interaction. At this meso-level we can directly observe patterns of movement associated with joint action as well as collaboration with artifacts in the environment. These provide insights into how team members monitor actions with each other and/or with cognitive artifacts to carry out collective goals. This moves us beyond a discussion of the biological bases of interaction, to a discussion of the bodily forms of interaction. Further, at this level, and with this technology, we can study how contextual factors are related to collaboration. We provide more specific detail later, but, in brief, by linking this with the micro-level, we can begin to envision how to integrate assessments of the neural underpinnings of collaboration with the behavioral interactions between team members to improve our understanding and assessment of collaborative problem solving in situ (e.g., EEG measures of engagement with task/system correlated with team process measures (cf. Stevens, Galloway, Wang, & Berka, 2012), this volume, Chap. 20; eye tracking with use of material artifacts during collaborative problem solving (cf. Olsen et al., Chap. 10).

4.2.4 Level Three: Macro Level

With the goal of understanding behavior and the influence of others on our interactions, we transition to the level with the broadest scope, the macro-level. This includes the study of teams of teams or large networks where subgroups emerge out of the interactions of hundreds, and sometimes thousands, or millions, of individuals. Developments in network science and social network analysis help us study these broad patterns of interaction across multiple time scales.

As an example, macro-level analyses using bibliometrics are providing new ways for understanding collaboration as it occurs in the real world. In a study of 20 million patents and publications, over 50-years, researchers found that collaboration in science is on the rise and that teamwork in science is having an increasing impact on the production of knowledge (Jones et al., 2008; Wuchty et al., 2007). But this form of macro-level analyses can be even more fine-grained. For example, network analyses were used to study successful forms of interaction in complex teamwork environments. To illustrate, research on scientific teamwork produced analytic techniques that simultaneously took into account patterns of prior co-authorship coupled with analysis of citation overlap. In a study of over 1000 collaborative proposals, this was used to help determine team assembly as well as predict collaboration success in scientific teams (see Contractor, 2013, for a discussion). These studies provide insights into local interactions by studying broader patterns of collaboration across thousands of teams that unfold over long periods of time.

In sports, interaction networks are helping to assess the patterns of effective team performance. For example, in studying nearly 300,000 passes in professional soccer, using metrics such as network intensity (e.g., the passing rate), and network centrality (e.g., player dominance), high intensity and low centralization were related to more effective game play (Grund, 2012). In a study of over 12,000 video game production teams (with over 130,000 individuals), and over several years, network analyses helped uncover the factors contributing to development of games considered to be highly innovative (De Vaan, Stark, & Vedres, 2015). They found that the repertoire of skills acquired by individuals contributes to success if team members are stylistically different; that is, when individuals with differing skill sets leverage their strengths to collaborate more effectively. Specifically, when teams were found to have more diversity in these skills and styles, they were more likely to produce unique or distinctive games. These studies provide innovative approaches for understanding behavior but also point us towards new targets for assessment (e.g., collaborative competencies).

Social network analysis is also providing insights into performance within virtual settings, in the context of Massively Multi-player Online Games (MMOGs). With data collected over multiple months, over 7000 players, and millions of messages, factors such as alliances, trades, and cooperation were used to understand how teams accomplished goals (Wigand et al., 2012). When dealing with competition, network analyses documented that intensive communication and coordination enhanced team performance and that successful players were more likely to receive, than send, messages.

Others have also used social network analysis at this more macro-level to study how groups form in virtual worlds. For example, community detection algorithms were developed from interaction data (e.g., thousands of entries in chat rooms) to help understand the relationship between the type of interaction and group formation. Prior group membership, in this context, within guilds, was found to be most predictive of future membership. Additionally, network centrality was also shown to predict patterns of joining and be more important than member skill sets (see Alvari et al., 2014). Although these studies take place in virtual worlds, tracking behaviors of thousands of individuals, and over long periods of time, provide a window into collaboration not available using traditional laboratory studies.

In sum, these macro-level studies provide a level of understanding not attainable through analysis of neural pathways or behavioral observations. Further, they help us understand teamwork in both real and virtual worlds and across thousands of collaborating groups. By focusing on team dynamics at the macro-level, we can see the factors that contribute to successful interaction beyond an individual level and in high fidelity situations (e.g., sports teams, project production teams). While the work of neuroscientists and behavioral researchers is not to be overlooked, there is value in assessing teams beyond highly controlled lab studies. Specifically, by limiting our scope to only the micro or meso-levels of analysis, researchers overlook the value of understanding interaction more broadly. Further, network analyses provide a viable method for extracting factors that influence collaborative problem solving performance without interfering in the interactions or affecting the outcome of the interaction. This also has important implications given that studies at the neural (micro) level, and even behavioral (meso) level can be criticized for the potential influence of devices and methods in measuring the form or outcome of interactions. Thus, the predictive power of macro-level studies comes from both their scale and from their assessment of performance in situ.

4.3 Integrating Assessments Across Levels

Although looking within these levels is illuminating, we now turn considering the integration of levels. This requires a truly multi-level theoretical perspective where researchers assess collaborations at multiple levels in order to better specify how they are conceptualizing construct(s) that can cut across levels (see Dansereau & Yamarino, 2002; Fiore et al., 2012). Further, as noted earlier, shifting focus to a higher or a lower level can lead to new insights into causal mechanisms that shape team process and performance. As an analytical approach, bracketing the main phenomenon via a level above and a level below, can provide more precise explanations by specifying and crossing levels of analysis (Hackman, 2003). We similarly suggest that simultaneous consideration of micro-, meso-, and macro-levels of collaboration, in addition to bracketing phenomena, can provide a richer explanatory framework for understanding collaboration effectiveness.

To illustrate, research crossing what we would call the micro- and meso-levels is adding to our understanding of team cognition (Stevens et al., 2012). Research is demonstrating the utility of neurophysiological measures to augment our understanding of team process. In a simulated Submarine Piloting and Navigation (SPAN) task, temporal measures of engagement were mapped to team events. These measures tended to align with the frequency with which team members communicated with one another. This work in neurophysiological measures coupled with team communications, shows how to link the micro- and meso-levels, to improve and integrate novel and traditional methods for assessing collaboration (also see Stevens et al., Chap. 20, for further discussion of research on in situ assessment of collaboration). Others have discussed the value of what we consider crossing levels through the use of eye-tracking in collaborative tasks (Olsen, Ringenberg, Aleven, & Rummel, 2015). Using a "dual eye-tracking" paradigm, where eye gaze of collaborating teammates is used, this research examined how individual level gaze patterns are related to team level processes such as communication and learning outcomes (see also Olsen et al., this volume, Chap. 10). This work moves across these micro and meso levels by measuring joint visual attention in learning contexts. As such, researchers can collect data beyond the self-reporting procedures to study across levels where the individual interaction with their environment and other teammates plays a role in the outcome of learning sessions.

The aforementioned studies provide a direction for innovations in assessment. But our goal is to push the field towards more integration of assessment crossing levels. As such, to further illustrate the value of this way of pursuing research on teams, we use scientific problem solving as an example context for complex collaborative assessment that would benefit from a multi-level and multi-method assessment approach. Scientific teams are more the norm in research and development as the nature of the problems being studied is becoming increasingly more complex (Fiore, 2008; Hall et al., 2008; Stokols et al., 2008). Further, collaborative problem solving in science teams is not confined to a particular field as it is increasingly practiced within and across a variety of disciplines cutting across the physical, social, life/health and computational sciences (Asencio et al., 2012; Börner et al., 2010; Falk-Krzesinski et al., 2011; Olson & Olson, 2013). In this section, consideration of micro-, meso-, and macro-levels, and their interactions, can illuminate our understanding of collaborative problem solving in science.

When considering collaboration assessment via a multi-level lens, we must consider complementary approaches (Klein, Canella, & Tosi, 1999; Kozlowski & Klein, 2000). First, there can be assessment approaches envisioning how variables at higher levels might moderate the relations of variables at lower levels. In scientific collaboration, this could include how macro-level behaviors influence micro-level attitudes. In our science team example, this might be a macro-level factor, such as the data-sharing infrastructure across teams of teams as might occur with multi-university collaborations, and how this could have a downstream and proximal influence on a micro-level factor like team trust. Second, there can be models that examine how individual level factors shape higher level contexts. Continuing with our collaborative problem solving example of a science team, this kind of micro- to meso-level effect could occur when demographic factors (e.g., multidisciplinary team consisting of social scientists and life scientists) influences collaboration factors at the team level (e.g., coordination losses because of lack of shared knowledge across team members). Our point in describing complementary approaches is that, by not taking these into account, research in collaborative assessment of scientific problem solving might inaccurately specify the nature of relations of interest, or, they might even miss relationships entirely.

To ground the above distinctions in our micro-, meso-, macro-level framework, we next provide a set of specific examples to illustrate how integration of measures could be of value in the assessment of collaborative problem solving in science teams. First, micro- and meso-levels could be crossed such that we can study how neurophysiological indicators are related to broader interaction behaviors. As an example, research could examine how neural synchrony relates to the development of common ground in communications within teams. In a science team, this could be demonstrated by using EEG to assess patterns of synchrony while members work through hypotheses generation during proposal writing. Additionally, neuropeptides could be correlated with artifact construction and use. For example, higher levels of oxytocin might predict willingness to contribute to the development of material objects in the science team as they work on a proposal (e.g., drawings of a conceptual model).

Micro-level factors can also be connected to the more macro-level. For example, phase locking during initial interactions, as measured via EEG, might be indicative of later group formations. More specifically, it could be that science teams demonstrating greater phase locking during initial proposal meetings are more likely to continue and form teams who successfully complete or win a proposal. We can also envision how meso- and macro-levels of collaboration are related. Assessments studying broad patterns of collaborative science might be related to the degree of document sharing and/or idea integration at meso-levels. For example, analyses of proposal generation across entire fields, such as could be done using data from funding agencies, could be supplemented with follow-up methods that look at successful and unsuccessful proposals and how team interactions are related to behaviors like more openly sharing methods or findings within proposal writing teams.

In sum, we can improve explanatory power by using this cross-level assessment approach to better diagnose causal factors associated with collaboration effectiveness. By moving the analytical lens either one level up, or one level down, we may be able to shed new light on important factors associated with collaborative problem solving in science teams.

4.4 Conclusions

As the technological landscape evolves, so does our ability to study collaborative problem solving. And, although effective collaboration is our end goal, we need to recognize the importance of leveraging the complementary approaches found among different disciplines in order to optimize our processes and understanding. The methods of different disciplines can provide greater insight into the assessment of collaboration than those of any single discipline alone. Further, it seems that *understanding collaboration* from several levels of analysis provides its own *opportunity for collaboration*. In particular, theory building across levels presents the means through which researchers across disciplines can collaborate to develop robust methods of studying and assessing interaction and collaboration (cf. Cikara & Van Bavel, 2014). By encouraging a broader approach to existing research questions, we can use this collaboration to our advantage.

These levels, taken together and separately, can leverage our existing knowledge to ultimately design and build collaborative measures for better understanding and assessing collaborative skills. Using a multi-level approach, we can draw comparisons between these levels to better inform the design of educational assessment. We are not limited to measures at one isolated level; team members and students alike must integrate their own knowledge with the environment and with their other team members. Using the theoretical and empirical advances we have recently made in the educational domain requires a level of understanding from multiple domains: psychology, biology, neuroscience to name a few, and more importantly, effective assessments that can be deployed in the environment of the learner. Drawing from the tools of disciplines pursuing research on collaboration and the need to assess collaboration from a learning perspective, we can identify some intersections and pinpoint areas for further research if we focus on a multi-level approach.

In sum, the purpose of this chapter was to demonstrate how multiple levels of analysis can inform our understanding of collaboration and our ability to develop tools, methods, and novel approaches for assessing collaboration. Just as the microscope uncovered the hidden layers of biological systems, these technologies are revealing the complex inter-connections within and across social systems. What must be recognized, though, is that these technologies are helping us better understand the concepts and constructs and the theories we have already developed. That is, they are providing a new perspective on concepts such as coordination, or communication, or even cooperation and conflict. With this chapter, we hope to push the field forward so as to capitalize on these developments. To do this, groups and teams researchers need to broaden their own collaborations and share new methods and measures. Further, stronger ties with experts in psychometrics and assessment are an additional form of interdisciplinary collaboration necessary to enhance the accuracy and the precision of these new methods and technologies. Only then, can we begin to generate *new* constructs and concepts in groups and teams research. And, only then, can we reap the intellectual rewards that these technologies promise through the development of new theories that transcend disciplines and provide a fuller understanding of groups and teams.

Acknowledgements The writing of this chapter was partially supported by Grant SES-0915602 from the National Science Foundation and Grant NAKFICB10 from the National Academies of Science Keck Futures Initiative, both awarded to the first author. The views, opinions, and findings

contained in this article are the authors and should not be construed as official or as reflecting the views of the University of Central Florida, the National Science Foundation, or the National Academies of Science.

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