Cognitive and Motivational Effects in Peer-Assisted Learning

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Abstract

Peer-assisted learning has the potential to improve learning in academic settings and beyond. However, the cognitive and motivational effects of learning through interaction with other learners are not fully understood. Here we present an empirical study in which we compare a peer-assisted learning condition with two individual learning conditions. The empirical findings suggest that both positive and negative peer effects may be occurring. A computational cognitive model developed in the ACT-R cognitive architecture is presented and used to explain some of the mechanisms of peer-assisted learning.

Keywords: peer-assisted learning; cognitive modeling

Introduction and Background

Active learning pedagogies characterized by interaction among learners have recently demonstrated some potential to improve learning outcomes. For example, Ulrich, Brewer, Steele-Johnson, Juvina, Peyton, & Hammond (2017) found that implementing team-based learning (TBL) and other active learning pedagogies at a Midwestern university raised the scores on national standardized tests from below to above national averages. While evidence like this is encouraging, it often comes from field studies or classroom quasi-experiments that are notoriously difficult to interpret and replicate. Therefore, there is a need for controlled (and realistic) laboratory experiments in this area.

Humans have an unmatched ability to acquire new knowledge. Some of this learning occurs through interaction with other learners (Rendell, Fogarty, Hoppitt, Morgan, Webster, & Laland, 2011). Under the assumptions that knowledge is unevenly distributed in the population of learners and different learners have different learning experiences, interaction among learners provides opportunities for exchanging knowledge, filling the knowledge gaps in learners' minds, and even creating positive feedback loops that increase the amount of shared knowledge – an effect known in economics as *knowledge spillover* (Phelps, Yang, & Steensma, 2010).

Besides knowledge, engagement and motivation to study can be increased by interaction among learners, through mechanisms such as *social facilitation* (Guerin & Innes, 1984; Zajonc & Sales, 1965) and *positive peer pressure* (Smith & Fowler, 1984). The perceived presence of peers can increase affective arousal (Geen & Gange, 1977), induce a sense of responsibility for learning (Koles, Stolfi, Borges, Nelson, & Parmelee, 2010), or *nudge* individuals toward higher levels of effort (Hough, O'Neill, & Juvina, 2021; Horton & Zeckhauser, 2016).

However, learning from other learners may have negative consequences as well. For instance, individual learners may have incomplete, erroneous, or biased knowledge, which may be compounded by interaction among learners. To mitigate this risk, learners need to learn not only the instructional content but also who to trust among their peers (Collins & Juvina, 2021), so they can filter the information they receive from their peers, that is, learn from trusted peers and ignore or discard information from untrusted peers (Collins, Juvina, & Gluck, 2016). This learning about other learners adds cognitive load to the existing load of learning a particular material.

The presence of peers and peer interaction may add *ambient noise* that may further increase the attentional and cognitive load of peer-assisted learning. For example, Hoxby (2000) showed that boys and girls learn more when there is a larger share of girls among the students in a classroom, an effect attributed to the tendency of girls to be less disruptive to classroom learning activities. More generally, in work environments that require a high level of concentration, participants report higher levels of distraction and stress in open-plan offices as compared to cell offices (Seddigh, Berntson, Bodin Danielson, & Westerlund, 2014).

From a motivational perspective, learners may become too reliant on other learners and less inclined to exert sufficient effort individually to develop and maintain their knowledge base, an effect known in psychology as *social loafing* (Karau & Williams, 1993). Social loafing is a general finding across many types of tasks and subject populations; it occurs even in interventions designed to eliminate or minimize the effect (Karau & Williams, 1995).

An additional risk of learning in the presence of others is *negative peer pressure*. In environments where there are rewards for learning that arise from how one ranks among their peers, learners are made worse off by the studying efforts of their peers, and thus they tend to discourage and punish their peers' learning efforts (Bishop, 2003, 2006).

The work reported in this paper aims to uncover some of the cognitive and motivational mechanisms that underlie peer-assisted learning through a combination of empirical experimentation and computational cognitive modeling. Do learners take advantage of their peers' knowledge to increase or consolidate their own knowledge? Are they more or less willing to exert learning efforts when they are placed in a peer-interaction condition? Does their learning suffer from increased cognitive load or interference from their peers' incorrect knowledge? These are the main research questions addressed here.

The first part of this paper presents an in-depth analysis of data from an empirical study that contrasted a peer-assisted learning condition to two control conditions: an individual-active condition and an individual-passive condition. The second part presents a computational cognitive model that explains some of the effects presented in the first part. An extended version of this paper that includes more details on both the empirical study and the cognitive model will be submitted for publication to a journal.

Empirical Study

We describe here a secondary data analysis of a pooled dataset from two studies that were analyzed and reported separately in a master's thesis (Crowe, 2020)[1]. Their differences consisted of minor interface improvements and gamification features to improve task engagement and realism. The differences between the two studies were not consequential to the main results of the two studies, which justifies pooling their data into a common dataset. The analysis reported here and the cognitive modeling efforts go significantly beyond the analyses presented in the master's thesis.

Method

We set out to design a study that would be well anchored in the peer-assisted learning theory, achieve good experimental control of potential confounders, and be realistic enough to generalize beyond lab settings. Given that peer-assisted learning is an umbrella concept that applies to a variety of approaches (Olaussen, Reddy, Irvine, & Williams, 2016), it is important to acknowledge here that we restricted this research to a scope that could be realistically managed within a lab study: four learners, a simple associative learning task, and a restricted protocol of interaction among learners. A novel game paradigm, the PAL game, was developed and used to administer stimuli, support interaction among learners, and collect responses.

The PAL Game PAL stands for both *peer-assisted learning* and *paired-associate learning*. The PAL game added a simple form of interaction among learners to the classical paired-associate learning task (Anderson, 1981). Participants studied 60 arbitrary word[2]-number pairs (a.k.a., paired associates) and were subsequently tested for accuracy of recall. The game alternated between home-time and school-time sessions. During "home time", participants were given the options to study the word-number associations, play relaxation games (solitaire, chess, or minesweeper), use their phones (e.g., to do web browsing), or do nothing. "School time" consisted exclusively of studying the paired-associate learning task. A final session tested retention of all 60 word-number pairs presented over the course of the study. Participants performed the PAL game in groups of four, with each participant represented on the screen as a labeled rectangular box. Participants were physically separated in individual booths. Each member of the group viewed the first part of the word-number pair (i.e., the word) and was prompted to enter the second part (i.e., the number). After all 4 members gave individual answers to the same stimulus, they were given the opportunity to view any of their peers' answers by moving their mouse over their peers' answer boxes. To collect data on viewing behavior, the PAL software displayed participant answers and recorded viewing time only when another participant hovered over their answer box with the mouse. Upon viewing a peer's answer, a participant could decide to take it by clicking on that peer's answer box. This selection counted as a participant's second answer. If a participant did not take any of their peer's answers, their second answer was taken to be the same as their first answer. A group answer was computed as the mode of the players' second answers, with ties resolved by random selection. The game interface presented first, second, and group answers as well as their respective accuracies. The correct answer was shown to the participants at the end of each trial.

Participants and design A sample of 271 (195 female) volunteers (average age = 19, SD = 3) was recruited from the population of undergraduate students in Psychology at a medium size Midwestern university through Sona Systems (https://www.sona-systems.com/) in exchange for course credits. Three between-subjects experimental groups were formed: (1) the peer-assisted learning (PAL) group, (2) the individual active learning (IAL) group, and (3) the individual passive learning (IPL) group. The PAL group was further divided in subgroups of four participants (i.e., peers). The participants were pseudo-randomly allocated to the three experimental groups, according to the following protocol. Four slots were posted for a given time for volunteers to sign up. If all four slots were filled and four participants showed up for the experiment, they were all assigned as a subgroup to the PAL experimental group. If less than four participants showed up for the experiment, they were randomly assigned to either the IAL or the IPL group. The participants who did not complete the experiment (15) were excluded from analysis. Of the 256 participants who were retained, 136 participants (i.e., 34 groups of 4 participants) were assigned to the peer-assisted learning condition, 63 participants were assigned to the individual active learning condition, and 57 participants were assigned to the individual passive learning condition.

Procedure After reading and signing the informed consent, each participant was seated in an individual booth in front of a computer and prompted to read the instructions. Participants did not have verbal or visual contact with other participants during the course of the study. The only interaction afforded to participants in the peer-assisted learning condition was computer-mediated interaction during school time (i.e., they were shown information about

[1] See data sets, model code, and other supplementary material at https://science-math.wright.edu/lab/astecca-laboratory/software.

[2] Four-letter words with low meaningfulness, imagery, and concreteness were selected from Paivio, Yuille, and Madigan (1968).

each other's choices). The reasons for simplifying peer interaction were precision of measurement and experimental control.

The experiment was divided into six sessions, each composed of home time and school time, ending with a final seventh session that tested retention of all 60 stimuli (i.e., word-number pairs, trials) presented over the course of the study. In sessions 1 through 6 there were 20 stimuli administered per session. Sessions 2 to 5 included 10 stimuli from the previous session and 10 new stimuli. Session 6 included 10 stimuli from session 5 and 10 stimuli from session 1. Thus, each word-number pair was presented two times in the school-time learning sessions and one more time in the testing session. The number of additional presentations of the stimuli in home-time learning sessions was a function of how much time each participant decided to allocate to studying in home time.

Participants were allowed short breaks between sessions. State and trait trust scales, described in the next section, were administered as follows: the trait trust scale was administered before session 1 and after session 7, and the state trust scale was administered after sessions 2, 4, and 6.

In the PAL condition participants performed the PAL game in groups of four. At the start of each trial, the four participants in a group were presented with the same target word and given 5 seconds to respond with the corresponding number. Then each member of the group was given the opportunity to selectively view any of their peers' answers by moving their mouse over their peers' answer boxes. Next, participants gave a second answer, either retaining their initial answer or choosing (with a mouse click) an initial answer given by one of their peers. Finally, all participants received feedback (i.e., correct or incorrect) about their second answer. The PAL software also provided participants with data on who their peers selected for their second answers and the accuracy of their peers. Each trial lasted approximately 15 seconds.

In the individual active learning (IAL) and individual passive learning (IPL) conditions, participants performed the pair associate learning task individually, without the aid of peers. In the IAL condition, participants were presented with a target word, given a period of time to respond, and then received feedback on their response (correct or incorrect). In the IPL condition, participants were presented with the target word followed directly by the correct paired number, without being given the option to respond.

All conditions experienced the same duration of school time, approximately 5 minutes per session, and the same duration of home time, approximately 3 minutes per session.

Measures The following measures were recorded and calculated: the accuracy of the participant's first answer before seeing peers' answers, the accuracy of the participant's second answer, which could be chosen from peers' first answers, the accuracy of test (session 7) answers, a 24-item measure of a participant's trait trust[3] (i.e., general willingness to trust others), a 14-item measure of state trust[4], the peer's answer inspection and selection behavior, and the amount of time participants studied during home time.

Hypotheses We expect that learners in the PAL group will be able to identify the correct answer among their peers' first answers and take it as their second answer. During the learning sessions (1 through 6), this ability will be reflected in *hypothesis H1* stating that second answer accuracy will be higher than first answer accuracy. This may happen because the learners will learn from feedback not only the correct answers but also who can be trusted among their peers to give correct answers. *Hypothesis H2* states that there is a significant positive correlation between self reported trust in a peer and the peer's first answer accuracy.

Next, we hypothesize that identifying the correct answer through peer interaction may lead to consolidation of the learners' knowledge that will last beyond the learning sessions and should be detectable in the test session. Thus, *hypothesis H3* states that the PAL experimental group will perform better at test (session 7) than IAL and IPL groups.

As reviewed in the background section, there are reasons to expect that peer interaction may have negative effects on learning. Along these lines, peer interaction may trigger a social loafing effect, that is, learners may become less willing to exert learning efforts when they are placed in a peer-interaction condition. *Hypothesis H4* states that home study time will be lower in the PAL condition as compared to the other two conditions. Furthermore, learning in the PAL condition may suffer from interference from their peers' incorrect knowledge (*Hypothesis H5*) or increased cognitive load (*Hypothesis H6*).

Results and Discussion of the Empirical Study

Figure 1 below shows that second answer accuracy is much higher than first answer accuracy, supporting H1. However, H3 was not supported, as test accuracy in the PAL condition was not higher than in the IPL condition and it was actually lower than in the IAL condition. H1 suggests that a knowledge spillover effect occurred in the learning sessions. To test this peer effect more directly in the PAL condition, we computed the correlation between learner accuracy in session n and maximum peer accuracy in session n-1 and found that a 1-unit increase in peer accuracy causes a quarter-unit (0.25) increase in learner accuracy ($Y = 0.34 + 0.25*X$, $Adj.R^2 = 0.04$, $p < 0.001$). Thus, interacting with a knowledgeable peer in the previous session causes improved accuracy in the current session, and vice versa. Even though the effect size is small ($r = 0.20$), this indicates a significant knowledge spillover effect.

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[3] This scale included a selection of items from Rotter (1967), Yamagishi (1986), and Collins, Juvina, and Gluck (2016).

[4] This scale measured the trust in peers (in the PAL condition) and in the computer's feedback.

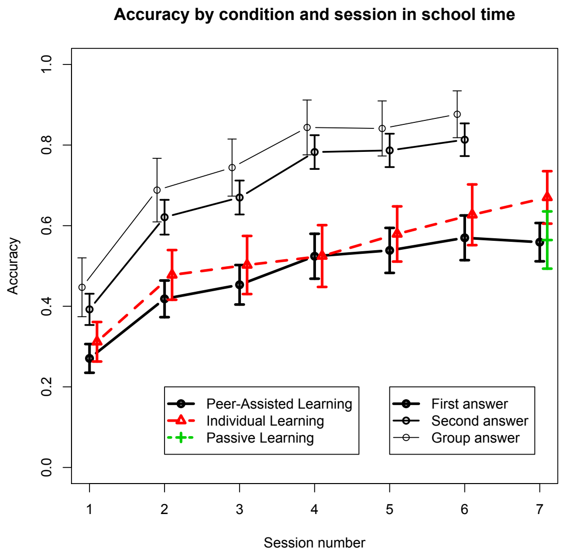

Figure 1: Accuracy by condition and session in school time. The dark solid line is the PAL condition, the red dashed line is the IAL condition, and the green dot is IPL condition. The PAL data are broken down into first answer accuracy, second answer accuracy, and group answer accuracy. The group answer was computed as the mode of individual second answers.

To further understand the knowledge spillover effect, we look at whether learners have any control over their peers' influences in the PAL condition. Figure 2 shows the frequency of taking a peer's answer, the accuracy of that answer, and the accuracy of the learner's own answer. Taking a peer's answer (black solid line) occurs quite frequently (about 50% of the time), even though it slightly decreases with learning across sessions. Taking a peer's answer generally occurs when learner accuracy is low (red dashed line), though increasing. In general, learners become increasingly able to recognize accurate responses in their peers or/and trust them to give accurate responses and take them (green dotted line). We take this as additional evidence in favor of the hypothesis (H2) that learners in the PAL condition learn whom they can trust among their peers to give correct answers. However, sometimes learners take inaccurate answers from their peers, as indicated by the accuracy of the taken answer starting low in session 1 (about 40%) and not reaching the ceiling by session 6 (about 80%). Thus, learners were exposed to both correct answers and errors in their peers, which might explain why the knowledge spillover effect did not transfer to the test session, contrary to H3. The results of testing hypotheses H4 through H6 may shed light on why H3 was not supported.

Next, we turn our attention to how long the participants studied at home in each condition, which addresses H4. Figure 3 shows that participants in the PAL condition did not study less at home. Thus, social loafing cannot explain their relatively poor performance at test. In fact, they studied significantly MORE than the other conditions. Home time practice was correlated with test performance and the magnitude of that correlation was higher in the PAL condition, $r(134) = 0.68$. Thus, the tests for H1 and H4 are consistent with a composite positive peer effect acting via two channels: knowledge (H1) and motivation (H4).

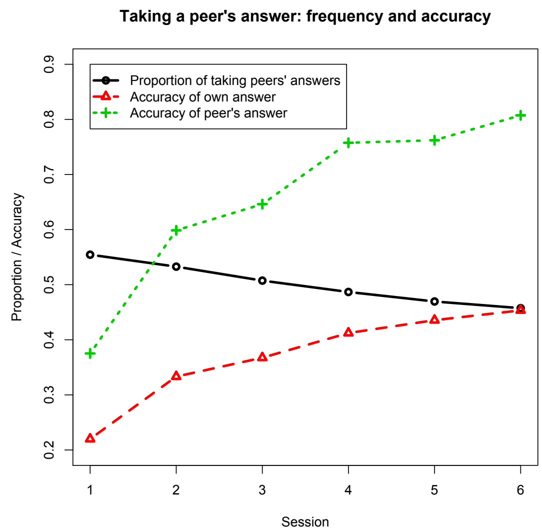

Figure 2: Frequency and accuracy of taking a peer's answer in the PAL condition by session in school time.

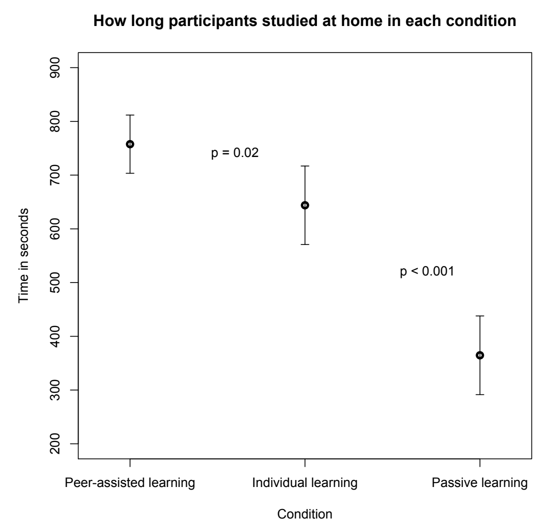

Figure 3: Time spent studying at home per condition.

A possible reason for the finding that the positive peer effect did not lead to better test performance is exposure to peer errors (H5). We have seen in Figure 2 above that exposure to error did occur, even though with less frequency as learning progressed across sessions. Further support for this hypothesis comes from peer inspection data. We used a mouse tracking procedure to record which of their peers' responses learners looked at. We found that, in the PAL condition, learners were exposed to roughly as many incorrect responses as correct ones. Even though learners became better at selecting the correct answers during the learning sessions, the incorrect answers might have persisted in memory and interfered with the retrieval of correct responses at test. Thus, the positive peer effect might have been offset by a negative interference effect. In the computational modeling section below, we will investigate in more depth how exposure to errors can cause a negative peer effect that can lead to relatively lower performance at test as compared to what would otherwise be expected based on the positive peer effect of knowledge spillover and increased motivation to study.

Lastly, the presence of peers can increase learners' cognitive load (H6), which can further impair learning. We cannot test this hypothesis directly, as we did not administer a measure of cognitive load. However, suggestive evidence in favor of H6 was found by analyzing the number of non–answers (NAs) during the learning sessions (1 through 6) in the PAL and IAL conditions (recall that participants did not answer in the IPL condition, they only passively observed the stimuli). The number of NAs varied widely between the two conditions: ~5% in the PAL condition and 0.3% in the IAL condition. One possible explanation for this discrepancy is that the cognitive load was much higher in the PAL condition than in IAL condition. The number of NAs predicted poor test performance, $r(197) = -0.35$, $p < 0.001$, suggesting that higher cognitive load explains part of the poorer performance in the PAL condition. When number of NAs was included as a covariate, the difference between the two conditions at test (session 7) became non-significant.

Computational Cognitive Modeling

We are now turning to using post-hoc computational cognitive modeling to explore mechanisms that might explain some of the empirical findings presented above. We focus here on modeling cognitive processes and behavior of the participants in the PAL condition.

Model Description

The model was developed in the ACT-R cognitive architecture (Anderson, 2007). A basic ACT-R model that performs the paired-associates task is available in the ACT-R tutorial[5]. This model performs the task well and fits the human data from a study using 20 paired associates in 8 trials (Anderson, 1981). We extended this model to perform the peer-assisted paired-associates task that human participants performed in the PAL condition of the empirical study presented above[6].

Just as human participants learned in groups of four, four instances of the model were created that were able to perform the task individually and interact with each other: the models first gave their own answer then chose either their own first answer or a peer's answer as their second answer. To give a first answer (i.e., a number associated with a presented word), the model first tries to retrieve an associate (i.e., word-number pair) from memory. If retrieval fails, the model randomly picks an integer between 0 and 9. When retrieval succeeds, the model takes the number from the retrieved associate and gives it as its first answer. When the model receives feedback, it updates its associate with the correct answer (if necessary) and stores it in memory. As the model encounters repetitions of associates (in home time and school time) the activation of the correct associates increases. This mechanism accounts for the observed increase of first answer accuracy across sessions.

To model individual differences in memory between the four instances of the model, we varied the activation decay, activation noise, and retrieval threshold parameters of the ACT-R architecture, assumed to reflect variability in memory encoding, retention, and retrieval between individuals. Therefore, each instance of the model had a different level of first answer accuracy.

After giving a first answer, the model "views" all first answers (including its own) and chooses one as its second answer. This choice is guided by ACT-R's utility learning mechanism. The model has a rule for each of the four peers that looks at the first answer of that peer and takes it as its own second answer. The four rules compete with each other and the one with the highest utility is selected. When the model is given feedback, if its second answer was correct, a positive reward value is assigned to the selected rule; if its second answer was incorrect, a negative reward value is assigned to the selected rule. This mechanism explains how the model gradually learns which peer is more like to respond accurately and picks their answer, which results in the observed effect of second answer accuracy being higher than first answer accuracy.

However, utility learning is slow and noisy (as governed by the ACT-R parameters learning rate and utility noise), which may lead to selection of incorrect answers. A model's second answer is saved in memory even if it is incorrect, affecting its future first answer (including test) accuracy. This mechanism accounts for the hypothesized mixture of positive and negative peer effects and the observed accuracy of human participants at test in the PAL condition.

Model Simulation Results and Discussion

The model was run for 100 repetitions. Figure 4 shows the model fit to the human data. For first answer accuracy, the correlation was 0.978 with a mean deviation of 0.024. Just as with the human data, the model's second answer accuracy was higher than first answer accuracy, though the fit was not as good. The correlation was 0.683 with a mean deviation of 0.135.

[5] Available at http://act-r.psy.cmu.edu/software/
[6] The model code can be downloaded from https://science-math.wright.edu/lab/astecca-laboratory/software

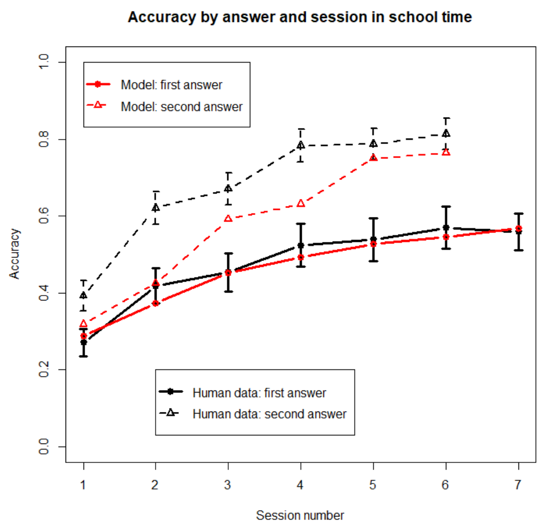

Figure 4: Comparison of model data (red lines) to human data (black lines) for first answer accuracy (solid lines) and second answer accuracy (dashed lines).

The difference between first and second answer accuracy varies between the four instances of the model or players (not shown here). As expected, player 1, who has the lowest decay rate, activation noise, and retrieval threshold, does not usually benefit from taking another player's answer, whereas players 2, 3, and 4 benefit progressively more.

Overall, the model accuracy at test was facilitated by repetition, exposure to correct responses from peers, and feedback, while being hindered by forgetting (i.e., activation decay in ACT-R) and exposure to incorrect peer responses.

General Discussion

To summarize, we found positive peer effects acting through both the knowledge channel (i.e., knowledge spillover among peers) and the motivation channel (i.e., increased willingness to practice in the PAL condition). These positive peer effects were offset by negative peer effects acting through the knowledge channel (i.e., exposure to incorrect responses from peers) and the attentional/cognitive channel (i.e., increased cognitive load in the PAL condition).

An ACT-R model using basic architectural mechanisms like base-level learning and utility learning accounted for some of the observed effects. Further modeling work is needed to account for the observed motivational and cognitive load effects of interaction among learners.

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