Title

Learning from Errors in Collaborative Learning: An Experimental Study of Erroneous Worked-Out Examples

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 48(0)

Authors

Shimojo, Shigen
Hayashi, Yugo

Publication Date

2026

Learning from Errors in Collaborative Learning: An Experimental Study of Erroneous Worked-Out Examples

Shigen Shimojo (sshimojo@fc.ritsumei.ac.jp)[1] & Yugo Hayashi[2]
[1]Research Organization of Open Innovation and Collaboration, Ritsumeikan University
[2]College of Comprehensive Psychology, Ritsumeikan University

Abstract

Collaborative learning facilitates cognitive activities such as knowledge elaboration through interaction. However, when extraneous cognitive load is high, the cognitive resources available for engaging in learning processes may be reduced. Erroneous worked-out examples (EWoEs), which present solutions containing misconceptions, can induce cognitive conflict and facilitate knowledge revision. This study examined the effectiveness of EWoEs and their underlying mechanisms in collaborative learning. To enable adaptive example presentation based on learners' knowledge, we employed a knowledge generation model based on the Adaptive Control of Thought–Rational (ACT-R). We used drawing performance as an indicator of knowledge elaboration and the Interactive–Constructive–Active–Passive (ICAP) framework as an indicator of learning processes. EWoEs enhanced drawing performance and the co-occurrence of Constructive and Interactive modes. Moreover, such co-occurrences were associated with improvements in drawing performance. These results suggest that EWoEs facilitate learning processes involving knowledge elaboration triggered by misconceptions.

Keywords: erroneous worked-out examples; ICAP framework; adaptive collaborative learning support; concept maps

Introduction

Collaborative learning gives rise to cognitive activities such as knowledge elaboration that occurs through interactions (Shirouzu et al., 2002). In Adaptive Control of Thought–Rational (ACT-R) theory (Anderson, 2007), the processes of learning and expertise are conceptualized as a series of transformations, including knowledge compilation in which declarative knowledge is converted into procedural knowledge, integrated with existing knowledge. From this perspective, learning is not merely an increase in the amount of knowledge, but rather lies in how learners elaborate knowledge. As a framework for capturing such processes of knowledge change, the Interactive–Constructive–Active–Passive (ICAP) has been proposed (Chi & Wylie, 2014). ICAP posits that Interactive mode, in which learners co-infer based on others' ideas, is most likely to induce knowledge elaboration (Chi & Wylie, 2014).

However, collaborative learning poses the challenge that cognitive load can make knowledge elaboration difficult. For example, even in Computer-Supported Collaborative Learning (CSCL) that visualize others' knowledge using concept maps, which are designed to facilitate Constructive and Interactive modes, learners have been shown to struggle to engage in Interactive mode(Shimojo & Hayashi, 2025a). From the perspective of cognitive load theory, it has been pointed out that increases in extraneous load reduce the cognitive resources available for learning (Paas et al., 2010), and as a consequence, Interactive mode is impeded (Shimojo & Hayashi, 2024). Therefore, there is a clear need for instructional support that facilitates Interactive mode in collaborative learning.

To address these challenges, worked-out examples (WoEs) have been shown to be an effective approach for reducing cognitive load and facilitating knowledge elaboration. WoEs present step-by-step procedures or final solution examples and are known to reduce extraneous cognitive load (Sweller, 1988). Furthermore, erroneous worked-out examples (EWoEs) are procedural or final solution examples that contain misconceptions. Such misconceptions induce cognitive conflict (Posner et al., 1982), which in turn facilitates knowledge elaboration through processes such as knowledge revision and restructuring (Schraw, 2006). Therefore, EWoEs can be considered a promising method for facilitating Interactive cognitive processes in collaborative learning.

In this study, we examine the effects of EWoEs in a CSCL environment in which peers' knowledge is made visible—specifically, the usefulness of learning from errors and the mechanisms underlying their effectiveness. Specifically, we investigate whether EWoEs facilitate learners' understanding (RQ1) and influence collaborative learning processes (RQ2). Based on the ICAP framework (Chi & Wylie, 2014), it is possible to systematically examine which cognitive processes are elicited by WoEs and EWoEs in collaborative learning contexts. In the following sections, we review related work on WoEs and EWoEs and then describe the objectives and hypotheses of the present study. This study contributes to understanding how learning from errors functions as a cognitive scaffold for knowledge elaboration in collaborative learning.

WoEs and EWoEs on Collaborative Learning

The effects of WoEs and EWoEs have also been demonstrated in collaborative learning contexts, in which learners can engage more actively in discussions with their peers. For example, Retnowati et al. (2010) showed that WoEs were more effective than problem-solving in both individual and collaborative learning settings. By reducing extraneous cognitive load, WoEs allow learners to efficiently acquire procedural knowledge and recognize key problem features, thereby freeing cognitive resources for engagement in high order learning processes and promoting understanding. In addition, EWoEs

In G. Boleda, I. Dautriche, M. Maldonado, C. Saldana and T. Torrent (Eds.), *Proceedings of the 48th Annual Conference of the Cognitive Science Society*

have been shown to enhance learning performance compared with both WoEs and problem-solving approaches (Barbieri & Booth, 2016). Exposure to misconceptions or contradictory examples is known to induce cognitive conflict (Posner et al., 1982), which in turn facilitates conceptual restructuring (Schraw, 2006). Furthermore, Vogel et al. (2016) found that discourse moves such as counterarguing against a partner's ideas and integrating differing opinions mediated the effectiveness of EWoEs-based learning through discussion skills. Accordingly, EWoEs can be said to promote the discussion of misconception-related knowledge and facilitate the restructuring of learners' knowledge in collaborative learning.

However, in collaborative learning contexts, WoEs and EWoEs do not necessarily facilitate learning and may, in some cases, even hinder it. For example, Retnowati et al. (2017) reported that learning outcomes with WoEs were higher in individual learning than in collaborative learning. Collaborative learning may require additional cognitive resources for interaction, regulation, and coordination. Yang et al. (2016) compared individual and collaborative learning using WoEs and EWoEs and found no differences in either learning performance or transfer performance. They argued that, in collaborative settings, the increased amount of information exchanged among learners elevates cognitive load, making it more difficult to detect misconceptions and process explanations. In addition, EWoEs may be challenging for novices, as they require learners to revise their existing misconceptions (Chi, 2005). Furthermore, prior studies on WoEs and EWoEs in collaborative learning have not sufficiently examined whether these examples actually facilitate collaborative learning processes at the dyadic level. Therefore, it is crucial to adaptively present examples that are relevant to the knowledge under discussion and to capture the nuances of the collaborative learning processes themselves.

WoEs and EWoEs in Learning Support Systems

To date, no studies have compared WoEs and EWoEs within adaptive learning support systems grounded in learners' cognitive processes in collaborative learning contexts. Adams et al. (2012) investigated individual learning and found that EWoEs led to higher delayed post-test performance than feedback. In our line of work, studies have examined instructional situations involving teachable agents (TAs) in collaborative learning. Hayashi et al. (2025b) investigated the effects of teaching a TA, while Hayashi et al. (2025a) compared egocentric and other-oriented knowledge generated by TAs. Although these studies do not directly address WoEs or EWoEs, they share a common framework with WoEs and EWoEs insofar as they present knowledge generated by cognitive models that reflect learners' knowledge states. However, these studies did not address verbally mediated collaborative interactions, and thus the examination of collaborative learning processes remains insufficient. Furthermore, differences in effects as measured by outcome indicators that assess knowledge structures have not been examined. In addition, methods for generating knowledge related to learners' actual misconceptions have not yet been explored. Consequently, empirical evidence regarding the effects of adaptively presenting EWoEs in collaborative learning contexts remains limited.

In summary, the effects of WoEs and EWoEs in collaborative learning have not been consistent, and prior research has not sufficiently examined how WoEs and EWoEs compare in terms of the extent to which they facilitate collaborative learning processes and knowledge elaboration. Moreover, no studies have systematically investigated the collaborative learning processes elicited by EWoEs. In addition, there is a lack of research on adaptive learning support systems that present examples aligned with content currently under discussion.

Goal and Hypothesis

The purpose of this study is to examine whether the adaptive presentation of EWoEs in collaborative learning facilitates both learning outcomes and collaborative learning processes. The hypotheses are as follows. First, we hypothesize that EWoEs will facilitate knowledge elaboration (H1). Second, we hypothesize that EWoEs will elicit deeper levels of collaborative learning processes (H2). Third, we hypothesize that such deeper collaborative processes will be associated with the knowledge elaboration (H3).

Method

Participants

Participants (hereafter referred to as learners) were 84 first- and second-year undergraduate students majoring in psychology (52 females, 32 males; $M = 19.42, SD = 2.39$). The experiment employed a one-factor between-participants design (control vs. WoEs vs. EWoEs). Participants were randomly assigned to the control condition (13 males, 17 females), the WoEs condition (10 males, 16 females), or the EWoEs condition (9 males, 19 females). Learners were paired with previously unknown partners and had no prior knowledge of the psychological concepts studied. Figure 1 illustrates the experimental setup. An a priori power analysis based on an effect size of $f = 0.37$ reported in Shimojo and Hayashi (2025b), with $\alpha = .05$ and $1 - \beta = .80$, indicated a required sample

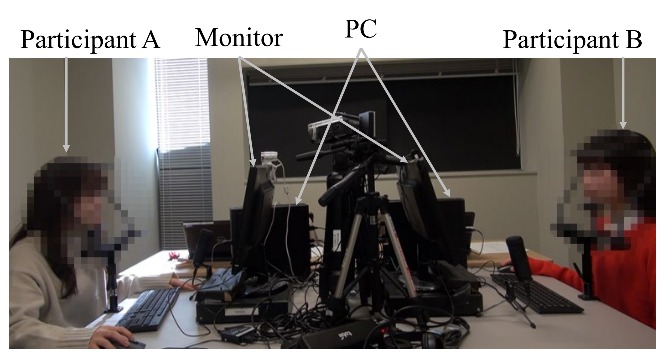

Figure 1: Experimental situation.

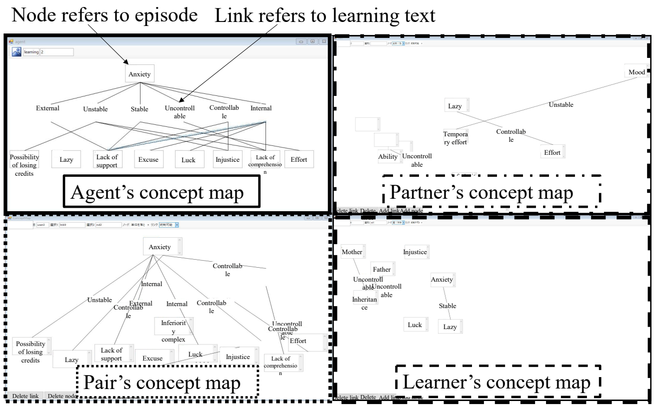

Figure 2: Screen capture of the collaborative phase. The "Learner" and "Partner" map were constructed during the individual phase. The "Pair" and "Agent"map was constructed during the collaborative phase.

size of 74 participants. This study was approved by the Ethics Committee of the authors' university.

Learning Task

The learning materials consisted of a learning text (Shimojo & Hayashi, 2025a) and an episode (Weinberger & Fischer, 2006). The learning text provided an overview of attribution theory, and the episode was a text-based student counseling scenario describing an interaction between a student and a counselor regarding the student's anxiety at the beginning of a new academic term. During the individual phase (15 minutes), learners inferred the causes of a student's anxiety at the beginning of a new academic term based on attribution theory and individually constructed a concept map. During the collaborative phase (20 minutes), learners referred to their individual maps, explained their reasoning to one another, and collaboratively constructed a concept map. In the collaborative phase, only the maps created during the individual phase were displayed in the control condition. In the WoEs condition, a map generated by an agent was additionally displayed, whereas in the EWoEs condition, a map containing misconceptions was displayed (Figure 2).

Experimental Procedure

Learners first studied a learning text on attribution theory. They then completed a pre-test on attribution theory, followed by the individual phase and the collaborative phase. After completing the learning tasks, learners took a post-test. Both the pre-test and post-test included the following open-ended question: "Please describe what you know about the attribution of causes for success and failure." However, the pre-test and post-test results are not analyzed in this study. The present paper focuses on knowledge elaboration as reflected in concept map construction.

Experimental System

In this study, we employed ACT-R (Anderson, 2007) as a cognitive architecture to implement an agent that presents example as solutions for learners' collaboratively constructed concept maps. ACT-R models cognition through interactions between declarative and procedural knowledge, thereby enabling modeling of knowledge retrieval processes.

The experimental system was implemented in C# and consisted of two components: (a) a concept map construction interface, and (b) an ACT-R–based agent. Learners externalized their understanding by manipulating nodes and links, and these operations were synchronized with the agent via TCP/IP communication. The declarative and procedural knowledge , as well as the associated parameters, were set based on concept map construction log data reported in Hayashi and Shimojo (2022), collected from 58 undergraduate psychology students. Consequently, the agent-generated propositions were designed to reflect solution examples and to be adaptively presented according to the knowledge state in the collaborative map.

Declarative Knowledge Declarative knowledge in ACT-R is a memory representation that stores factual knowledge, such as concepts and propositions, in the form of chunks. In the present study, propositions constituting concept maps were implemented as declarative knowledge. The nodes were selected from eight causes (e.g., effort) related to the episode phenomenon of "anxiety," which were identified through discussion with co-authors based on the learning task described in Shimojo and Hayashi (2025a). The links were derived from the three dimensions of attribution theory presented in the learning text: internal–external, stable–unstable, and controllable–uncontrollable. In addition, combinations of misconceptions were extracted from learner log data, and their frequencies were calculated. The mean frequency was 2.42, and combinations occurring at or above this threshold were implemented as declarative knowledge. Figure 3 shows examples of the implemented chunks. For instance, p1 represents episode-related knowledge, whereas p2 represents learning text-related knowledge.

Each declarative knowledge chunk i is assigned an activation value, A_i, which represents the accessibility of that knowledge during retrieval. In the present study, among multiple declarative knowledge chunks, propositions with higher activation values were preferentially selected and presented as WoEs or EWoEs. Equation (1) defines the activation value

```
(chunk−type episode phenomenon cause)
(chunk−type learningtext dimension cause2)
(chunk−type is−member phenomenon2 judgment)
(chunk−type conceptmap node1 node2 link)
(p1 ISA episode phenomenon anxiety cause "excuse")
(p2 ISA learningtext dimension "internal" cause2 " excuse")
(g1 ISA is−member phenomenon2 anxiety)
```

Figure 3: Example of chunks.

A_i for each chunk i as a function of the base-level activation B_i, a spreading activation term ($\sum_k \sum_j W_{kj} S_{ji}$), and a noise term ($\varepsilon$). This formulation reflects both the frequency of use and the temporal recency of each knowledge chunk. Equation (2) defines the base-level activation B_i, which represents the extent to which a given knowledge chunk has been utilized in the past. The value of B_i is updated based on the frequency of use n, the decay rate d, and the elapsed time L since the knowledge was last used. In the present study, L was initialized to 1 at the beginning of the experiment and was subsequently updated sequentially to reflect temporal information derived from learners' interaction logs accumulated during the experiment. The decay rate d was set to 0.5. Thus, knowledge chunks that are used more frequently in the collaborative map become more highly activated and more readily retrievable, whereas less frequently used chunks become progressively less activated. Consequently, WoEs or EWoEs corresponding to the knowledge represented in the collaborative map are presented.

$$A_i = B_i + \sum_k \sum_j W_{kj} S_{ji} + \varepsilon \tag{1}$$

$$B_i = \ln\left(\frac{n}{1-d}\right) - d \cdot \ln(L) \tag{2}$$

Procedural Knowledge Procedural knowledge specifies how declarative knowledge is used to select actions, and in the present study it was implemented as a strategy for generating propositions in concept maps. Specifically, a sequence of processes was represented as production rules: (a) referencing the collaborative map, (b) retrieving propositions, (c) encoding, (d) using retrieved knowledge from the collaborative map, or alternatively (e) using the agent's own knowledge, followed by (f) searching for and generating a proposition. The selection probability of a production (3) was determined by its utility value (4), which reflects its expected usefulness, combined with a noise term (ε). Steps (d) and (e) could compete with one another during production selection. Therefore, based on the findings reported in Hayashi and Shimojo (2022), appropriate utility values were determined. Sensitivity analyses were conducted by varying the utility parameters, and the results indicated that setting the utility value (4) to 9.0 for (d) and 10.0 for (e) yielded the best fit to the empirical data. Accordingly, in the present study, the agent adopted knowledge retrieval strategies in proportions comparable to those of actual learners, selecting whether to use knowledge retrieved from the collaborative map or solution examples stored in the agent's own knowledge base based on the utility values associated with each strategy. As a result, propositions that are both consistent with the current knowledge structure of the collaborative map and have high activation values are preferentially presented on the concept map as WoEs or EWoEs.

$$\text{Probability}(i) = \frac{e^{U_i/\sqrt{2}s}}{\sum_j e^{U_j/\sqrt{2}s}} \tag{3}$$

$$U_i(n) = U_i(n-1) + \alpha\,[R_i(n) - U_i(n-1)] \tag{4}$$

Dependent Variables

In this study, the hypotheses were tested using drawing performance and collaborative learning processes.

Drawing Performance Drawing performance is an indicator of the extent to which learners revise and structure their knowledge throughout the learning process (Novak et al., 1984). In the present study, we used a gain score calculated by subtracting the map score of the individual phase (Individual Concept Map: ICM) from that of the collaborative phase (Collaborative Concept Map: CCM). Traditionally, concept map assessment has relied on objective reproducibility measures based on the correctness of nodes and links as compared with an expert map (Engelmann & Hesse, 2010). In contrast, the present study evaluated the degree of knowledge elaboration by examining the extent to which learners represented the dimensions of attribution theory in an integrative manner, relative to an expert map. Two coders independently rated each map on a 5-point scale using a coding scheme adapted from Shimojo and Hayashi (2025a) (Krippendorff's $\alpha = .84$). Discrepancies were resolved through discussion. A score of 1 indicated representation of a single dimension; 2 indicated two dimensions; 3 indicated all three dimensions; 4 indicated all three dimensions plus relations between two dimensions; and 5 indicated all three dimensions (internal/external, stable/unstable, controllable/uncontrollable) as well as relations among all three dimensions. To test H1 regarding drawing performance, a one-way between-participants analysis of variance was conducted.

Collaborative Learning Process Collaborative learning processes were examined using epistemic network analysis (ENA) to analyze the relationships among Active, Constructive, and Interactive utterances in the ICAP framework. Specifically, connection strengths and coordinates on the X- and Y-axes were used as indicators of collaborative learning processes. Utterance data were collected from video recordings of the collaborative learning sessions. The recordings were transcribed verbatim. ICAP coding was conducted using a double-coding procedure based on a coding scheme adapted from Shimojo and Hayashi (2025a) (Krippendorff's $\alpha = .80$). Discrepancies between coders were resolved through discussion to reach consensus. Active utterances included repetition, summarization, and references to the concept map. Constructive utterances included opinions accompanied by justification, self-explanations, self-reflections, and questions. Interactive utterances included incorporating concepts into the concept map, disagreeing, agreeing, explaining to others, posing and responding to questions, summarising a partner's contributions, checking a partner's understanding, and making revisions prompted by a partner's feedback. Utterance proportions were calculated by dividing the number of utterances in each category by the total number of Active, Constructive,

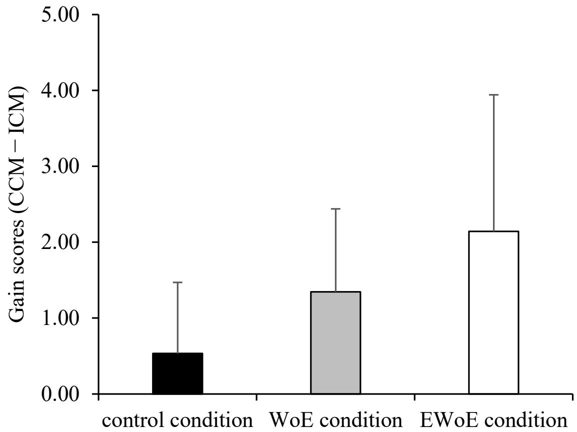

Figure 4: Between-condition comparison of drawing performance. Error bars indicate standard deviations.

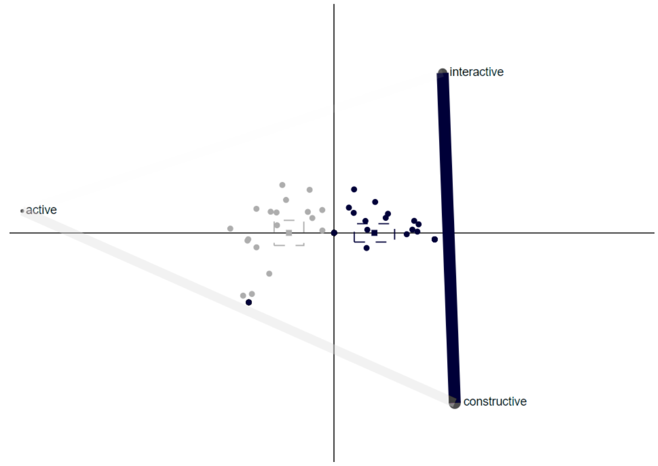

Figure 5: Difference graph between WoEs (grey) and EWoEs (black).

and Interactive utterances. To test H2 regarding collaborative learning processes, ENA was conducted. The ENA was implemented using the rENA package in R . A window size of seven utterances was used . For analysis, principal components in the ENA space (MR1, SVD2) were computed (MR1: maximum between-group separation; SVD2: second principal component), and networks for the WoEs and EWoEs conditions were compared based on normality tests. To test H3, multiple regression analyses were conducted with the ENA space as predictors and drawing performance as the outcome variable.

Results

Drawing Performance

In this section, we examine whether drawing performance was enhanced by EWoEs (H1). Figure 4 presents the comparison of drawing performance across conditions. A one-way between-participants ANOVA revealed a significant effect of condition, $F(2, 81) = 10.65, p < .001, \eta_p^2 = .21$. Multiple comparisons using Shaffer's method indicated that drawing performance in the EWoEs condition was significantly higher than that in both the control condition and the WoEs condition ($p < .001$; $p = .030$). In addition, drawing performance in the WoEs condition was significantly higher than that in the control condition ($p = .025$). Although gain scores indicate changes in the amount of learning, they do not directly reflect qualitative changes in learning content, such as the extent to which learners can provide integrative explanations across attributional dimensions. Therefore, we also calculated the median scores of drawing performance for the ICM and CCM to interpret qualitative changes in learning content. Because this scale is an ordinal scale ranging from 1 to 5, medians were used as representative values. In the WoEs condition, the median ICM score was 1.00, and the median CCM score was 2.00, suggesting an expansion of knowledge representations from one-dimensional explanations to two-dimensional explanations. In the EWoEs condition, the median ICM score was 1.00 and the median CCM score was 3.00, suggesting that learners progressed from one-dimensional explanations to explanations incorporating all three dimensions. Thus, in both the WoEs and EWoEs, knowledge representations were reconstructed into more multidimensional forms through collaborative learning. Overall, these results support H1.

Collaborative Learning Process

In this section, we examine whether EWoEs elicit deeper collaborative learning processes (H2) and whether such deeper collaborative processes are associated with knowledge elaboration (H3). Figure 5 illustrates the difference graph between the WoEs (gray) and EWoEs (black). Differences between the WoEs and EWoEs conditions were analyzed using rENA. Along the X-axis, a significant difference was observed between the EWoEs condition (mean = 0.27) and the WoEs condition (mean = −0.30), whereas no difference was found along the Y-axis ($t(48.09) = -7.03, p < .001$, Cohen's $d = -1.94$; $t(44.97) = 0.00, p = 1.00$, Cohen's $d = 0.00$). The WoEs condition exhibited stronger connection strengths among Active utterances and between Active and Interactive utterances. In contrast, the EWoEs condition showed stronger connection strengths among Constructive and Interactive utterances.

We further examined the relationship between drawing performance and the MR1 and SVD2 dimensions in the ENA space. The results indicated that higher MR1 values were associated with improved drawing performance ($\beta = 1.45, SE = 0.49, t = 2.97, p = .005$). In contrast, no significant association was found for the SVD2 dimension ($\beta = 0.34, SE = 0.69, t = 0.49, p = .624$). These findings suggest that EWoEs promote the co-occurrence of Constructive and Interactive modes, which in turn facilitates drawing performance. Accordingly, EWoEs were shown to enhance Constructive and Interactive modes and to be associated with the elaboration of learners' knowledge structures.

Discussion

This study investigated the effects of EWoEs in collaborative learning using concept maps. In the following, we discuss whether EWoEs facilitate learners' understanding (RQ1) and how they influence collaborative learning processes (RQ2).

Effects of EWoEs on Understanding

In this section, we discuss whether EWoEs facilitate learners' understanding (RQ1). The results for drawing performance showed that the EWoEs condition yielded higher performance than both the control and WoEs conditions. In addition, drawing performance in the WoEs condition was higher than in the control condition (Figure 4). These findings are consistent with prior research demonstrating that reducing extraneous cognitive load facilitates understanding (Sweller, 1988), as well as with evidence that examining misconceptions induces cognitive conflict (Posner et al., 1982), which in turn facilitates knowledge elaboration (Schraw, 2006).

Taken together, this study has theoretical significance in demonstrating that EWoEs make a substantial contribution to the elaboration of learners' knowledge structures. Whereas prior research has primarily relied on test-based performance measures, the present study provides a novel perspective by capturing the effects of EWoEs in terms of changes in knowledge structure through drawing performance.

Effects of EWoEs on Collaborative Learning Processes

In this section, we discuss how EWoEs influence collaborative learning processes (RQ2). The results showed that the WoEs condition exhibited stronger co-occurrences between Active and Constructive modes, whereas the EWoEs condition exhibited stronger co-occurrences between Constructive and Interactive modes (Figure 5). Furthermore, higher MR1 values in the ENA space were associated with improved drawing performance, whereas no such relationship was found for the SVD2 dimension. These findings indicate that EWoEs promote the co-occurrence of Constructive and Interactive modes, which in turn facilitates drawing performance.

From the perspective of the ICAP framework (Chi & Wylie, 2014), these results indicate that EWoEs guided learners toward deeper collaborative learning processes. In the EWoEs condition, learners were required to identify the sources of misconceptions and to evaluate and revise their validity, which led them beyond mere reproduction to explaining and reasoning about why an answer was incorrect (Durkin & Rittle-Johnson, 2012). Through this process, learners updated their understanding by considering their peers' feedback, thereby promoting Interactive mode. Indeed, in the EWoEs condition, utterances such as "Lack of support doesn't seem right" and interpretive revisions like "Because it cannot be controlled by anyone, it might be related to inferiority feelings" were observed, indicating deep meaningful discussions among learners. Accordingly, EWoEs are suggested to increase both Constructive and Interactive modes.

Previous research has indicated that when novices learn new concepts, misconceptions tend to interfere with learning, making it difficult to achieve conceptual understanding (Chi, 2005). In particular, because novices often lack sufficiently developed metacognitive abilities to appropriately monitor and revise their own misconceptions, such misconceptions are likely to persist throughout the learning process (Schraw, 2006). Although prior studies have suggested that learning from errors is more effective for more advanced learners, the results of the present study indicate that, when embedded in collaborative learning and adaptively tailored to learners' knowledge states, even novices can benefit from EWoEs. Specifically, such adaptive presentation promotes the externalization of individual ideas (Constructive) and discussions with others (Interactive), thereby leading to enhanced knowledge elaboration. These findings suggest that the adaptive presentation of EWoEs in collaborative learning contexts effectively supports novices' learning from errors.

Taken together, this study provides empirical evidence that EWoEs trigger Constructive and Interactive modes by leveraging misconceptions and that the co-occurrence of these processes facilitates knowledge elaboration.

Limitations and Future Work

This study has several limitations. First, the WoEs and EWoEs were generated from pre-modeled, prototypical misconceptions and were not fully adaptive to individual learners' understanding, which may have constrained support for misconception revision. Second, this study focused on understanding and knowledge structure elaboration, and did not examine deeper learning outcomes such as transfer or long-term retention.

Future research should address these limitations by developing more fine-grained adaptive mechanisms that dynamically diagnose learners' misconceptions and tailor support accordingly. In addition, future studies should examine the effects of EWoEs on transfer and retention across diverse domains, tasks, group sizes, and learning environments. Finally, future work should use ACT-R–based simulations to clarify the cognitive mechanisms underlying learning from errors.

Conclusion

This study examined the effects of EWoEs in learning contexts using concept maps, employing an ACT-R–based knowledge generation model for adaptive example presentation. The results showed that the EWoEs condition yielded higher drawing performance than WoEs conditions, and that the WoEs condition also outperformed the control condition. In addition, EWoEs promoted the co-occurrence of Constructive and Interactive modes, and this co-occurrence was found to be associated with improved drawing performance. These findings suggest that EWoEs trigger Constructive and Interactive modes by introducing misconceptions, thereby contributing to the refinement of learners' knowledge structures. Future research should further investigate the effectiveness of EWoEs by incorporating transfer performance as an outcome measure.

Acknowledgments

This work was supported by JSPS KAKENHI Grant Number JP23H03510.

References

Adams, D., McLaren, B. M., Durkin, K., Mayer, R. E., Rittle-Johnson, B., Isotani, S., & Velsen, M. V. (2012). Erroneous examples versus problem solving: Can we improve how middle school students learn decimals? *Proceedings of the 34th Meeting of the Cognitive Science Society*, *34*, 1260–1265.

Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* Oxford University Press.

Barbieri, C., & Booth, J. L. (2016). Support for struggling students in algebra: Contributions of incorrect worked examples. *Learning and Individual Differences*, *48*, 36–44. https://doi.org/10.1016/j.lindif.2016.04.001

Chi, M. T. H. (2005). Commonsense conceptions of emergent processes: Why some misconceptions are robust. *Journal of the Learning Sciences*, *14*(2), 161–199. https://doi.org/10.1207/s15327809jls1402_1

Chi, M. T. H., & Wylie, R. (2014). The icap framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–243. https://doi.org/10.1080/00461520.2014.965823

Durkin, K., & Rittle-Johnson, B. (2012). The effectiveness of using incorrect examples to support learning about decimal magnitude. *Learning and Instruction*, *22*(3), 206–214. https://doi.org/10.1016/j.learninstruc.2011.11.001

Engelmann, T., & Hesse, F. W. (2010). How digital concept maps about the collaborators' knowledge and information influence computer-supported collaborative problem solving. *Computer-Supported Collaborative Learning*, *5*, 299–319. https://doi.org/10.1007/s11412-010-9089-1

Hayashi, Y., & Shimojo, S. (2022). Modeling perspective taking and knowledge use in collaborative explanation: Investigation by laboratory experiment and computer simulation using act-r. *Proceedings of the 23rd International Conference on Artificial Intelligence in Education*, 647–652. https://doi.org/10.1007/978-3-031-11644-5_62

Hayashi, Y., Shimojo, S., & Kawamura, T. (2025a). Do errors teach better? the role of exocentric feedback from erroneous teachable agents in collaborative learning [submitted]. *Computer Assisted Instruction*.

Hayashi, Y., Shimojo, S., & Kawamura, T. (2025b). Scripted interventions versus reciprocal teaching in collaborative learning: A comparison of pedagogical and teachable agents using a cognitive architecture. *Learning and Instruction*, *96*, 102057. https://doi.org/10.1016/j.learninstruc.2024.102057

Novak, J. D., Gowin, D. B., & Bob, G. D. (1984). *Learning how to learn*. Cambridge University Press.

Paas, F., van Gog, T., & Sweller, J. (2010). Cognitive load theory: New conceptualizations, specifications, and integrated research perspectives. *Educational Psychology Review*, *22*, 115–121. https://doi.org/10.1007/s10648-010-9133-8

Posner, G. J., Strike, K. A., Hewson, P. W., & Gertzog, W. A. (1982). Accommodation of a scientific conception: Toward a theory of conceptual change. *Science Education*, *66*(2), 211–227. https://doi.org/10.1002/sce.3730660207

Retnowati, E., Ayres, P., & Sweller, J. (2010). Worked example effects in individual and group work settings. *Educational Psychology*, *30*(3), 349–367. https://doi.org/10.1080/01443411003659960

Retnowati, E., Ayres, P., & Sweller, J. (2017). Can collaborative learning improve the effectiveness of worked examples in learning mathematics? *Journal of Educational Psychology*, *109*(5), 666–678. https://doi.org/10.1037/edu0000167

Schraw, G. (2006). Knowledge: Structures and processes. In P. A. Alexander & P. H. Winne (Eds.), *Handbook of educational psychology* (pp. 245–263). Lawrence Erlbaum Associates.

Shimojo, S., & Hayashi, Y. (2024). How working memory influences knowledge reconstruction in collaborative learning: Investigation using human experimentation and act-r simulation. *Proceedings of the 22nd International Conference of Cognitive Modeling*, 165–171.

Shimojo, S., & Hayashi, Y. (2025a). Age-related differences in explanatory activities during collaborative learning with concept maps: Experimental investigation using epistemic network analysis. *International Journal of Computer-Supported Collaborative Learning*, *20*, 491–518. https://doi.org/10.1007/s11412-025-09456-5

Shimojo, S., & Hayashi, Y. (2025b). Using erroneous worked-out examples for supporting collaborative learning: An investigation based on the cognitive model of link errors using act-r. *Proceedings of the 46th Annual Meeting of the Cognitive Science Society*, *47*, 6308.

Shirouzu, H., Miyake, N., & Masukawa, H. (2002). Cognitively active externalization for situated reflection. *Cognitive Science*, *26*(4), 469–501.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Vogel, F., Kollar, I., Ufer, S., Reichersdorfer, E., Reiss, K., & Fischer, F. (2016). Developing argumentation skills in mathematics through computer-supported collaborative learning: The role of transactivity. *Instructional Science*, *44*(5), 477–500. https://doi.org/10.1007/s11251-016-9380-2

Weinberger, A., & Fischer, F. (2006). A framework to analyze argumentative knowledge construction in computer supported collaborative learning. *Computers & Education*, *46*(1), 71–95. https://doi.org/10.1016/j.compedu.2005.04.003

Yang, Z., Wang, M., Cheng, H. N. H., Liu, S., Liu, L., & Chan, T. (2016). The effects of learning from correct and erroneous examples in individual and collaborative settings. *The Asia-Pacific Education Researcher*, *25*(2), 219–227. https://doi.org/10.1007/s40299-015-0253-2