International Society of
the Learning Sciences

What Brings Students Together?: Investigating the Causal Relationship Between Joint Mental Effort and Joint Visual Attention

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Abstract: Computer-supported collaborative learning has a long history of increasing our understanding of the collaborative process and what fruitful collaborative actions entail. Often, we study the correlational relationships between collaborative process variables but investigating causal relationships may deepen our understanding of the collaboration process by highlighting the nature of the relationship between different collaborative behaviors. In this paper, we examine causal relations between joint mental effort and joint visual attention using Granger's definition of causality. We apply this analysis to dual eye-tracking data from 41 dyads collaborating to create a concept map. The results show that for high-performing dyads, joint mental effort causes joint visual attention and power of the causal relation changes with different division of labor episodes (i.e., role-based, task-based, concurrent). No causality can be claimed for low-performing dyads. We discuss how our results can support our understanding of the cognitive processes students use during the collaboration process.

Introduction and Background

Collaborative learning has the potential to support students in developing a deeper conceptual understanding of the domain material when it is done effectively (Teasley, 1995). To support and scaffold effective collaboration, we need to understand what the collaboration process entails and how students engage with the process. Research on collaborative learning broadly, and computer-supported collaborative learning (CSCL) specifically, has a long history of increasing our understanding of the collaborative process and what fruitful collaborative actions entail (Lou et al., 2001). As part of this effort, researchers have investigated the correlation between different collaborative process measures to find which measures can be used to assess collaboration quality (Olsen et al., 2018; Sharma et al., 2017). More recently, CSCL research has challenged the idea that the presence of fruitful collaborative actions alone is beneficial to learning and, instead, when these actions occur during the learning process may be as important (Csanadi et al., 2018). Although this work has investigated how different collaborative behaviors are correlated and change over time (Olsen et al., 2020; Starr et al., 2018), there is less work on if there is a causal relationship between these measures. These causal relationships are important to investigate because they deepen our understanding of the collaboration process by highlighting the nature of the relationship between different collaborative behaviors. These relationships help us to understand what the collaborative process may entail and how it changes between different groups of students. In this paper, we explore these causal relationships between the joint mental effort and joint visual attention of students working on a collaborative concept map.

Previous research shows that effective collaborative processes for students are those that have students engage in co-construction through which students are able to reflect on their mental model, incorporate their partner's ideas into their model, and construct new knowledge by building upon their partner's ideas (Hausmann et al., 2004). Collaborative learning behaviors can be classified under different schemas, such as transactivity (Joshi & Rosé, 2007) and accountable talk (Michaels et al., 2002), but they all include an element of interactivity between students to be considered effective (Chi & Wylie, 2014). This interactivity can be assessed through a range of measures including coded transcripts, audio, activity logs, and eye tracking (Olsen et al., 2018; Jermann, 2004; Li et al., 2020; Viswanathan, & Vanlehn, 2019). Many of these measures are correlated with one another but also can provide unique information about the collaboration process (Sharma et al., 2021a). Although these correlations inform us of which measures are related, and can, therefore, be used as proxies, they are limited in the knowledge they can provide about the collaboration process in terms of how these relationships are connected. Extending these analyses beyond correlations to investigate the causal relationship between collaboration measures increases our understanding of how these measures relate and can provide insights about what is occurring at the cognitive processes level during the collaborative learning process.

In this paper, we focus our analyses on the information that can be provided through dual eye tracking (DUET). Researchers have used DUET to explain the socio-cognitive mechanisms underlying collaborative learning (Jermann & Nuessli, 2012; Olsen et al., 2018). Information extracted from DUET data can be used to explain collaboration quality (Schneider et al., 2019), task-performance (Jermann & Nuessli, 2012), and learning gains (Olsen et al., 2020). In terms of collaborative learning, Duet can be used to explain certain processes such as mutual modelling (Lemaignan & Dillenbourg, 2015), repairs of misunderstanding (Cherubini et al., 2008), and shared understanding (Richardson et al., 2007). Additionally, DUET can be applied to provide collaborative awareness to peers involved in problem solving (Schneider & Pea, 2015, D'Angelo & Begel, 2017). In most of these studies, Joint Visual Attention (JVA) is used to measure the collaborative mechanisms. All of these studies emphasize a social extension of the eye-mind hypothesis, "what you see is what you process", to "looking together is processing together". More recently, researchers have used Joint Mental Effort (JME), another DUET measure, to complement JVA (Sharma et al, 2021a). This measurement is inspired by Kirscher's view (Kirschner et al., 2018) of how transactive activities can exert cognitive loads on collaborating peers and that the absence of synchrony in the collaboration can be detrimental for collaborative performance (Popov et al., 2017). JME provides an attempt to create a proxy for the collaborative cognitive load synchrony.

In this paper, we aim to answer the research questions of (R1) if there is a causal relationship between JVA and JME for high and low performing students and (R2) if this relationship changes based on the students' current division of labor. We analysed 82 master students working in pairs to construct a concept map related to the resting membrane potential using Granger Causality to answer these questions. Based on previous studies (Sharma et al., 2021a & 2021b), we hypothesized that JME would lead to JVA with high performing students and the opposite with low performing students. Additionally, the current division of labor would impact this causal relationship. Based on the results of these research questions, we discuss our understanding of the collaboration process and how these results inform the development of interventions.

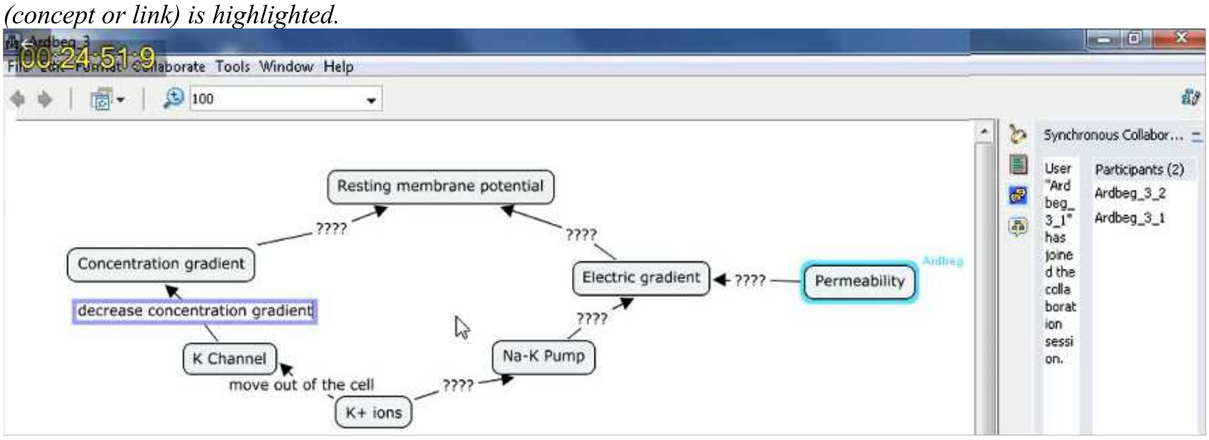
Methodology

Participants, procedure and Data Collection

Eighty-Two master students (16 female) participated in the present study in pairs. To begin the study, all participants individually watched two videos about "resting membrane potential", a topic about which the students had no prior knowledge. The total length of the videos was 17.05 minutes. The videos contained the information required to create concept maps. While watching the videos, the participants had full control over the video player and no time constraints. After completing the videos, the peers were asked to collaboratively create a concept-map using IHMC CMap tools (Figure 1). The collaborative concept-map phase was 10-12 minutes long. Each student worked at their own computer with synchronized screens (i.e., the students could see their partners' actions) and could verbally communicate with one another. There were 14 concepts preloaded on the Concept map tool and the main task for the pairs was to connect the given concepts with correct relationships. They could also add new concepts if they wanted.

Figure 1

An example of the concept map under construction in the CMap tools. The two participants' names are on the top-right side, and their pointers have different colors. Whenever they perform an action, the relevant object (concept or link) is highlighted.



From the interaction of the dyad with the concept map tool, we collected eye tracking and log data. We collected *eye-tracking* data using two SMI remote eye-tracking devices (SMI RED 250) at the sampling rate of

250 Hz. We use a 5-point calibration and a 5-point validation mechanism. The fixation and saccades were identified using the built-in algorithm of the BeGaze software. The *log data* contained all student actions with the system and tracked the timestamp, peer ID, action type (add, delete, move, resize, text edit), conceptID and metadata (Figure 2). For example, if a student adds two concepts with a link, the system would log the time the action took place, the ID of the student, the action as an "Add", the object as "Connection", a newly generated object ID, and metadata tracking the two concepts that were linked.

Figure 2
Snapshot of the log file produced from CMap.

timestamp	SubjectID	Action	Object	ObjectID	Metadata
Mon Oct 28 19:11:30:168	Clynelish_1_1	Move	Concept	ge:1M5NG8B0L-1BJ5XH8-B9	'Resting membrane potential' x:134 y:43 w:188 h:28
Mon Oct 28 19:11:52:232	Clynelish_1_2	Add	Connection	ge:1M88V4FYD-3G09QV-PT	from:ge:1M88V4B39-1JK1H3M-KR to:ge:1M88V4FY8-G83G3M
Mon Oct 28 19:11:53:272	Clynelish_1_2	Move	Concept	ge:1M88V4FY8-G83G3M-PH	'????' x:516 y:280 w:44 h:26
Mon Oct 28 19:12:23:356	Clynelish_1_1	Add	Concept	ge:1M88V5H7G-MLDB4J-2TH	'????' x:488 y:271 w:44 h:26
Mon Oct 28 19:12:24:751	Clynelish_1_1	Delete	Concept	ge:1M88V5H7G-MLDB4J-2TH	'????' x:488 y:271 w:44 h:26
Mon Oct 28 19:12:31:756	Clynelish_1_1	Modify Text	Linking Phrase	ge:1M88V4B39-1JK1H3M-KR	'' x:512 y:282 w:4 h:18
Mon Oct 28 19:12:31:845	Clynelish_1_1	Move	Concept	ge:1M5NG9QK9-Y0RB8H-FX	'Cl channel' x:469 y:325 w:80 h:26

Measurements

Cognitive load similarity as joint mental effort (JME): We calculated the students' JME, a *measure of the cognitive load similarity* using pupil diameter from the eye-tracking data. To calculate JME, we first used the method proposed by Duchowski et al. (2020) to compute the individual cognitive load. Next, we discretized cognitive load to an integer value between zero and ten. Using the cognitive load for both peers in the dyad, we computed a cross-recurrence between two time-series, using the method proposed by Richardson et al. (2007).

Gaze similarity as joint visual attention (JVA): JVA is a *measure of how similar two individual gaze patterns are*. The similarity between the gaze patterns of two collaborating students is the similarity between the two proportionality vectors using the reverse function (1/(1+x)) of the correlation matrix of the two vectors (where x is the distance between the two proportionality vectors). The proportionality vector is created using the proportion of time spent on each concept on the screen. A similarity value of 1 shows complete similarity between the two gaze patterns during a given time window. A lower value of similarity shows that the two participants spent less time looking at a similar set of objects on the screen during the same time window.

Division of labor (DoL): We computed the division of labor using the number actions taken on a specific concept by one member of the dyad and the definition provided by Jermann (2004). Specifically, we compute the Sum of Differences (SD) and Sum of absolute differences (SAD) between members of a dyad using the formulae (1) and (2).

$$SD = \frac{\sum_i (S_1C_i - S_2C_i)}{S_1C + S_2C} \quad (1) \quad SAD = \frac{\sum_i |S_1C_i - S_2C_i|}{S_1C + S_2C} \quad (2)$$

In formulae (1) and (2), S1 and S2 are the peers in a dyad. C is the concept. S1C and S2C are the total number of actions done by peers S1 and S2, respectively. S1Ci and S2Ci are the actions done on concept Ci by S1 and S2, respectively. SD has a range of [-1, +1] with -1 indicating that S2 did all the actions, +1 indicating that S1 did all the actions and 0 depicting equal participation. SAD has a range of [0, 1] with 0 indicating equal participation and 1 indicating that all the actions were done by one peer.

We define three DoL strategies– role, task and concurrent – based on SD and SAD values. The DoL strategy is classified as *role-based* if SAD is in the range [0.5, 1] and SD in either [0.33, 1] or [-1, -0.33] indicating that one student did all of the actions within a certain time window - implying the other student was either a free-rider or acting as a navigator. The DoL strategy is classified as *concurrent* if SAD is in the range [0, 0.5] and SD in range [-0.33, 0.33] during the time window, indicating that the students had equal participation on the same concepts. Finally, the DoL strategy is classified as *task-based* if SAD is in the range [0.5, 1] and SD in either [-0.33, 0.33] during the time window indicating that the students were each participating in taking actions on the concept map, but on different concepts.

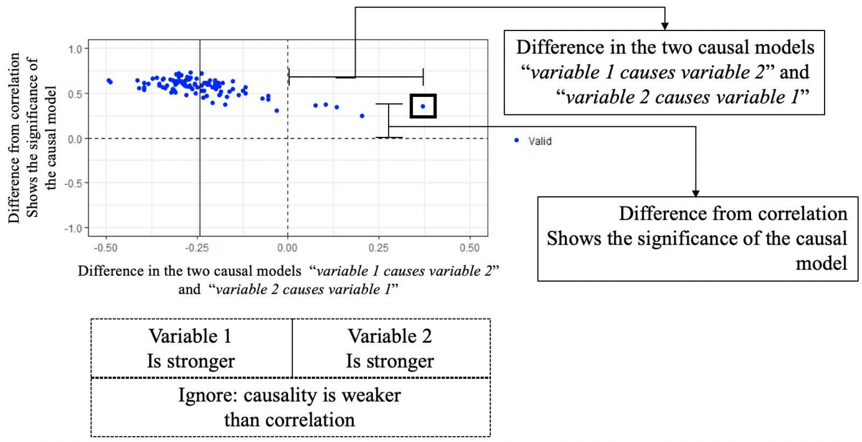
Learning performance: The learning performance for this activity is the *correctness of the concept map*. We asked two domain experts to create a map using the same 14 concepts. All the participant maps were compared against this expert map. We followed the following map-evaluation scheme: 1) 2 points for conrrect link and correct label; 2) 1 point for correct link and no label; and 3) 0.5 point for correct link and incorrect correct label. The sum of all the points was the dyad's performance score. Finally, we applied a median split to divide the dyads into high and low performance groups.

Data analysis

To identify causal relations between JVA and JME, we used the Granger causality test. Granger causality (Granger, 1969) has two assumptions, first is that cause occurs before effect and second is that the cause has information about the effect that is more important than the history of the effect. Granger causality was selected since it has proven usefulness in the context of learning technologies (Sharma et al, 2021a and 2021b). For more details and the mathematical formulation of Granger Causality in the context of learning technologies please see Sharma et al, 2021b. Here we provide a summary of steps so the method can be replicated based on this paper only. Let's assume that we are modelling the Granger causality between two variables X and Y. For each group compute the partial η^2 for the model "X Granger causes Y", the partial η^2 for the model "Y Granger causes X", the partial η^2 for the model "Y linearly predicts X" (this is similar to a correlational model), the difference between the η^2 of the two Granger causal models (this is the effect size or the strength of the Granger causality where a positive value indicates "X Granger causes Y" while a negative value indicates "Y Granger causes X") and the difference between the Granger causal model with higher η^2 and the η^2 of the correlational model (this is the significance of the Granger causality). Once we have the effect size and the significance of the Granger causality for each group, plot them on a Cartesian-coordinate system (Figure 3).

Figure 3

A visualization to summarize causality results for multiple dyads. For dyads, we calculate the difference between the two causal models ('x causes y' and 'y causes x') and the respective difference between causal and correlational models.



Results

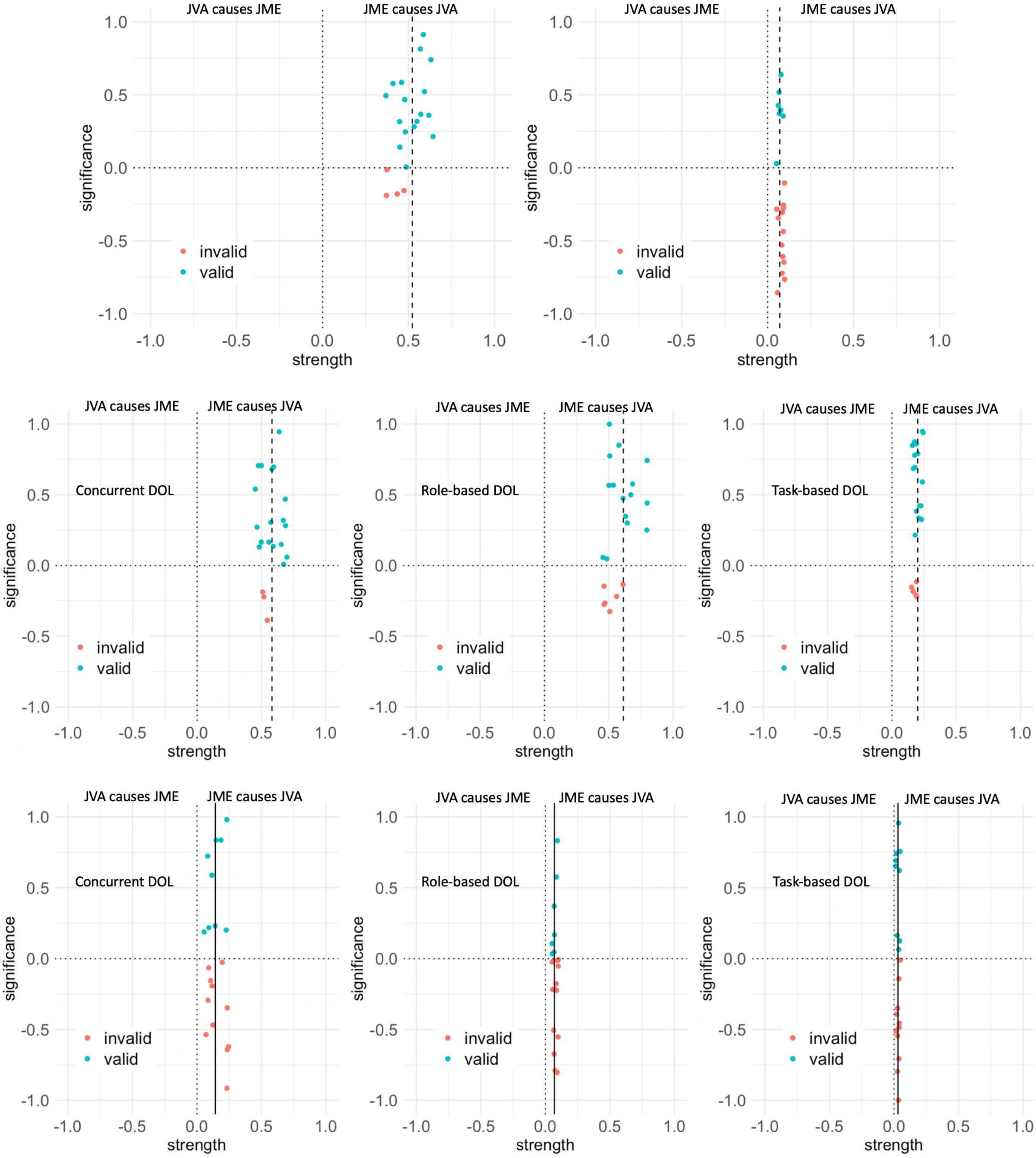
First, we address the research question of if there is a causal relationship between JVA and JME for high and low performing students. For the high performing students, we can observe from the top, left panel of Figure 4 that the most of the points are in the first quadrant. There are also four pairs where the causality does not hold because for these pairs correlation explains the relation between JVA and JME more than any causal model. These points are considered to be invalid in our causal analysis. However, based on the valid points, we can conclude that for the high performing pairs *JME is causing JVA (mean strength = 0.52, SD = 0.08, theoretical max = 1.0, theoretical min = -1.0).* On the other hand, in the top, right panel of Figure 4, there are many invalid points in the set of pairs with low performance levels (many points in the fourth quadrant of the graph). With only the valid points in the analysis we can still say that for all pairs with low performance, JME is causing JVA (mean strength = 0.07, SD = 0.01)**.** However, since there are many invalid points in this set of pairs and the strength of the causal relation for the valid points is very low, we *cannot conclude causality*. However, for most of the low performing dyads, there was a significant correlation between JME and JVA.

Second, we aimed to address our research question of how division of labor may influence causal relationship between JVA and JME. Similar to the above analysis, in the middle of Figure 4, we can observe the causal analysis between JME and JVA for the high performing pairs according to the different DoL-based phases. The average strength of *JME causing JVA* for high performing pairs is the highest for the role DoL (*M* = 0.61, *SD* = 0.11), then concurrent (*M* = 0.58, *SD* = 0.08) and lowest for the task based DoL (*M* = 0.20, *SD* = 0.02).

Furthermore, we can also observe at the bottom of Figure 4 that we can not conclude any causality for the pairs in the low performing group during the role-based (M = 0.06, SD = 0.01) and task-based (M = 0.03, SD = 0.01) DoL phases. This is because for the role and task based DOL phases, there are many invalid points and the strength is very low for the valid points. When we focus on the concurrent DoL-based phases for the low performing groups, we observe that the strength of JME causing JVA increases for the valid points (M = 0.14 SD = 0.06). We can observe weak trends of JME causing JVA for low performing pairs when they are in a concurrent DoL phase.

Figure 4

(Top) Causal relation between JME and JVA for high-performing (left) and low-performing pairs (right), (Middle) Causal relation between JME and JVA for high-performing pairs during different DOL-based phases, (Bottome) Causal relation between JME and JVA for low-performing pairs during different DOL-based phases.



Discussion and conclusion

In this paper, we presented results from a causal analysis between joint mental effort (JME) and joint visual attention (JVA), showing that JME causes JVA for high performing pairs but no causality can be claimed for the low performing pairs. It is important to recall when analysing the results from the causal analysis that a significant causal relationship does not mean that those actions occur more. It just means that when they do occur, one action tends to lead to the other occurring. When the causality is not present, students may still be engaging in these actions.

With this in mind, we can look towards our first research question of how the causal relationship changes between high and low performing students. From previous research, we can form a plausible reason for the differences that we see in causality between high and lower performers. As we know from previous research, effective collaboration has students engaging in co-construction to build on each other's knowledge and actions (Hausmann et al., 2004). Students who are higher performers tend to engage in these types of collaborative processes. During co-construction, students reflect on and incorporate their partner's ideas into their own mental models. If both students are engaged in this process, we would expect them to have high and low mental effort at the same time, leading to a high JME score. Because they are then engaged in this effective co-construction collaborative process, they will look at the same elements at the same time (Richardson et al., 2007; Jermann & Nüssli, 2012). On the other hand, unlike what we had hypothesized, we did not find a causal relationship for low performing students. Students who have lower performance, tend to engage in fewer effective collaborative actions (Chi & Wylie, 2014). In this case, episodes of JME are less likely to be stemming from moments of co-construction. Rather these moments of high JME or JVA may be random or due to other stimuli. Without the underlying cognitive processes driving the collaboration, we may not find a connection between our mental and visual measures.

For our second research question, how the DoL influences the causal relationship between JME and JVA, we will primarily focus on high performance students as no causal relationship was found with lower performance students. We observed that the strength of the causality is lower in the task-based DoL compared to the concurrent and role-based DoL. When students are in a task-based DoL phase, they are working on different parts of the task simultaneously (Jermann, 2004). In this case, we would not expect there to be any relationship between their mental effort as the task may require different levels of mental effort. We would also not expect students to be looking at the same place at the same time as they are working on separate tasks. When students have moments of JME, it may be due to chance rather than collaboration, which may explain the weaker causality in task-based DoL phases. However, there may still be moments when the students consult with their partners, which would first lead to JME followed by JVA if they reference the concept map. In contrast, the concurrent results may seem surprising as the students are already working in the same area of the concept map, so we would expect high JVA but are working on different tasks, so may not necessarily have high JME. Just because students may be looking at the same part of the problem, this did not lead to higher JME. Rather JME leading to JVA indicates that in the moments of high JME, the students may have been more likely to be engaged in collaboration in which they would focus on the same area of the problem. Finally, with roles, previous research has indicated that high performance students tend to have higher JVA and JME than low performing students (ANONYMOUS, year), which may explain the difference in causal relationships. Low performing students may be free-riding while high performing students are effectively collaborating. High performing students may then be co-constructing (Hausmann et al., 2004) leading to high JME and JVA. Low performance students would be more likely to have it be due to chance when they have high JME and JVA if they have free-riding behaviors. What we see from these results is that it is not enough for JME and JVA to just be present, but through an analysis of the causal relationship, we can better understand how the collaborating students engage with one another.

Combining our analyses with existing work on cognitive load estimation from pupil diameter (Duchowski et al., 2020), we can say that JME measures the collaborative process at the cognitive level and JVA measures the same process at an attentive level. Therefore, our analysis extends and strengthens the current knowledge about the problem-solving process by showing that for the high-performing pairs there is not only a top-down process (Gregory, 1950; Friston et al., 2012), but a top-down causal process. That is, the higher-level cognitive process (JME) is causing the lower-level attentional process (JVA). This process is missing for the low-performing pairs, for whom the problem-solving processes are usually bottom-up (Gibson, 2002). For these students, there is still a strong correlation between the cognitive and attentive processes but both JVA and JME are at low levels. This result depicts the fact that there is a lack of collaborative skills for the low-performing pairs (Rummel & Spada, 2005; Weinberger et al., 2005). That is, they cannot communicate in a manner that enables them to share similar levels of mental effort or attention spans.

Although the work in this paper contributes to our understanding of the collaboration process, there are several limitations. We focused on dividing the collaborative session based on the division of labor strategies used by the students. We know from prior works that the dialogues can also be used for this purpose (Sharma et al., 2021a), which is a clear direction to extend the current work. Furthermore, we do not see the causal direction changing in different phases, while other contributions have reported the directionality of causation to change based on the different covariates (Sharma et al., 2021a & 2021b). Future work is needed to understand what may lead to these differences. Finally, we acknowledge that these results and implications are based on a single context and one educational setting, and there is a need for further studies to examine the causality between different process variables to obtain a certain level of generalization.

In terms of practical applications, our results suggest certain feedback options for supporting students. For example, if we observe that a pair's JME is causing their JVA, then we can support them to maintain similar levels of mental efforts by proving them prompts for further discussion or having them to rephrase the content-based dialogues (Wolters et al., 2009; Li et al., 2020). On the other hand, for pairs where we do not see any causality, we can intervene using either JME or JVA. The JME based interventions could include the prompts mentioned above or could also include defining clear roles during teamwork (Costley, 2021; Route, 2009) as the students are more likely to lack these internal scripts. However, it may also be beneficial to guide students' focus to a part of the problem, which may lead to more collaboration (Schneider and Pea, 2015, D'Angelo and Begel, 2017). Past JVA-based interventions have focused on supporting all students rather than focusing only on those that may struggle collaborating as indicated by their lack of causal relationship. Thus, our results could also contribute to informing adaptive collaborative learning support so that the pairs can get the required type of support (JME or JVA-based) at the correct time (Soller et al., 2005; Waler et al., 2011). By understanding how JVA and JME relate to students' cognitive processes, as this paper allows us to explore, we can more effectively use them in interventions.

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