Citation: Chi, M. T. H., & Menekse, M. (2015). Dialogue patterns that promote learning. In L. B. Resnick, C. Asterhan, & S. N. Clarke (Eds.), *Socializing intelligence through academic talk and dialogue* (Chi. 21, pp. 263-274). Washington, DC: AERA.

Dialogue Patterns in Peer Collaboration That Promote Learning

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Interactions often promote greater learning, as evidenced by the advantage of working collaboratively with peers (Dillenbourg, Baker, Blaye, & O'Malley, 1995). The estimated effect size of an individual's learning after working collaboratively ranges from $d = 0.21$ to 0.32 (Slavin, 1995)[1] to $d = 0.66$ (Johnson & Johnson, 1992). However, a significant number of studies have also shown that collaborative learning in small groups (such as triads) does not necessarily promote greater learning (Barron, 2003). In a meta-analysis of classroom learning studies, Lou et al. (1996) found an overall effect size of only 0.17 favoring individuals' learning in small groups compared with no-grouping solo learning, and approximately 28% of the studies they reviewed had null results or negative results. This chapter provides an explanation as to why the findings are discrepant, particularly with regard to small-group learning in dyads. The explanation is derived from a framework we developed for engagement activities that compares *interactive*, *constructive*, *active*, and *passive* (ICAP) ways of engaging with learning materials. The ICAP framework can be applied to all domains and all age groups (Chi, 2009; Chi & Wylie, 2014; Menekse, Stump, Krause, & Chi, 2013).

Our Learning Perspective, Framework, and Examples of Dialogue Patterns

We propose that the benefit of learning from collaboration depends on the type of dialogue patterns the dyads are engaged in. That is, we propose that some dialogue patterns promote greater learning than other dialogue patterns. We start with a brief introduction to our perspective on learning and our framework for overt engagement activities, followed by some examples to illustrate the different dialogue patterns.

A Framework for Engagement Activities and the Constructive-Active-Passive Hypothesis

In order to understand what type of interaction is most effective for learning, we must first understand how an individual benefits from learning without a partner. Thus, we initially developed the framework to differentiate among three kinds of observable activities students can undertake while engaging with learning materials alone (Chi, 2009). We refer to these overt activities as *engagement* activities, to differentiate them from *learning* tasks (such as reading a text passage, listening to an explanation, or solving a problem, to be elaborated below). Our claim is that students' overt activities reflect the covert cognitive processes they are undertaking and, moreover, that overt activities can be differentiated to correspond to underlying cognitive processes. These overt activities, which are supplementary to the learning tasks, can serve as indices for assessing the cognitive processes undertaken by the students, thereby reflecting how engaged they are with the learning materials. Our framework proposes that these activities can be classified and rank ordered (by their benefit to learning) because they correspond to different cognitive processes related to how information is encoded and how knowledge changes as a result of the encoded information. The framework is more fully described in Chi (2009), Chi and Wylie (2014), and Menekse et al. (2013).

To provide a brief illustration, we look at the learning task of reading. A *passive* kind of engagement activity in the context of reading is reading *silently*, during which very little overt behavior is manifested other than that the student is *oriented* toward the text (instead of looking around, for example). The associated cognitive process might be direct storing of the reading materials in an isolated (not integrated) format. Such directly stored knowledge may be inert and not retrievable unless the same specific context is provided.

An *active* engagement activity for the task of reading might be reading *a specifically selected passage out loud* or *highlighting a specific passage* within the text. The defining overt manifestation of an *active* activity is that the student is clearly doing something with the instructional materials, such as selecting an important passage by highlighting it, but the *doing* activity only manipulates the selected materials in some way, without adding any other information to it. The cognitive processes associated with an *active* activity differ from those associated with a *passive* activity. Not only can the selected (or highlighted) passage itself be strengthened in the reader's memory, but the selected passage can also activate a relevant schema related to that passage. This allows new information from the passage to be encoded and embedded with this activated schema, filling gaps.

A *constructive* engagement activity for the learning task of reading might be *self-explaining*, *taking notes*, or *drawing* a diagram about the passages while reading. The defining overt manifestation of a *constructive* activity is that the student generates some new knowledge and inferences beyond what was presented in the materials. For example, the notes and/or diagrams would be new knowledge the student overtly produced. These overt constructive activities reflect cognitive processes such as generating new elaborations, representing information in a diagram, inferring new hypotheses, drawing conclusions, integrating knowledge from two sources, and so on, thereby making the activated schema relevant to the passages richer and more elaborated. Many other examples of engagement activities for various learning tasks can be gleaned from Chi (2009), Chi and Wylie (2014), and Menekse et al. (2013).

The cognitive processes of engagement activities have several characteristics. First, the same cognitive processes are associated with the same kind of overt engagement, even if they are manifested in different types of activities. For example, *highlighting* a selected text passage and *copying* a selected text passage are different activities, but because they are both *active*, the same cognitive processes are associated with them.

Second, the cognitive processes of engagement activities refer to how knowledge is activated, changed, and stored, corresponding to the three modes of overt activities. In contrast, the cognitive processes of learning tasks refer to the information-processing aspects specific to the learning task. For example, reading is a learning task that involves processes of decoding and seeking referential coherence. Problem solving is a learning task that involves searching a problem space and setting goals. These processes of decoding, seeking referential coherence, searching a problem space, and setting goals are not processes that concern which knowledge is activated and how knowledge changes.

Third, each subsequent set of processes subsumes or includes the prior set. That is, the cognitive processes associated with *constructive* (activating a relevant schema, filling gaps, and generating new inferences and new knowledge about the schema) include the cognitive processes associated with *active* (activating a relevant schema and filling gaps or storing the gaps with new information) and with *passive* (storing information directly without integrating with existing knowledge). For example, in order to *construct* more knowledge, a student must first activate the relevant knowledge through *active* activities.

Finally and most important, the cognitive processes postulated for each mode of engagement activity predict the order of the learning outcomes, so that one learns more by undertaking *constructive* activities than by undertaking *active* activities, which in turn enhance learning more than *passive* activities. We call this ordering of levels of learning the constructive-active-passive (CAP) hypothesis.

The results of hundreds of studies in the literature support the CAP hypothesis, as summarized in Chi (2009), Chi and Wylie (2014), and Menekse et al. (2013).

A Variety of Dialogue Patterns in the CAP Framework

The CAP framework and the engagement activities introduced above are tailored to individual learners. In order to understand how dyads learn, we focus on their dialogues. Dialoguing is also an overt activity, as it can be heard and seen. However, our proposal is that the utterances by each partner within a dyad can also be classified as *passive*, *active*, or *constructive* engagement activities, as shown in Table 1. Rows 1 to 5 and columns 3 and 4 identify the activity each partner can be engaged in during dialogue.

In this context, we define *passive* to be the case in which a partner listens and utters agreements such as "uh huh," "okay," "right," and so forth. We define *active* to be the case in which the partner describes what has been stated or repeats what was stated by the other partner or presented in the instructional materials. We define *constructive* to be the case in which one partner elaborates on what he or she said previously or what his or her partner said. By these definitions, we assume that partners cannot both be *passive*; otherwise, there would be no dialogue. Thus, Table 1 shows the options that can occur when two partners dialogue.

In summary, each partner can contribute to the dialogue in different ways. For example, one partner can be *passive*, listening without saying much while the other partner describes (*active*) the learning materials (Table 1, row 1). Both partners can be *active* by restating information in the passage or repeating what the partner said (row 2). One partner may be *constructive* by building on the other partner's idea, while the other partner merely agrees (*passive*) with what was offered (row 3). One partner may explain or elaborate (*constructive*), whereas the other partner repeats or redescribes (*active*) what the first partner said (row 4). Finally, both partners may build on each other's contributions, rejecting some, offering alternatives, and so on (row 5). Thus, when we consider collaborative learning by two indi-

Table 1. Ways Individuals Can Engage While Learning Solo or in Dyads

	Solo		Dyad Partner 1	Partner 2
1.	Passive	<	Passive	Active
2.	Passive	<	Active	Active
3.	Passive	<	Passive	Constructive
4.	Passive	<	Active	Constructive
5.	Passive	<	Constructive	Constructive
6.	Active	=	Passive	Active
7.	Active	≤	Active	Active
8.	Active	<	Passive	Constructive
9.	Active	<	Active	Constructive
10.	Active	<	Constructive	Constructive
11.	Constructive	>	Passive	Active
12.	Constructive	>	Active	Active
13.	Constructive	=	Passive	Constructive
14.	Constructive	≤	Active	Constructive
15.	Constructive	≤	Constructive	Constructive

Note. The less-than, equal-to, and greater-than symbols compare the overall average performance of the two individuals within the dyads with the learning of individuals in the solo context.

viduals, it is obvious that how successfully each learns depends on how each acts or contributes to the dialogue, whether in *passive*, *active*, or *constructive* ways. In Tables 2 to 4, we illustrate these patterns with snippets of dialogues gathered from various studies in our lab.

Table 2 shows a snippet of dialogue from a pair of students collaborating to decide whether to close a less profitable store and/or open a new store, collected in the study of Chi, McGregor, and Hausmann (2000). In that study, 12 pairs of high school students watched a computerized workplace simulation in which the user assumes the role of a new vice president at a small local bank. The vice president is required to solve problems arising at the bank, such as facilities upgrades and customer relations. In the dialogue snippet, Partner A seems to be describing the trends in the revenues (as explained in the simulation materials) in order to make a decision about whether a new branch should open. Partner A's statements that "revenues and expenses at the downtown branch changed" and "revenues have just start like increase and decrease" describe the graphs and other information provided in the simulation; therefore, Partner A is being *active*, whereas Partner B's "Uhh" and "Umm" utterances are *passive*. We are less certain about whether Partner A's subsequent statements about "fluctuating, but now it's leveled off and…" are *active* or *constructive*.

Table 3 presents a snippet of dialogue, slightly modified, between a resident and an attending physician on rounds. The first statement by the resident can be classified as *active* because he is just describing the patient's test results and other measures. The attending physician's first response of "Uh huh" is *passive*, because he is just listening and storing the information. The resident continues with his *active* description, and this time, the attending physician responds, "You said her hemoglobin was 7.7?" This is selective repetition (in the form of a question) of one of the many measures the resident reported, and is therefore an *active* statement. Aside from the passive "Uh huh" the attending physician uttered, the latter part of this dialogue snippet is an example of *active*-*active*.

Table 2. Active-Passive Dialogue

Partner A: "Revenues and expenses at the downtown branch changed…"
Partner B: "Uhh"
Partner A: "revenues have just start like increase and decrease and then leveled off so…"
Partner B: "Umm… yeah… [typing] how do you spell fluctuate"
Partner A: "fluctuating, but now it's leveled off and…"

Table 3. Active-Active Dialogue

Resident:	"Her serum ketones were negative. Her blood gases were a pH 7.29…Her white blood count was 21,000. Her hemoglobin is 7.7 which is slightly lower than the baseline which runs between 8 and 9…"
Attending:	"Uh huh."
Resident:	"Her platelet count was in the high 500s. Umm…"
Attending:	"You said her hemoglobin was 7.7?"

We have defined being *constructive*, for the case of an individual, as stating some new knowledge that was not presented in the instructional materials, through the processes of inferring, deriving, elaborating, postulating, and so forth. However, in the context of dialoguing, a partner's contribution can be *constructive* in two ways. One way is for each partner to build upon his or her own line of reasoning, without considering or extending the other partner's contribution. This type of dialogue pattern could be called *constructive-constructive without interacting*, rather than *co-constructive*. When partners are both *constructive* and *interactive*, in the sense that they build on each other's contributions, we refer to this type of dialogue pattern as *co-constructive*. This definition is analogous to the idea that one partner extends the other partner's ideas (Tao & Gunstone, 1999; Hogan, Nastasi, & Pressley, 1999; van Boxtel, van der Linden, & Kanselaar, 2000). *Co-constructive* dialogues are the most powerful for learning because each partner can benefit from the other partner's perspective, feedback, and knowledge, and they can jointly create new knowledge that neither partner could have created alone.

We are not aware of any coded data that differentiate between these two types of joint construction. In this chapter, we simply assume that the joint constructions in our data are *interactive* by the way we have coded them (to be described below).

Tables 4a and 4b present two snippets of *co-constructive* dialogue patterns. In Table 4a, the dialogue is taken from a dyad of college students revising a bridge design in a simulated environment (Hausmann, 2007), in which the goal is to optimize the given bridge by making it as cheap as possible to build but still able to carry a load. In the dialogue, Mike is being *constructive* by suggesting that they try to make the cross-members smaller in diameter. Dan's response is also *constructive* in adding constraints, such as making the middle cross-members smaller but not the end ones. This is an example of *co-construction* in the sense that they are building on each other's ideas.

Table 4b is a protocol snippet collected in the same study by Chi et al. (2000) described above for Table 2, in which pairs of high school students had to make decisions about a bank. Partner A suggested that the new ATM system would "give the employees…" but did not finish his thought. Nevertheless, it was a *constructive* comment because he presented the idea that the ATM system could give the employees something. And Partner B concluded that it could give the employees more time to deal with the customers. So this is an example

Table 4a. Co-Constructive Dialogue

Mike:	"'Cause usually, I don't know, do you want to try making the cross members smaller (diameter)?"
Dan:	"Um, we could—just the ones in the middle and not the ones on the end."

Table 4b. Co-Constructive Dialogue

Partner A:	"Okay, the new system would give the—give the employees…"
Partner B:	"More time to deal with the customers."

of co-construction in which a complete new idea was generated that presumably neither partner could have generated alone.

In summary, what we have illustrated above (and in Table 1, rows 1 to 5, for dyads) is that dialogue can fall into five different patterns. Only one of the patterns is *co-constructive*. Assuming that we do not differentiate between the two partners and only consider whether a dialogue exchange is active-constructive, active-active, and so on, and assuming that each of the five patterns occur with equal frequency, then Table 1 (rows 1 to 5) predicts that only 20% of the dialogue interactions may be the *co-constructive* kind. In our analyses of two different sets of data, one to be described below on students working on kinematics problems (Hausmann, chi & Roy, 2004, Fig. 1), and the other one described above on learning from a computerized workplace simulation with protocol snippets shown in Tables 2 and Table 4a (Chi et al., 2000), we coded and counted the frequency of the *co-constructive* dialogue pattern and found them to be 20% in both sets of data, exactly the proportion that our framework in Table 1 (rows 1 to 5) predicts.

Collaborative Learning Data

In this section, we present data collected in our lab that support the interpretation suggested by our framework: that different dialogue patterns promote differential amounts of learning. Two predictions need to be confirmed: the degree of an individual partner's learning within a specific type of dyadic interaction (such as how much each partner learns in the context of a *constructive-passive* dialogue pattern) and the degree of learning as a function of the dyadic pattern of dialoguing (such as comparing *constructive-passive* with *constructive-constructive*). For both cases, we assess the individual partner's learning as a function of the type of dialogue pattern they participated in.

Individual Partner's Learning Within Constructive-Passive

The first prediction is that the contribution of each partner in a dialogue determines the degree to which each partner learns; therefore, we should see evidence of differential learning for each partner as a function of his or her engagement activities. For example, if dyads participate in a *constructive-passive* type of dialogue pattern, our framework predicts that the *constructive* partner should learn more than the *passive* partner.

The data for this prediction were taken from a larger study (Chi, Roy, & Hausmann, 2008). We analyzed data from two of the five conditions from that study (Hausmann et al., 2004). The two conditions were 10 pairs of undergraduate partners solving kinematics problems with a text and 10 solo undergraduates solving the same problems with the same text.

The participants had to learn the first four chapters of the text and the conceptual part of the fifth chapter to a criterion. Then they were given a pretest that assessed their understanding of nine concepts related to kinematics. After the pretest, they were randomly assigned either to solve three problems taken from the fifth chapter with a partner or to solve the three problems alone. Finally, they took a posttest that was identical to the pretest. A total of 59 problem-solving episodes from the collaborative condition were analyzed from this corpus. An episode was defined as several dialogue turns dedicated to a single concept.

Of the 59 episodes, only 12 (20%) were co-constructed (we did not differentiate *co-constructive* from *constructive-constructive* without interactions), providing exactly the proportion predicted by our framework (see Table 1, rows 1 to 5, of the dyad columns; only row 5 is the *co-constructive* row). Of these 12 co-constructed episodes, 8 (67%) led to learning gain on the posttest of the concepts discussed with a partner.

Some of the remaining non-co-constructed episodes clearly show one partner being *constructive*. The pretest allowed us to determine precisely whether a student had learned a specific concept before a collaboration episode. Thus, for each of the non-co-constructive episodes, we could determine whether each partner already knew the concept or did not know and therefore must have been in the process of learning it while discussing it with his or her partner. When a partner who did not know the concept talked about it during collaboration (asking questions, explaining, etc.), we considered this a *constructive* contribution. However, if the partner already knew the concept, then he or she merely retrieved and repeated what he or she already knew, and we considered this an *active* contribution. There were 17 non-co-constructed episodes in which one partner was *constructive* as determined by lack of knowledge at the time of the pretest ("the speaker") and the other partner was *passive* ("the listener"). The number of concepts gained by the speaker was 71%, whereas the listener gained only 29%. Such differential gains by the two partners confirm our framework.

Dialogue Pattern Determines Amount of Learning

The second prediction of our CAP framework is that some dialogue patterns produce greater learning compared with other dialogue patterns. Rows 1 to 5 for dyads in Table 1 suggest that learning for dyads should be the greatest in the *constructive-constructive* dialogue pattern, followed by *constructive-active*, *constructive-passive*, and *active-passive*. Because we are examining the individual partner's learning within a dyad, we predict that partners who participate in a dialogue pattern that involves at least one *constructive* partner will learn more than partners without any *constructive* contribution, and so on.

Our data for this prediction are taken from a study in which Menekse and Chi (2013) investigated to what degree pairs' collaborative dialogues influenced the learning outcomes of the individual partners. This study consisted of a sample of 48 undergraduate engineering students (24 pairs) at a large state university. Their task was to solve a problem related to atomic bonding and physical properties, using two graphs, two figures, and a worksheet. Taken together, the materials provided a guided inquiry-oriented activity in which the data and/or information embedded within the graphs and figures followed by question prompts supported students in constructing their own reasoning and conclusions. Each student was randomly matched with another student and asked to work collaboratively while we videotaped them.

We used a pretest-posttest design to measure students' prior knowledge and their learning from the intervention. The pretest included 24 questions closely aligned with the content covered in the learning materials; the posttest consisted of the same questions and 6 additional questions.

We coded students' dialogue for each worksheet question in a holistic manner on an ordinal scale ranging from a score of 1 (i.e., consisting mostly of contributions from one student) to a score of 3 (i.e., consisting mostly of both students contributing and building upon each other's comments in a *co-constructive* manner). The coding was based only on contributions that were "substantive," which we have previously defined as meaningful comments pertaining to the ongoing discussion (Chi et al., 2008). The coding focused on capturing instances of a shared line of reasoning rather than two distinct lines (i.e., *co-construction with interaction* would get a score of 3, whereas *construction-construction without interaction* would get a score of 2).

This three-step holistic coding could not map exactly to our five-level framework, because our unit of analysis is the dialogue contribution produced while answering each of the worksheet questions, and each segment of dialogue can have a mixture of dialogue patterns.

Two raters coded 10 of the 24 transcribed protocols individually. The initial agreement was 82% for the dialogue-pattern scores. The disagreements between raters were discussed and resolved. The rest of the transcripts were coded by one of the raters. Each pair received one score as an average across five question segments. Overall, the average dialogue pattern scores for pairs ranged from 1.00 to 3.00. The average score across 24 pairs was 1.83. The proportion of dialogue patterns scored as 3 was 21.4%.

We correlated (using the Pearson product-moment correlation coefficient) the pairs' dialogue pattern scores and their average normalized gain scores, computed by the following formula: normalized gain score = (posttest % – pretest %)/(100 – pretest %). The correlation was significant, $r(22) = .47$, $p < .05$.

The correlation confirms that the effectiveness of collaborative learning may depend on the dialogue patterns. To further confirm our interpretation, we compared the normalized learning gain scores between the 12 pairs with low collaboration scores and the other 12 pairs with higher collaboration scores. The one-way analysis of variance results was significant, $F(1, 22) = 14.10$, $p < .01$, $\eta^2 = .39$, suggesting that dyads with more constructive dialogue patterns overall learned more than dyads with less constructive dialogue patterns.

In sum, the two sets of data presented here suggest that the success of collaborative learning depends on the dialogue patterns in which dyads engage. The first set of data shows that within a collaborative dyad, the more constructive partner (the speaker) learns more than the less constructive partner (the listener), and the more constructive the speaker is, the more likely it is that he or she learns. Moreover, the fact that there are learning differences suggests that our approach—to reduce dialogue to its individual contributions—is legitimate. The second set of data shows that some dialogue patterns enhance learning more than other dialogue patterns. More specifically, the *co-constructive* type of dialogue pattern is the most enhancing, because the dyads contributed to each other's ideas in an interactive way.

Why Collaborative Learning Is Not Always Better Than Individual Learning

In this section, we explain why the data in the literature show discrepant results with respect to how well individuals learn in a dyadic context as compared to how well individuals learn in a solo context. As mentioned above, although the value of collaborative learning has been well documented across domains, some studies showed that collaboration does not facilitate learning (e.g., Barron, 2003; Dillenbourg et al., 1996; Phelps & Damon, 1989). Numerous reasons have been proposed, including (a) the lack of elaborated explanations, (b) the poor quality of arguments, (c) no negotiation of meanings (Dillenbourg & Hong, 2008), (d) the lack of mutual regulation of cognitive processes, (e) the lack of discussion of proposed ideas or failure to build on them (Barron, 2003), (f) few unique ideas generated, and (g) not enough time given to evaluating alternative explanations (Sampson & Clark, 2011).

To explain more specifically the conditions under which dialoguing can enhance learning, we must revisit Table 1. Column 2 of Table 1 makes a prediction about each row, comparing the individual's learning outcomes in the solo and the dyad conditions. When an individual in a solo context is *passive* (rows 1 to 5), it is reasonable to assume that dyads (rows 1 to 5) would all learn more, since there are benefits to dyads even when neither partner is *constructive*. However, when individuals learning alone are *constructive* (rows 11 to 15), collaboration would produce greater learning only when both partners undertake *constructive* activities (row 15) or when one partner is *constructive* and the other is *active* (row 14). This is because the *active* partner at a minimum hears the *constructive* partner's contributions and can activate the relevant knowledge and embed the new contribution (as assumed in the processes of being *active*). Using the cognitive processes associated with each type of engagement activity, we can predict similar comparisons among the other dialogue patterns (rows 6 to 10).

With regard to the question of when individual learning is greater, in four of these comparisons (rows 6, 11, 12, and 13) we might agree that the individuals could learn more than the dyads (assessed individually). This suggests that 26.6% (4 of 15) of the time, we might get results showing that collaborative learning by dyads is no better than learning individually or may be worse. Note that this estimated percentage matches pretty closely the 28% of published studies showing null or reversed effects, when individual learning is compared to small group learning, from the meta-analysis carried out by Lou et al. (1996).

One way to support our conjecture that collaborative learning cannot always be more productive than individual learning is to compare the data we described in Menekse and Chi's (2013) study with another condition from the same experiment. The data we described above were collected from the collaborative condition, in which students were encouraged to dialogue and interact. Menekse (2012) also ran 24 participants in a solo condition, in which they were given the same materials and instructions as the collaborative condition (interpreting the graph with the scaffolded worksheet questions).

We can compare how much students in this solo condition learned, as compared with participants in the collaborative condition, according to their dialogue-pattern scores (as described earlier). Figure 1 shows the average adjusted learning gain scores for students in the solo *constructive* condition compared with the students in the collaborative condition, with the latter divided into those with high dialogue-pattern scores and those with low dialogue-pattern scores. If we assume that a high dialogue-pattern score means the partners

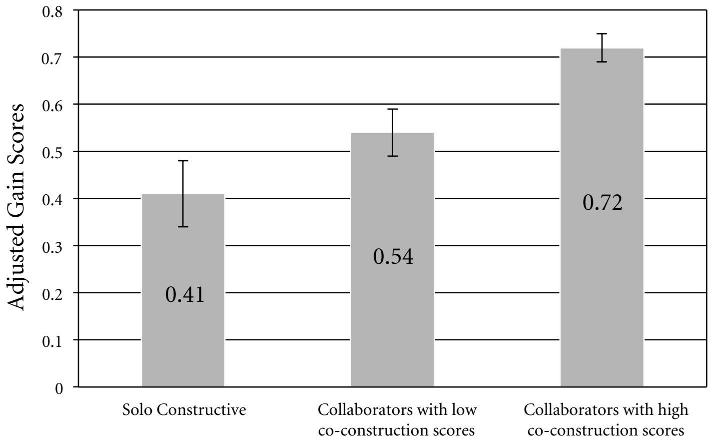

Figure 1. Average adjusted gain scores across students in the solo constructive condition and collaborative condition.

participated more in a *co-constructive* dialogue pattern (more like row 15), and a low dialogue-pattern score means the partners participated in more of a *passive-constructive* pattern (row 13), then the results in Figure 1 support our prediction. Figure 1 shows an equivalent (not significantly different) amount of learning between solo versus collaborative conditions for pairs with low dialogue-pattern scores and greater (significant) learning in the collaborative over the solo condition for participants with high dialogue-pattern scores.

In addition, when both partners undertake *constructive* activities, then interactive learning can be more productive than solo *constructive* learning because interactions have additional benefits. For example, if each partner *constructs* in response to his or her partner's contributions—building on each other's ideas, challenging each other, trying to take the partner's perspective—then they can create a solution or a product that neither partner could build on his or her own.

We do not know the probability of each dialogue pattern's occurrence. If we imagine them to be equal, the collaborative condition can enhance learning more than the solo condition about 75% of the time. In practice, our framework suggests that more often than not, *interactive* learning in dyads is better than *constructive* learning alone, which in turn is better than *active* learning alone, which is better than *passive* learning alone. We call this the ICAP (interactive-constructive-active-passive) hypothesis (Chi & Wylie, 2014; Menekse et al., 2013). ICAP can also provide a coherent interpretation of why interactive learning is not always better than solo learning. ICAP's explanation, moreover, is consistent with the majority of the reasons provided in the literature (listed above).

Conclusions

The goal of this chapter is to understand why collaborative learning is not always better than solo learning, as shown by the findings in about 28% of the studies. To explain this finding, we started with the assumption that certain dialogue patterns promote greater learning compared with other dialogue patterns. We analyzed dialogue patterns by applying the ICAP framework to each partner's contribution within a dialogue. The CAP part of the ICAP frameworks states that individual students can engage overtly with the learning materials in one of three ways, by being *passive*, *active*, or *constructive*. These engagement activities reflect cognitive processes that supplement the learning processes of a specific learning activity, such as reading or solving problems. Dialoguing can also be considered a type of overt activity, and we operationalized what it means to be *passive*, *active*, or *constructive* in the context of dialoguing. By naming each partner's discourse contribution as *passive*, *active*, or *constructive*, we arrive at five distinct dialogue patterns: *passive-active*, *passive-constructive*, *active-active*, *active-constructive*, and *constructive-constructive* (assuming there is no dialogue in the *passive-passive* case). On the basis of the underlying cognitive processes proposed for each kind of engagement, *constructive-constructive* should be the dialogue pattern that promotes the greatest learning. One set of our data shows a significant correlation between the *constructive-constructive* dialogue pattern and learning. In other words, the more often dyads engage in the *constructive-constructive* dialogue pattern, the more likely they are to learn. Therefore, this set of data gives credibility to the application of the CAP framework to individual speakers within a dialogue.

Our dialogue-pattern framework is further supported by three additional sets of our data, showing that the *constructive-constructive* dialogue pattern occurs only about 20% of the time (one in five dialogue patterns). Because it has the potential to create new knowledge that neither partner could create alone, this pattern produces the greatest learning (assuming the *constructive-constructive* pattern is with interaction).

In order to explain why collaborative learning is not better than solo learning about 28% of the time, we again applied the CAP framework, and associated the five dialogue patterns with the solo individual's contributions as either *passive*, *active*, or *constructive*. On the basis of the underlying cognitive processes of engagement, we can predict more or less which dialogue pattern produces greater learning compared with the solo condition. Again, we estimated that in about 4 of the 15 comparisons (26.6%), solo learning could be equal to or better than dyadic learning. This proportion is compatible with the meta-analysis.

Acknowledgment

We are grateful for funding from the National Science Foundation (Award 0935235) and the Institute of Education Sciences (Award R305A110090) in support of this research.

Note

1. The median effect size is 0.32 based on all tests and 0.21 based on standardized measures.

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