Missing Something? Authority in Collaborative Learning

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Abstract: Past research in individual learning settings has shown that student dispositions such as self-efficacy are predictive of learning and other beneficial outcomes, but the relationship is less clear in a collaborative learning environment. This paper explores authoritativeness of stance within a conversation as a social factor influencing learning and related to self-efficacy in a computer-supported collaborative learning setting. Our results indicate that this authoritativeness measure predicts learning, where an individual's self-efficacy does not, and that student and partner authoritativeness predicts group self-efficacy. Further research is required to better determine the relationship between conversational authoritativeness, individual dispositions, and learning.

Introduction

Research in individual learning settings connected with popular dispositional constructshas demonstrated that intrinsic motivation, mastery-learning oriented goals, and high self-efficacy are predictive of learning as well as positive traits such as persistence (Sheldon & Kasser, 1995; Harackiewicz et al, 2002; Coutinho & Newman, 2008). However, this leaves open the question of what happens when an additional student is added to the learning activity, and we then have a collaborative learning task. Will self-efficacy still predict learning and behavior in this collaborative setting? Or does the absence of considered social factors in these dispositional constructs dilute their predictive value in the face of social comparison, social identity, positioning, and other factors introduced by a collaborative setting?

At the same time that the introduction of a learning partner introduces complications that may interfere with the predictive value of motivational assessments largely optimized for use within individual learning settings, the advantage is that the social interaction makes self-concepts visible through linguistic strategies speakers employ to position themselves within their groups. Thus, as an important part of our work investigating the applicability of constructs such as self-efficacy within a group learning setting, we develop a behavioral measure in the form of a categorical coding scheme through which we can quantify the relative level of authoritativeness of stance between the collaborative partners. In this paper we apply this coding scheme to conversational data by hand, although in the long term, our hope is to be able to automate its application by means of machine learning technology as has been used in prior work on collaborative learning process analysis (Rosé et al., 2008; Mayfield & Rosé, 2011). In this paper we explore the relationship between this proposed behavioral measure of authoritativeness and dispositional attributes such as self-efficacy. If behavioral measures of authoritativeness (or some other automated coding scheme) can be used to predict student learning or persistence, and if these measures can be automated, then the Computer-Supported Learning (CSCL) research community could leverage some of the benefits of individual disposition research, automatically assessed through chat contributions, in naturalistic collaborative learning environments. For example, if we could automatically measure self-efficacy through chat behavior, we may not need to use self-report questionnaires. Self-report questionnaires, while useful in a research atmosphere, are not as plausible in more natural CSCL environments where there may not be an experimenter, or even a permanent instructor.

In the remainder of this paper, we begin by outlining the prior research on assessment of dispositional attitudes. Next, we introduce our operationalization of "authoritativeness" as a behavioral measure capturing one factor that may exist on the social dimension of collaborative learning. We use our measure of authority in knowledge along with self-efficacy to examine learning in a collaborative context as a reanalysis of a dataset from an earlier computer supported collaborative learning study (Ai et al., 2010). We conclude with a discussion of our current directions and future work.

Prior Work

Much prior work has examined the effects of dispositional attributes on learning in individual contexts. In general, measures of intrinsic motivation have been associated with a variety of positive implications. For example, studies have shown that students pursuing intrinsic goals are not only intrinsically motivated, but also portray behaviors enhancing their well-being (Sheldon & Kasser, 1995). Both the pursuit of intrinsic or extrinsic goals and the possession of autonomous or external motives have independent effects on well-being (Sheldon et al., 2004). Additional research based upon help seeking and achievement goal theory (Eccles & Wigfield, 2002; Dweck, 1986; Nicholls, 1984; Harackiewicz et al., 2002) shows that an intrinsic goal-orientation reduces help seeking avoidance and increases the likelihood of more optimal help seeking strategies (Newman, 1990; Ryan

& Pintrich, 1997). Self-efficacy is a strong predictor of learning and motivation in individual environments (Zimmerman, 1999), which strongly suggests it may have invaluable potential for collaborative environments. In this paper we will focus on Bandura's (1977) theory of self-efficacy in a thermodynamics collaborative task. Academic self-efficacy is a student's perceptions of her academic capabilities, interpreted from previous mastery experience, vicarious experience, verbal and social persuasions, and emotional and physiological states. Self-efficacy beliefs contribute to the choices students make, as well as their persistence and effort expended.

Despite this substantial body of positive results, these constructs would seem logically to have implications within collaborative learning settings as they have been demonstrated to have in individual learning settings, but little work has investigated how these traits influence behaviors within those social contexts. When these dispositions are examined in collaborative settings, the picture is far more complex. These measures sometimes continue to predict learning, but often predict something else at the same time. For example, Darnon et al (2006) shows that differing achievement goal orientations result in different approaches to mediating conflict through epistemic regulation for mastery-oriented students and through relational regulation for performance-oriented students. However, beyond this, little work has been done to unite self-efficacy with collaborative learning. One explanation for the murkiness of the relationship between individual dispositions and collaborative learning is that two students collaborating together is more than just two individuals with a common task. The same discussion that produces the cognitive conflict leading to learning (Piaget, 1985) adds a dynamic social dimension to the learning activity that may introduce other factors that interfere with the causal relationship between individual dispositions and learning.

For group situations, collective efficacy has been proposed as an alternative. According to Bandura (1997), collective efficacy is several individuals' combined perception of the group's capabilities to perform given tasks. As an example of its application, Wang & Lin (2007) examine self-efficacy in a collaborative learning task, where they incorporate collective efficacy to determine how the self-efficacy configuration of three-person groups predicts collective efficacy and usage of high-level cognitive skills during discussion. While Wang & Lin (2007)'s results suggest a relationship between homogenous collective efficacy, high-level cognitive skills, and group performance, the results are less clear for heterogeneous self-efficacy groups.

In this paper, we propose a conversational analysis framework for encapsulating the social positioning dimension of collaborative tasks, with the goal of eventually automating the process of identifying instances of social shift. We introduce an abbreviated framework for identifying authority in dialogue, which we later use to examine social positioning.

The Authoritativeness Framework

It is reasonable to believe that the social interactions that occur during a collaborative task influence learning and the effect that dispositional attributes have on learning. So, in addition to examining traditional dispositions (in this study, self-efficacy) via self-report, we propose a framework for looking at authoritativeness of knowledge presentation. In short, an authoritative presentation of knowledge is one that is presented without seeking external validation for the knowledge.

The Authoritativeness Framework we introduce in this paper is rooted in Martin's Negotiation Framework (Martin, 1992), from the systemic functional linguistics community. This work highlights the moves that are made in a dialogue as they reflect the authoritativeness with which those moves were made, and gives structure to exchanges back and forth between participants. Previous work has studied the complexity of, for instance, the difference between authority to alter the direction of a conversation and authority to contribute new information to a conversation (Martin, 2000). In its use within the systemic functional linguistics community, it has been used as a way to distinguish between classrooms where the reasoning of the teacher is at center stage from those where student reasoning is the focus (Veel, 1999). It has also been used to investigate subtleties about distribution of power in juvenile trials (Martin et al., 2008), in keeping with the emphasis in the systemic functional linguistics community for using analysis of language to support social justice. We are interested in this framework because of its descriptiveness for social interactions, and how it boils down the intricacies of power management within an interaction to a few simple codes, making it easy to track shifts in positioning over time.

While the Negotiation framework as formulated by Martin is highly descriptive for sociolinguists, and has been widely used by Martin himself as well as by other sociolinguistics, it is difficult to replicate reliably from the previously published formulations, as this was not a methodological goal of the original researchers. This makes its immediate use for quantitative analysis difficult without introducing threats to internal validity. To remedy this, we have worked iteratively on a coding manual that incorporates the insights from that framework that are relevant to our task and makes them precise and concrete enough to be reproducible. Our inter-rater agreement for this coding has achieved a Cohen's Kappa of 0.78. A full treatment of the details of our development process is beyond the scope of this paper, but is discussed more in depth in Howley et al (2011). We would like to acknowledge that we developed this Authoritativeness Framework through consultation with

experts from a variety of backgrounds (sociolinguists, computational linguistics, computer scientists, interaction analysts, learning scientists, sociocultural and education researchers, etc).

Our formulation of the Authoritativeness framework is comprised of two dimensions with six and three codes, respectively, and incorporates structural and pragmatic knowledge of language based on the Negotiation framework. To simplify our analysis for this paper, we will focus on two moves in particular. The first is K1, or 'primary knower', and the second is K2, or 'secondary knower'. A 'primary knower' move includes a statement of fact, an opinion, or an answer to a factual question, such as 'yes' or 'no'. It only counts as 'primary knower' if it is not presented in such a way as to elicit an evaluation from another participant in the discussion. Conversely, a 'secondary knower' move includes statements where the speaker is not positioned as authoritative on the topic at hand, such as asking a question eliciting information, or presenting information in a context where evaluation is the expected response or formulated in such a way as to elicit feedback. A brief overview of the codes from our Authoritativeness framework is shown in Figure 1.

Code	Meaning	Example
K1	Primary Knower	"This is the end."
K2	Secondary Knower	"Is this the end?" and "This is the end, right?"
A1	Primary Actor	"I'm going to the end."
A2	Secondary Actor	"Go to the end."
ch	Challenge	"I don't have an end marked."
o	Other	"So…"

Figure 1. An overview of the codes included in our Authoritativeness Framework.

There is no strict form-function relationship between these codes and the text being analyzed. The simplest example of this is a line such as 'yeah', which could be authoritative in response to a question or could be non-authoritative response to someone else's evaluation. Additionally, factual statements where the speaker is uncertain of their correctness and is looking for approval from a listener would be coded as a K2 move, even though it is structurally similar to most K1 moves. The roles that speakers take through these codes can shift rapidly within a conversation, and are dynamic, being heavily based on the context of what has happened leading up to an utterance, and how that utterance is responded to by other participants.

	Name	Text	Authority
1	**Student1**	any idea what we open to start?	K2
2	**Student2**	I just opened the reheat cycle.	K1
3	**Student2**	It's blank, and it's already a system.	K1
4	**Student2**	We can substitute values in as we go.	K1
5	**Student1**	hm okay	o
6	**Student1**	do you understand how to maximize the efficiency of a reheat cycle?	K2
7	**Student2**	I think I do, but since we have opposing goals I'll be helping you along to a point. =)	K1
8	**Student2**	Anyway, we have constants that we have to deal with such as the material being SS and the fluid being water	K1
9	**Student1**	woah woah woah	o
10	**Student1**	what's your goal?	K2
11	**Student1**	efficiency?	K2
12	**Student2**	No, no, I'm going for green	K1
13	**Student2**	Yay team.	o
14	**Student2**	Anyway, did you want to do reheat or simple?	K2
15	**Student2**	You seemed to have reservations before.	o
16	**Student1**	I think reheat.	K1
17	**Student1**	I'll explore the simple one quickly.	A1
18	**Student2**	By the way, I take it your goal is power?	K2
19	**Student1**	yup	K1
20	**Student2**	Great...	o

Figure 2. An example analysis using Martin & Rose's (2003) Negotiation system, labeled as Authority.

For example, looking at Figure 2, we will see that the roles of primary and secondary speakers is highly volatile and does not appear to carry any particular lasting significance with respect to status distribution within the conversation. Rather than signify any persistent difference in status distribution between the two students in Figure 2, this frequent shifting in speech roles serves to underscore the equal footing between the two students despite the fact that Student2 is clearly more knowledgeable. Furthermore, speech roles are meaningful even where transitory in that they signify which speakers are treated as the source and recipient respectively of the information or goods and services being exchanged. Thus, it allows us to ask not only which speakers are cast as authoritative within an interaction, but authoritative with respect to what.

We can examine the working dynamics of group members and compare what group behaviors are visible in teams with different compositions of authoritativeness and learning gain. Groups where both students are highly authoritative share characteristics. Their exchanges largely consist of statements of fact or proposals for answers to questions from the tutor. Both students appear to understand the concepts that they are discussing, and they often come to similar conclusions. Thus, there is little debate before coming to a consensus.

Figure 3 is an example of a group in which both students are highly authoritative. The only secondary knower (K2) move, line 2, is a proposal for an answer to the tutor, albeit one that is phrased to ask for evaluation from the other student. The rest of the moves are assertions. While there is a disagreement between lines 1 and 2, the justification of each student's stance are given as factual statements (at lines 3 and 5), and the consensus is phrased by each student as if they are authorizing the final decision (lines 7 and 8).

	Name	Text	Authority
1	**Student5**	alright so around 11,000 kPa	K1
2	**Student6**	So that would be, like, 14,000 kPa?	K2
3	**Student6**	Because right after that your graph starts going down faster	K1
4	**Student5**	Yea	K1
5	**Student5**	But the peak is a little higher towards 11,000	K1
6	**Student5**	But whatevs	-
7	**Student5**	I'll take 14,000	K1
8	**Student6**	Cool. 14,000 kPa it is.	K1

Figure 3. A sample of discussion from two students with high authoritativeness ratios.

In other common situations, however, the authoritativeness of the two students is very distinct, with one student taking on an authoritative tone and the other being much more submissive. This usually comes in the form of one student asking 'permission' when suggesting new ideas, and the other student making a habit of affirming those questions and giving new information as primary knower (K1) moves.

	Name	Text	Authority
1	**Student9**	you want lowest waste heat...	K1
2	**Student9**	So 20,000 kpa?	K2
3	**Student9**	and mine is that peak at the net power output	K1
4	**Student8**	need to watch out for the quality	K1
5	**Student8**	Oh	-
6	**Student9**	So we want the same pressure then basically?	K2
7	**Student8**	cant have pmax more than 6,574ish	K1
8	**Student8**	but that could change based on the temperature coices	K1
9	**Student9**	So...like...	-
10	**Student9**	6800? Or something?	K2
11	**Student8**	That's probably about right	K1

Figure 4. A chat example between two students with unequal amounts of authoritativeness.

Above, in Figure 4, is an exchange with an unequal ratio of authority, a common pattern. Despite the fact that both students are proposing new ideas, one student repeatedly phrases them without authority (lines 2, 6, and 10). In this case, since the more authoritative student disagrees with these proposals (lines 4 and 7), the tone of the student becomes less authoritative over time. Meanwhile, the more authoritative student has taken on a tutor-like role, confirming or rejecting suggestions from the less authoritative student as seen on line 11.

Figure 5 shows a sample discussion from two students with learning losses (i.e., negative learning outcomes). In this chat log there were very few exchanges of authoritative statements, and this example is exemplary of the other authoritative exchanges through the rest of the discussion. Notice that many of the contributions are responses submitted to be evaluated, often denoted by question marks and coded as secondary knower statements. The two primary knower statements on lines 5 and 8 are either uncertain evaluations of the other student's authoritative contribution, or are very brief. Similar to Figure 4, we also see here a trend throughout the design activity where Student3 performed more primary knower statements than his partner. We performed analyses similar to (and including) the examples above in order to explore authoritativeness as a social factor affecting learning in collaborative settings.

	Name	Text	Authority
1	Tutor	...Remember the important relationship between Pmin and Environmental impact. Try to think about how much Pmin can be reduced without violating any constraints.	
2	Student3	so if pmin is about...110? Kpa	K2
3	Student4	is that above .85?	K2
4	Student4	quality	
5	Student3	probably not, i can't eyeball it	K1
6	Tutor	Right .	
7	Student4	125ish?	K2
8	Student3	k	K1
9	Student4	i think tutor's insulting my ability to read graphs	

Figure 5. A sample of discussion between two students with poor learning gains, coded for authoritativeness.

Methods

The data we analyze in this paper was collected as part of a research study in which alternative forms of support for online learning were contrasted in a mechanical engineering course. 106 undergraduate students from a thermodynamics class at Carnegie Mellon University participated in the study by attending one of six lab sessions, in which time was strictly controlled. Students were given software training and practice (60 minutes), a pre-questionnaire and pre-test (10 minutes), the experimental manipulation (40 minutes), and then the post-test and post-questionnaire (15 minutes). The experimental design activity consisted of randomizing students to pairs, and then assigning each partner to design either an eco-friendly power plant or a power- proficient power plant. Opposing goals were used to encourage discussion and negotiation amongst partners. In all conditions, a tutor agent participated with the students in the chat in order to offer support. The entire lab session took place in a single computer lab, in which the researchers ensured that partners did not sit next to each other. The experimental manipulation took place during an online collaborative design discussion and consisted of modifying tutor behaviors only. In all other respects, the student experience in all conditions was the same. Results of the experimental manipulation are not discussed in this paper as they have been published separately (Ai et al., 2010).

Software

Students used Cyclepad (Kumar et al, 2007), a computer software simulator that allows users to implement thermodynamics design ideas via a graphical interface. Specifically, students must consider trade-offs between power output and environmental friendliness in designing a Rankine cycle, which is a type of heat engine. Essentially, students use Cyclepad to design simulated power plants.

Pairs of students used ConcertChat (Stahl, 2006), collaboration software enabling communication through a chat window (similar to instant messaging) and a whiteboard for sharing graphical information. ConcertChat has its origins in explicit referencing research, as discussed in Muehlpfordt & Wessner (2005) and Pfister & Muehlpfordt (2002).

Experimental Design

The experimental manipulation was a 3X3 between-subjects design. Each student pair was randomly assigned to one of nine conditions. The first independent variable contrasted 3 social conditions (High, Low, and None) where tutoring agents presented differing amounts of social behavior within the chat environment. Our dialogue agent exhibited three different types of socio-emotional behavior in the chat window: showing solidarity, tension release, and agreeing. The frequency of social behavior in our socially capable tutors was determined by a percentage of tutor turns that can be social prompts; specifically, the threshold parameter was 15% in the Low social tutor condition and 30% in the High social tutor. There was no social behavior in the Non-social condition. The task related behavior of the tutor was the same in all three of these conditions. Only the social aspects of the tutor's behavior changed.

For the second three-level independent variable, we designed 3 conditions in which the dialogue agent showed goal alignment either with the Green goal students, the Power goal students, or neither. This manipulation affected only the manner in which task related contributions were made in the conversation, but content was held constant. In this way, students could be in one of three different conditions in relation to the tutor agent, namely: Match (where the student's goal orientation condition matched the alignment of the tutor), Mismatch (where the student's condition is the opposite of the goal alignment exhibited by the tutor), or Neutral (where the tutor showed no bias). In all cases, the tutor presented the same task information. The only difference between conditions was the bias exhibited. For example, where the Green biased tutor might say "What is bad

about increasing the heat input to the cycle is that it increases the heat rejected to the environment," the neutral tutor would say "Increasing heat input to the cycle increases the heat rejected to the environment."

Outcome Measures

As outcome measures, we examined:

- Learning gains between the Pre- and Post- test. 35 isomorphic multiple choice and short answer questions were used to test analytical and conceptual knowledge of Rankine cycles.
- The pre-questionnaire consisted of a brief scale for measuring mastery related beliefs (said to predict self-efficacy), and an alternate version of a self-efficacy question as shown in Figure 6. We combined the mean response of these four questions to form a self-efficacy scale.
- The post-questionnaire was a measure of students' perceptions of task success, and assessment of the quality of the interaction with their partner and with the agent.
- We also analyzed conversational behavior in the chat logs, with respect to their green and power biased statements.
- Conversational behavior was also analyzed with our Authoritativeness Framework.

Q10	I have always had a natural talent for engineering-related subjects.
Q11	I received good grades in my high school math classes.
Q12	I have always done well on science course assignments.
Q13	I am certain I will have completed the "Thermodynamics 1" course well.

Figure 6. Sample pre-questionnaire items measuring self-efficacy and mastery beliefs.

Results

Main effects of data from this study were originally reported and discussed in depth in Ai et al (2010), so here we will discuss new findings related to the self-efficacy pre-questionnaire and authoritativeness analysis. The main effects from the original analysis can be quickly summarized as follows: with the two independent variables (i.e., social manipulation and tutor goal map), the objective section of the pretest as covariate, and lab session as a random variable, there was a significant effect of Social Manipulation ($F(2,94) = 5.27$, $p < .01$) on learning where the Low Social condition was significantly better than the other two, with an effect size of .83 standard deviations in both cases. Other results related to post-questionnaire data and goal-biased conversational data are reported in Ai et al (2010).

Throughout this new analysis, "authoritative ratio" refers to the total number of primary knowing (i.e., K1) statements, over the total number of authoritativeness statements (i.e., K1+K2). Additionally, our results related to authoritativeness did not show statistically significant differences between conditions, and as such, we are not including tutor behavior in our analysis.

Learning Outcomes

The first dimension of our analysis involves examining learning outcomes and how various factors affected student learning. Posttest scores were regressed on the pretest and self-efficacy, but the relationship between self-efficacy and posttest was not significant. In short, individual self-efficacy does not seem to predict learning in this experiment. We can combine authoritativeness ratio and partner-ratio to predict group self-efficacy (the mean of both partner's self-efficacy), and we find a marginal effect of group self-efficacy on learning ($F(1, 103) = 3.29$, $p = 0.073$*).

It is important to note that group self-efficacy can be an important factor to consider. Wang & Lin (2007) found that individual student self-efficacy predicted collective efficacy, and collective efficacy predicted use of high-level cognitive skills in discussion, as well as group performance. In this study we are not currently looking at the usage of high-level cognitive skills in discussion, but we are curious about what other outcomes group self-efficacy may predict.

Looking at our other factor of interest, a linear regression analysis finds that authoritativeness ratio has a significant effect on learning ($F(1, 103) = 4.58$, $p = .0347$**), explaining 41% of the variance ($R^2 = .41$) or 3% of the variance beyond what is explained by the pretest. Where self-efficacy does not predict learning, authoritativeness appears to do so.

Self-Efficacy Beliefs and Authoritativeness

Since authoritativeness predicted performance and self-efficacy unexpectedly did not, it is not surprising that individual self-efficacy is not correlated with authoritativeness by itself. However, when we look at group self-efficacy we find a significant relationship ($F(1, 103) = 8.60$, $p = 0.0041$**) which explains 12% of the variance. So, despite authoritativeness and individual self-efficacy not being related on an individual level, when both partners' authoritativeness ratios are included in an analysis, authoritativeness can predict the group's self-efficacy, which may be more important in a collaborative setting.

Self-Efficacy Beliefs and Goal-Biased Conversation

In our originally published analysis, we investigated how our experimental manipulation affected the goal related bias displayed by students in their conversational behavior. For this analysis, we measure the bias of a student utterance towards the "green goal" or the "power goal" by applying a topic discovery model on our dialogues (Paul & Girju, 2009). Latent Dirichlet Allocation (LDA) models have been widely used to discover topics on large collections of unannotated data by modeling the word distributions represented in the data (Blei et al, 2003). We are using LDA models for the purpose of modeling how users are interacting with each other. For each utterance, we compute a score to represent to which degree the utterance displays a bias towards the green or power goals. When referring to the score for a student's bias towards his own goal, we will affix the word "self." So, if we want to know the average score towards the green goal, for a student who was assigned the green (i.e., environmentally friendly) power plant, then we will look at her Self-Average goal-biased conversation score.

Looking at partner's authoritativeness ratio along with one's own authoritativeness ratio, we find that partner's authoritativeness ratio predicts the Self-Average goal-bias, $F(1, 103) = 4.47$, $p = 0.0369$**, but it only accounts for 4% of the variance ($R^2 = .4$), so this relationship is not particularly informative. Nevertheless, it is interesting that we find evidence that suggests that speakers may respond to the authoritativeness with which their partner is positioned by exaggerating the distinction between his or her goal affiliation and his or her partner's. Further supporting the interpretation that a student's positioning is sensitive to the positioning of her or her partner, we find a negative correlation between the student's authoritativeness ratio and that of the partner, $R(106) = -.27$, $p = .0053$**.

Conclusion

We have seen with this set of data that authoritativeness predicts student learning from a collaborative activity better than self-efficacy. Additionally, both partners' authoritativeness predicts their group self-efficacy (even though individual authoritativeness does not predict individual self-efficacy). We also see a relationship between partner authoritativeness and how a student presents him or herself, both in terms of the extent to which topic affiliation is emphasized as well as personal authoritativeness. Whereas in studies of individual learning self-efficacy predicts learning, in this collaborative learning setting we find that there is a relationship between authoritativeness and self-efficacy, and authoritativeness and learning, but not self-efficacy and learning. These findings suggest that we cannot always rely on disposition research originating in individual settings to predict the same outcomes in collaborative learning settings. Other research on collaborative learning shows that these individual dispositions can predict other behaviors, such as method of conflict resolution, but our results suggest that authoritativeness may be a new disposition that is related to self-efficacy and that can predict learning in collaborative settings. While dispositions are typically considered to have personal causality, the authors believe authoritativeness to be influenced both by personal causes and situational causes to some extent.

This research reveals a considerable amount of potential for explaining collaborative learning through student dispositions and social behaviors. Future work will involve looking closer at the relationship between authoritativeness and other dispositions used to predict learning, such as achievement goal orientation. Additionally, knowing what authoritative combinations of partners produces the best learning gains could also be beneficial for the research community. It would also be necessary to explore how generalizable the effect of authoritativeness is, and if it is applicable to other domains or even learning tasks that are not project-based. Further work is also necessary to automate the process of assessing authoritativeness. If authoritativeness can be measured automatically via computer, it will have additional benefits beyond dispositional factors that are measured through self-report.

In conclusion, this paper shows that authoritativeness is an influential factor in discussion-based collaborative learning tasks that predicts learning and is related to a group's self-efficacy. Further research is required to refine the measurement of authoritativeness, and explore exactly how it is related to other dispositions. The end goal is to better understand the factors that influence learning in collaborative settings so that they may be automatically assessed in real world settings.

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