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Reciprocal Kit Build Approach for Peer-to-peer Communication: Relationship between Similarities on Knowledge, Transfer of Knowledge, and Affective Responses

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Abstract: The present paper describes the Reciprocal Kit Build approach as a designed activity for collaborative concept mapping. We aimed to investigate the effect of differences in individual knowledge (both prior knowledge and knowledge on task) on knowledge transfer, collaborative product, and learners' affective responses during co-construction of a concept map with the Reciprocal Kit Build (RKB) approach. We categorized learners into two groups based on their prior knowledge equivalence and their degree of shared knowledge reflected in the individual maps. The RKB approach allowed learners to create an individual map, to reconstruct a concept map from their partner's map components (nodes and links), and to discuss similarities (or differences) between the initial map with the reconstructed map. The results showed that, following our proposed activity, transfers of individual knowledge regarding the shared and unshared knowledge were considerably high. Although, learners' differences on prior and shared knowledge did not significantly affect the knowledge transfers and the final collaborative products, different group composition influenced the experiences of learners.

Keywords: computer-supported collaborative learning, kit-build, collaborative concept map, knowledge convergence

1. Introduction

In collaborative learning, knowledge is exchanged and converge through social interaction (Weinberger, Stegmann, & Fischer, 2007). Scripts, scenarios, or visualization tools are designed to trigger meaningful interactions within group members. Concept map as a representational tool has been widely employed during collaboration to facilitate ideas generation, communication, and negotiation of meaning. Studies found that creating collaborative concept map have increased students' learning achievements and their positive attitudes, i.e.: motivation and responsibility (Basque & Lavoie, 2006).

Gnesdilow & Bopardikar (2010) suggested that the level of convergence achieved during collaborative concept mapping could have influenced individual performances after collaboration. Mutual understanding of the partner's perspectives and shared interpretations of the problem is an important requirement for collaboration (Jeong & Chi, 2007; Stoyanova & Kommers, 2002). Divergent ideas between group members have a significant impact on collaboration (Gnesdilow & Bopardikar, 2010; Stahl, 2003; Weinberger et al., 2007). Individual prerequisites and diverge in knowledge influence the benefits experienced by group members when learning together (Weinberger et al., 2007). They suggested heterogenous group composition to promote negotiation perspectives towards a shared understanding of classroom collaborative activities.

Another way to attain convergence is by nurturing group members to use the knowledge available to them, both shared and unshared knowledge resources, from their prior knowledge and from learning material (Frank Fischer & Mandl, 2002). Unfortunately, groups more often neglect unshared resources – that is, knowledge and information that only a few numbers of group members possessed or have access to (Frank Fischer & Mandl, 2002). Providing an open communication environment where individual's shared and unshared knowledge is acknowledged, built, and elaborated is expected to foster knowledge convergence. Hence, improving learning outcomes in tasks and supporting conceptual change through discussion.

We have extended the collaborative concept mapping with Kit-Build, a closed-ended concept mapping approach to assess common understanding between the teacher and his students (Hirashima, Yamasaki, Fukuda, & Funaoi, 2015). In a practical classroom, Kit Build analyzer has been used to find learners' misconceptions and to improve the teacher's lesson plan in the subsequent class (Pailai, Wunnasri, Yoshida, Hayashi, & Hirashima, 2017; Yoshida et al., 2013). In a peer-to-peer context, this approach promotes exploratory talk during group discussion (Wunnasri, Pailai, Hayashi, & Hirashima, 2018a) and aids learners in dyads to share understanding based on individual pre- and post-maps (Wunnasri, Pailai, Hayashi, & Hirashima, 2018b). However, those studies have not identified how individual knowledge has been taken into consideration for constructing a collaborative map, an artifact where group members have to negotiate individual knowledge differences and to reach a common consensus on task. The use of RKB for collaborative concept mapping has shown that most groups produce better high-quality collaborative maps and there was an association between difference map visualization with score gain from individual to collaborative maps (Sadita et al., 2018). The preliminary study has not investigated how similarities of knowledge among each pair may influence the collaborative product as well as knowledge transfer from individual-to-group.

In the present study, we measure the level of convergence prior to collaborative concept mapping in regards to knowledge equivalence and shared knowledge (Weinberger et al., 2007) to gain a deeper understanding on how to form a group and whether our proposed activity let learners to constructively build on individual knowledge. First, we identify the effect of different group composition to learning effectiveness at two dimensions, i.e. as an interaction between group members and as a group achievement (Khamesan & Hammond, 2004; Molinari, 2013; Stoyanova & Kommers, 2002). Second, we survey the learners' affective responses to find out students' experiences after following our proposed activities on different group compositions.

2. Literature Review

2.1 Concept Map to Facilitate Communication in Collaborative Learning

Concept mapping as a representational tool is beneficial for collaborative learning at the individual level and group level (Stoyanova & Kommers, 2002). It makes individual knowledge more explicit and provides a room for reflection and elaboration of cognition (Stoyanova & Kommers, 2002). At a group level, it promotes establishing a common ground as a basis for building a shared understanding within group members (Jeong & Hmelo-Silver, 2016; Roschelle & Teasley, 1995; Stoyanova & Kommers, 2002). Prior studies have also shown that a concept map is an effective tool for elicitation of knowledge and communicating complex ideas (Frank Fischer & Mandl, 2002; Stoyanova & Kommers, 2002; Suthers, 2006; van Boxtel, van der Linden, & Kanselaar, 2000).

2.2 Reciprocal Kit Build

We have employed the Reciprocal Kit-Build (RKB) approach to allow students to generate and exchange ideas with their partner before collaborative concept mapping activities. There are three main parts of the RKB approach, i.e. individual map building, individual map reconstruction by partners, and difference map discussion (Wunnasri et al., 2018a). Prior studies have shown that individual map building in a private space helped students to explain their ideas during the collaborative session (F. Fischer, Bruhn, Gräsel, & Mandl, 2002; Gracia-Moreno, Cerisier, Devauchelle, Gamboa, & Pierrot, 2017).

Through the reconstruction of partner's map and difference map discussion, each group member is feasible to detect partner's comprehension and it leads to the elicitation of knowledge. Awareness of partner's knowledge is beneficial to maintain shared focus during problem-solving, and therefore, students solve the problem faster and more accuracy (Engelmann & Hesse, 2010). Specifically, in collaborative concept mapping with individual preparation, they may have more sociocognitive conflicts during collaborative concept mapping when they have first overcome a reflective thinking process in a personal workspace (de Weerd, Tan, & Stoyanov, 2017; Gracia-Moreno et al., 2017). It possibly will hinder students to express their unshared knowledge or resources.

Providing a room to assist students to externalize own ideas or to review different perspectives from their partner in an active manner is expected to enrich interaction between group members. Different from standard individual map interchange, the RKB approach encourages students to produce more exploratory talk, which is valued for advancing critical thinking, reasoning, and problem-solving skills (Wunnasri et al., 2018a). After following the RKB activities, students in dyads are having similar knowledge on their post individual maps which indicate that they have higher knowledge convergence. However, previous researches on RKB have not explored how differences in prior knowledge affect the collaborative product, where they have to resolve individual differences to reach a common consensus, and how the differences influence the experiences of learners on collaborative learning (Sadita et al., 2018; Wunnasri et al., 2018a, 2018b).

3. Methods

3.1 Experimental Settings

We run the study in a Linear Algebra class for the first year of Computer Science students in one of a public university in Indonesia. The teacher selected topics that facilitated students to draw conceptual knowledge, i.e. the General Vector Spaces and the Inner Product Spaces. An introductory explanation about these topics and the relevant learning resources were delivered by the teacher before conducting the experiment. The participants consisted of 42 students who work in dyads, where 71% of them are men. They were familiar with concept mapping activities since the teacher usually draws a diagram to show the relationship among concepts or asks the students to create it by themselves after finishing a topic. The teacher determined some essential nodes ($n = 15$) be included in the map to aid students with common references, therefore they could maintain focus during the discussion.

We administered the experiment in a computer laboratory for about two hours, which was divided into two main phases, i.e. the individual and the collaborative phase. First, the students created an individual map in 25 minutes. During the collaborative phase, the students reconstructed a map given a set of unconnected nodes and links (components) from their partners' map (20 minutes), discussed a difference map (10 minutes), and created a group map collaboratively (30 minutes). Each group member worked in a close-proximity to build an individual map with a personal computer or laptop, then they used a single computer to draw a collaborative map.

3.2 Variables and Measurements

Knowledge convergence is defined as a process by which two or more people share mutual understanding through social interaction (Jeong & Chi, 2007). Weinberger, Stegmann, & Fischer (2007) have conceptualized knowledge convergence as knowledge equivalence and shared knowledge which can be evaluated prior to, during, or after collaboration. Knowledge equivalence refers to learners in a group possessing a similar degree of knowledge related to a specified subject, regardless of the specific concepts constituting knowledge content (Weinberger et al., 2007). While, shared knowledge alludes to the knowledge of specific concepts that learners within a group have in common (Weinberger et al., 2007).

We first measured knowledge convergence at group level prior to collaboration using two different measures, i.e. prior knowledge equivalence and shared knowledge on task. Afterward, we evaluated the learning effectiveness of collaborative problem solving operationalized in two dimensions as follows (Khamesan & Hammond, 2004; Molinari, 2013):

- at the level of the group as a whole, scored numerically on group concept map
- as an interaction between individual and group achievements, scored numerically on individual map and group concept map

We excluded the effectiveness at the level of the individual since we did not collect individual post-collaboration maps because of some limitations in a practical classroom situation. Those three metrics are originally introduced by Stoyanova & Kommers (2002) to provide a deeper quantitative understanding of the processes of both learning and collaboration in collaborative concept mapping. Khamesan and Hammond (2004) have computed the reliability of the metrics with three raters and demonstrated high interrater reliability for most of the categories.

3.3 Knowledge Convergence Prior to Collaboration

Prior knowledge equivalence scores were calculated from the results of the mid-term test conducted a few days before the experiment. The questions in the test covered essential introductory materials required to understand the main topic in the concept map, but not included the conceptual knowledge that could be drawn in a map form such relationship among concepts. Measures of dispersion were used to analyze differences in prior knowledge between learners as in the prior study (Weinberger et al., 2007). First, individual mid-term tests were evaluated by the teacher. Second, standard deviations between the individual scores in each group were calculated. Last, the standard deviation was divided by the mean score to measure the coefficient of variation as a prior knowledge equivalence score.

Table 1

Sample of 4 Essential Information Included in The Map and Its Possible Substructure

No	Type of information	Possible nodes included in the substructure
1	An inner product space is a vector space with an additional structure called the inner product function	Inner Product (IP) Space – Vector Space (VS)
2	An inner product function takes each ordered pair in a vector space *V* to a number in *R*	IP function – domain: *V*x*V* & codomain: *R*
3	An inner product function is a function that has to satisfy the following axioms: additivity, homogeneity, positivity, & symmetry	IP function – 4 axioms: additivity, homogeneity, positivity, & symmetry
4	Vector is an element of a vector space *V*	vector – IPS (if the IPS is connected to VS), or vector – VS

Note: “ – ” represents a link / connection between nodes / concepts

We assessed shared knowledge quantitatively from individual concept maps using the approach proposed by Weinberger et al. (2007). First, the teacher defined what are essential information should be included in the maps, given a set of nodes as initial components to build a map. Then, she listed all possible and common substructures from all students' generated maps. A substructure may consist of two or more connected nodes (concepts) which convey one information only (see Table 1). The propositions may have a few variations depending on the linking words written by the students. Second, the teacher marked whether a student's map presented any essential information or not. Seven key substructures were expected to appear in the maps. Third, if a pair of learners share the ability to apply a specific concept, then we added the shared prior knowledge score of 1. Finally, we normalized the score by dividing it with the group mean value. In addition, we also defined unshared knowledge at the individual level to identify the degree of information that only possessed by a single member.

Table 2

Sample of Knowledge Distribution in a Group

No	Substructures	Group 01		
		Student A's map	Student B's map	Group map
1	Inner Product (IP) Space – Vector Space (VS)	○	○	○
2	IP function – domain: *V*x*V* & codomain: *R*	X	X	○
3	IP function – 4 axioms	○	X	○
4	Vector – IP Space or VS	○	○	X

Note:
○ : *the substructure was available and correct*
X : *the substructure was not available or incorrect*

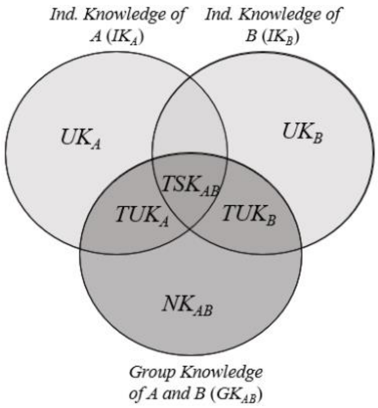
Following the above procedures, individual knowledge scores of student A's and B's in Group 01 were 3 and 2 consecutively based on the number of correct substructures. Hence, resulting in a mean of 2.5 (Table 2). Group 01 achieved a shared knowledge value of 2 because both members were able to draw the first and the fourth substructures correctly. Subsequently, the normalized shared knowledge score of this group was 2 / 2.5 or equal to 0.8.

The normalized prior knowledge equivalence score and shared knowledge score were applied to categorize the group. The groups which have normalized prior knowledge equivalence less than 0.2 were categorized as high knowledge equivalence groups and the groups with normalized shared knowledge score more than 0.7 were included in high shared knowledge groups. The prior knowledge equivalence scores provided the differences of individual performances on prior relevant topics, while the shared knowledge scores were more specific to knowledge on the task itself.

3.4 Learning Effectiveness Measures

We examined the learning effectiveness by using the concept map measures (Figure 1) proposed by Khamesan and Hammond (2004):

1. Individual-to-group transfer of shared knowledge (TSK_{AB}): the number of substructures shared by both individual and transferred to the collaborative map. The score was normalized with the number of shared substructures.
2. Individual-to-group transfer of unshared knowledge ($TUK_{A\ (\mathrm{or}\ B)}$): the number of unshared substructures in each individual and transferred to the collaborative map. The score was normalized with the number of unshared substructures.
3. Individual-to-group transfer (TK_{AB}: $TSK_{AB} \cup TUK_A \cup TUK_B$): the total number of transferred substructures from individual maps to the collaborative map. The score was normalized with the number of shared and unshared substructures.
4. Lost knowledge (LK_{AB}: $(IK_A \cup IK_B) \setminus TK_{AB}$): the number of individual substructures not transferred from individual maps to the collaborative map.
5. Group creativity (NK_{AB}): the number of new substructures in the collaborative map that was not included in both individual maps. The score was normalized with the number of unknown substructures.
6. Group achievement (GK_{AB}): the score of the collaborative map.



Legend

$IK_{A\ (\mathrm{or}\ B)}$	Individual knowledge of *A* or *B*
SK_{AB}	Shared knowledge of *A* or *B*
$UK_{A\ (\mathrm{or}\ B)}$	Unshared knowledge of *A* or *B*
TSK_{AB}	Transfer of shared knowledge of *A* or *B*
$TUK_{A\ (\mathrm{or}\ B)}$	Transfer of unshared knowledge of *A* or *B*
NK_{AB}	New knowledge of Group *A* and *B*
GK_{AB}	Group knowledge (achievement) of *A* and *B*

Figure 1. The Illustration of Learning Effectiveness Measures

As an example, from the Table 2, substructures (1) and (4) were the shared knowledge on the task before collaboration, substructure (3) was the unshared knowledge of student B, and substructure (2) was the unknown substructures of Group 01 (ignorance). After the collaboration, the students wrote the substructures (1) to (3) correctly, so we regarded those substructures as Group Knowledge. Specifically, substructure (1) was considered as the individual-to-group transfer of shared knowledge, substructure (2) was categorized as new knowledge, and substructure (3) was referred as the individual-to-group transfer of unshared knowledge. Unfortunately, the Group 01 members did not write substructure (4), thus it became the lost knowledge.

3.5 Affective Responses

We conducted a survey to capture participants' experiences while following RKB activities. The questionnaire consisted of 15 closed-ended items related to attractiveness, stimulation, and perspicuity subscales adapted from an Indonesian language version of User Experience Questionnaire (Santoso, Schrepp, Kartono, Yudha, & Priyogi, 2016). The students were requested to choose a Likert scale from 1 to 7. Six open-ended questions were delivered to capture learners' positive and negatives experiences in each step of collaborative learning activities. All questionnaire items had been face-validated by the teacher before distributed to the students. Cronbach's alpha coefficients were 0.74, 0.84, and 0.77 for attractiveness, stimulation, and perspicuity subscale, respectively, showing good internal consistency.

4. Results

4.1 Learning Effectiveness

Before creating collaborative maps, 82% percent of the important substructures were written in students' individual maps, while the number of the substructures that were not included in the individual maps was as many as 18% (n = 27). More than half of those written substructures were shared knowledge (Figure 2). Those shared and unshared knowledge were available in the collaborative maps as many as 91.67%, the remaining became non-transferred (lost) knowledge. Almost all shared knowledge was transferred to the collaborative map, while the percentage of neglected unshared knowledge was 15% of total unshared knowledge. There are 14 groups who were feasible to extend their group map with new information (substructures), that did not exist in their individual maps. From those groups, we found that they were able to draw 8 new important substructures. The number of unknown information (ignorance) in the collaborative maps were also decreasing, from 18% to 13%.

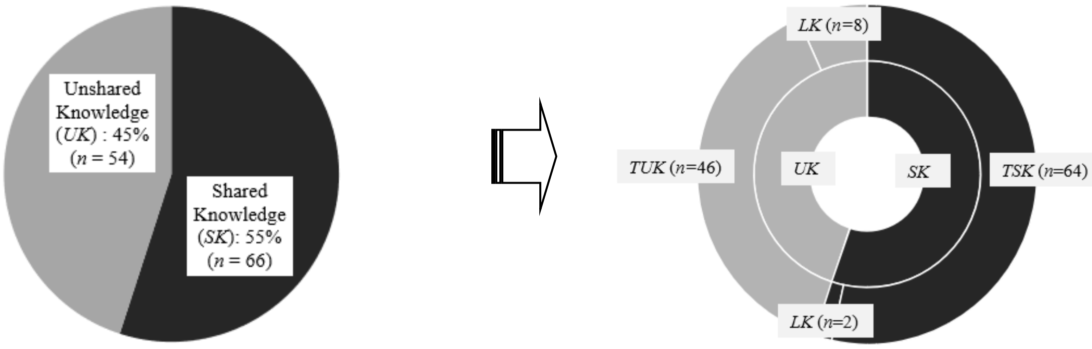


Figure 2. Distribution of The Amount of Shared and Unshared Knowledge in The Individual Maps Prior to Collaboration (left-side) and Distribution of The Individual Knowledge Transferred to Collaborative Maps in All Groups (right-side).
(*Note:* Please see Section 3.4 to understand the abbreviations in the graph)

Figure 3 and 4 display the distribution of knowledge transfer and group creativity among different conditions regarding their prior knowledge equivalence and shared knowledge on the individual concept maps. Transfer of shared and unshared knowledge in most of the groups in all conditions have similar median values with different score distribution. Two groups of high prior knowledge equivalence and high shared knowledge conditions did not convey their understanding or reach different consensus, i.e. Group 09 and Group 14. There are three out of 11 groups in high shared knowledge condition who did not have unshared knowledge. The remaining groups with the unshared knowledge in low prior knowledge equivalence and low shared knowledge condition have higher agreement to transfer the knowledge. From the 14 groups who had new knowledge, the number of groups in each condition was similarly distributed (n = 7). The groups with low shared knowledge had a higher tendency to create new knowledge (Figure 4).

Furthermore, we also investigated whether individual ability affected group tendency to transfer the unshared knowledge by calculating the correlation between individual map score and the normalized score of individual unshared knowledge transfer. Results of the Pearson correlation indicated that there was no association between individual map score and number of unshared knowledge transfer, ($r(22) = -.06014$, $p = .7801$). The student with lower individual performance than their partner could possibly to transfer his unshared knowledge, and vice versa, the one with higher individual performance might unable to convey the unshared knowledge.

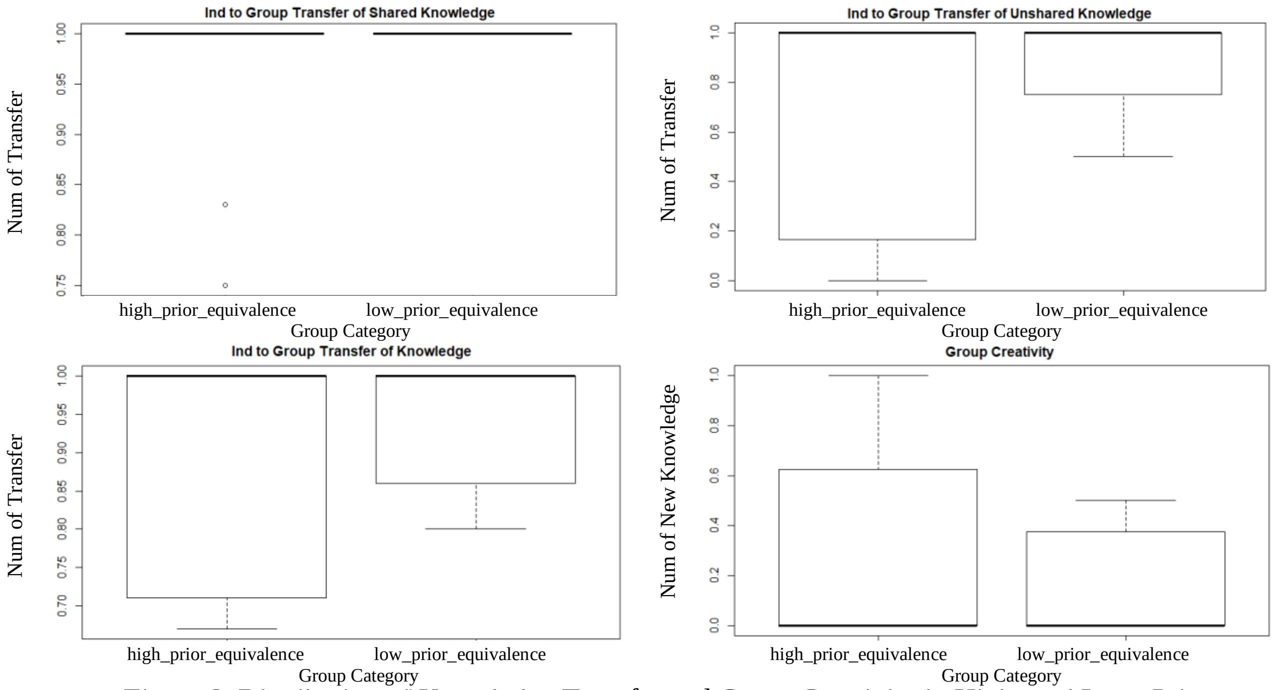


Figure 3. Distribution of Knowledge Transfer and Group Creativity in High- and Low- Prior Knowledge Equivalence Groups ($n = 11$ and $n = 10$, respectively).

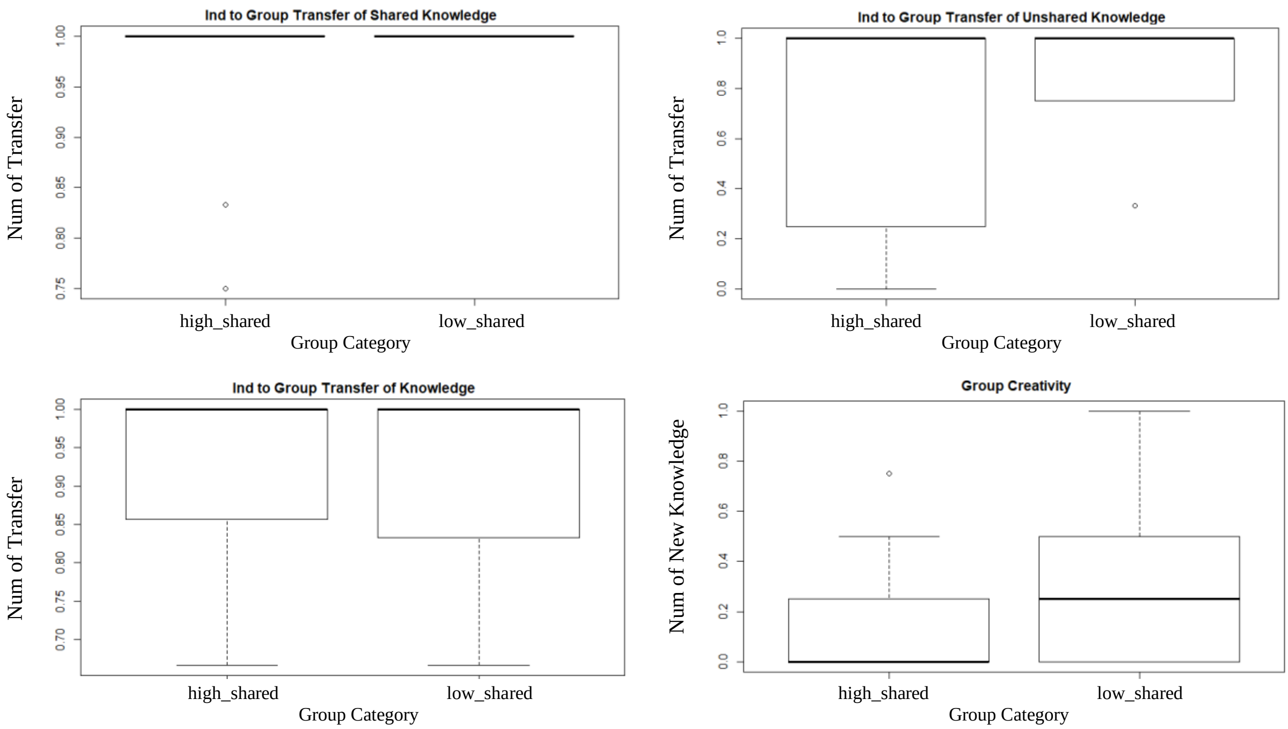


Figure 4. Distribution of Knowledge Transfer and Group Creativity in High- and Low- Shared Knowledge Groups ($n = 10$ and $n = 11$, respectively).

All collaborative map scores were in the range of 75-100 for all conditions ($M = 90$, $SD = 7.49$). These scores were higher than individual map scores (M = 72.21, $SD = 25.76$). Group achievements did not differ significantly between low- and high-prior knowledge equivalence conditions ($p = 0.47$), or between low- and high-shared knowledge conditions (p = 0.302), though there is dissimilarity of distribution among them (Figure 5).

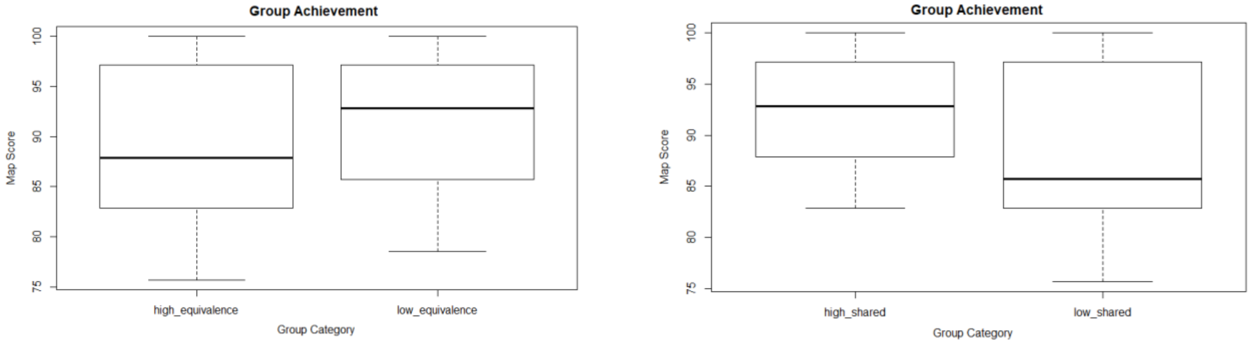


Figure 5. The Collaborative Map Scores Differentiated by Prior Knowledge Equivalence (left-side) and Shared Knowledge on Task (right-side)

4.2 *Learners' Affective Responses*

Figure 6 shows the distribution of the affective scores among groups with different shared knowledge scores. A Kruskall Wallis rank-sum test indicated that there was a significantly different between the groups in higher similarity scores and lower similarity scores ($H(13) = 56.885$, $p < .001$). However, the differences were rather small, which demonstrated that the low similarity users were still positive towards the activities, though less positive. Stimulation subscale received the highest rating, followed by attractiveness then perspicuity subscales.

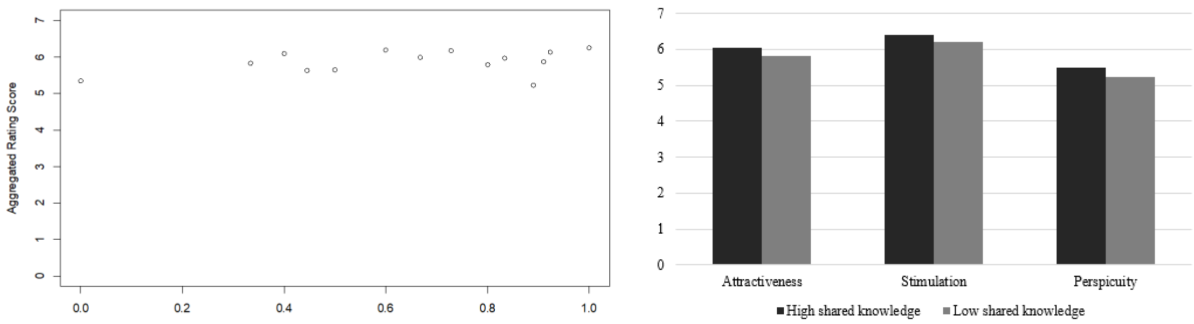


Figure 6. Distribution of Affective Responses Across Different Shared Knowledge Scores

From the open-ended questions, we found that some participants in both conditions mentioned comparable on-task difficulties concerning dissimilarities of ideas or opinions, i.e.: "Difficult to read when the number of visualized differences is too many (n = 6).", "It was hard to read or understand the difference map (n = 2).", "It was difficult to integrate different opinions in order to reach a (group) consensus or determine which one is the correct representation (n = 5).", "The use of ambiguous links makes it hard to select the most suitable relation between two concepts (n = 1)".

5. Discussion and Conclusion

Collaborative concept mapping with Reciprocal Kit Build approach allows learners to represent and manipulate their individual cognitive structures and let their partners provide feedbacks after initial map reconstruction and difference map visualization. This activity provides an active means to review individual maps and to elicit new information. Reviewing members' individual maps as access to distributed cognitive resources positively influence the broadness of group problem solution (Stoyanova & Kommers, 2002). Her study has also suggested that a process of knowledge acquisition and creation through direct interaction have an impact on group learning effectiveness, which consistent with our preliminary findings (Sadita et al., 2018).

The present study displays the learning effectiveness as the interaction between individual to group knowledge, specifically knowledge transfer. The results show that the amount of knowledge transfer is considerably high in all group conditions. Furthermore, the degree of knowledge differences within the group members may not significantly affect the amount of knowledge transfer. While some studies have reported that groups often abandon the unshared knowledge or resources (Frank Fischer & Mandl, 2002; Gracia-Moreno et al., 2017), our study indicates that transfer of both shared and unshared individual knowledge is more than 85% when using RKB. It is interesting to note that a few groups such as Group 09 and Group 14, who were the high prior knowledge convergence condition did not transfer all of their shared knowledge. Further investigation of their behavior is essential to reveal these specific group problems.

Moreover, we found the weak correlation between individual map scores and normalized transfer of unshared knowledge. It is indicating that during collaboration students were able to detect important substructures with less consideration on who are the source of information. The students more often to not merely follow a certain group member. They acknowledge the partner's perspectives and take into account differences in knowledge.

The affective responses of the groups with different shared knowledge scores demonstrated that learners in higher shared knowledge are slightly more positive than the lower shared knowledge conditions. Participants in both conditions show similar patterns, they thought that our activities were more stimulating and attractive, rather than perspicuous. Difficulties appeared when they faced differences in ideas or perspectives and need to resolve those conflicts in order to reach a single group solution. Though pursuing conflict resolution is essential for conceptual change and advancement of knowledge in collaborative learning (Chan, Burtis, & Bereiter, 1997; Roschelle, 1992; van Boxtel, van der Linden, Roelofs, & Erkens, 2002), the learners may feel less positive and it may influence overall learning experiences in collaborative situations. Further research on how computer-based visualization can be utilized to aid learners during conflict-oriented consensus building and integration-oriented consensus building is indispensable.

In summary, our study found that learners in different prior knowledge levels benefit similarly, with respect to the transfer of their individual knowledge, following the proposed activities. Different group composition is not necessarily affected knowledge transfer and collaborative outcomes. However, the amount of joint knowledge between the group members can possibly have more effects on the group outcomes, since the RKB system enables individual knowledge structures more tangible and are ready to be manipulated by their partners. Different opinions or understanding with regard to the collaborative task can affect overall learners' experiences in a collaborative environment.

Our current works have evaluated the learning effectiveness only at two different dimensions (i.e. group and interaction level). It seems that our approach can attain learning effectiveness at the individual level as well, because of high knowledge transfer during collaboration. However, there is a lack of evidence related to individual performances after collaboration. Further studies with a large number of participants from different subjects should be conducted to identify the broadness of our approach. For the future works, it is also interesting to compare the results of groups with reciprocal teaching activity and conventional collaborative concept map without the reciprocal cycle.

References

Basque, J., & Lavoie, M.-C.-. C. (2006). Collaborative concept mapping in education: Major research trends. *Concept Maps: Theory, Methodology, Technology. Proc. of the Second Int. Conference on Concept Mapping.*, *1*, 79–86. Retrieved from http://eprint.ihmc.us/119/

Chan, C., Burtis, J., & Bereiter, C. (1997). Knowledge building as a mediator of conflict in conceptual change. *Cognition and Instruction*. https://doi.org/10.1207/s1532690xci1501_1

de Weerd, J., Tan, E., & Stoyanov, S. (2017). Fostering interdisciplinary knowledge construction in computer-assisted collaborative concept mapping. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *10474 LNCS*(Ccm), 391–396. https://doi.org/10.1007/978-3-319-66610-5_32

Engelmann, T., & Hesse, F. W. (2010). How digital concept maps about the collaborators' knowledge and information influence computer-supported collaborative problem solving. *International Journal of Computer-Supported Collaborative Learning*, *5*(3), 299–319. https://doi.org/10.1007/s11412-010-9089-1

Fischer, F., Bruhn, J., Gräsel, C., & Mandl, H. (2002). Fostering collaborative knowledge construction with visualization tools. *Learning and Instruction*, *12*(2), 213–232. https://doi.org/10.1016/S0959-4752(01)00005-6

Fischer, Frank, & Mandl, H. (2002). Facilitating knowledge convergence in videoconferencing environments: the role of external representation tools. In *Proceedings of the Conference on Computer Support for Collaborative Learning: Foundations for a CSCL Community* (pp. 623–624).

Gnesdilow, D., & Bopardikar, A. (2010). Exploring convergence of science ideas through collaborative concept mapping. *The Journal of the Learning Sciences*, *1*, 698–705. Retrieved from http://dl.acm.org/citation.cfm?id=1854449

Gracia-Moreno, C., Cerisier, J.-F., Devauchelle, B., Gamboa, F., & Pierrot, L. (2017). Collaborative knowledge building through simultaneous private and public workspaces. *Data Driven Approaches in Digital Education*, *10474*, 553–556. https://doi.org/10.1007/978-3-319-66610-5

Hirashima, T., Yamasaki, K., Fukuda, H., & Funaoi, H. (2015). Framework of kit-build concept map for automatic diagnosis and its preliminary use. *Research and Practice in Technology Enhanced Learning*, *10*(1), 17. https://doi.org/10.1186/s41039-015-0018-9

Jeong, H., & Chi, M. T. H. (2007). Knowledge convergence and collaborative learning. *Instructional Science*, *35*(4), 287–315. https://doi.org/10.1007/s11251-006-9008-z

Jeong, H., & Hmelo-Silver, C. E. (2016). Seven affordances of computer-supported collaborative learning: How to support collaborative learning? How can technologies help? *Educational Psychologist*, *51*(2), 247–265. https://doi.org/10.1080/00461520.2016.1158654

Khamesan, A., & Hammond, N. (2004). Taxonomy of analysis levels of learning effectiveness in collaborative concept mapping. *Proc. of the First Int. Conference on Concept Mapping*.

Molinari, G. (2013). From learners' concept maps of their similar or complementary prior knowledge to collaborative concept map: Dual eye-tracking and concept map analyses. *Psychologie Francaise*, *62*(3), 1–19. https://doi.org/10.1016/j.psfr.2015.11.001

Pailai, J., Wunnasri, W., Yoshida, K., Hayashi, Y., & Hirashima, T. (2017). The practical use of Kit-Build concept map on formative assessment. *Research and Practice in Technology Enhanced Learning*, *12*(1), 20. https://doi.org/10.1186/s41039-017-0060-x

Roschelle, J. (1992). Learning by collaborating: Convergent conceptual change. *Journal of the Learning Sciences*. https://doi.org/10.1207/s15327809jls0203_1

Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In *Computer Supported Collaborative Learning*. https://doi.org/10.1007/978-3-642-85098-1_5

Sadita, L., Hirashima, T., Hayashi, Y., Wunnasri, W., Pailai, J., Junus, K., & Santoso, H. B. (2018). Preliminary Study on the Use of Reciprocal Kit Build for Collaborative Learning. In *The 26th International Conference on Computers in Education (ICCE 2018)* (pp. 133–142).

Santoso, H., Schrepp, M., Kartono, Y., Yudha, A., & Priyogi, B. (2016). Measuring user experience of the student-centered e-learning environment. *The Journal of Educators Online*. https://doi.org/10.9743/JEO.2016.1.5

Stahl, G. (2003). Building collaborative knowing: Elements of a social theory of learning. In *What we know about CSCL in higher education.* https://doi.org/10.1007/1-4020-7921-4_3

Stoyanova, N., & Kommers, P. (2002). Concept mapping as a medium of shared cognition in computer-supported collaborative problem solving. *Journal of Interactive Learning Research*. https://doi.org/10.1161/CIRCOUTCOMES.110.942318

Suthers, D. D. (2006). Technology affordances for intersubjective meaning making: A research agenda for CSCL. In *International Journal of Computer-Supported Collaborative Learning* (Vol. 1, pp. 315–337). https://doi.org/10.1007/s11412-006-9660-y

van Boxtel, C., van der Linden, J., & Kanselaar, G. (2000). Collaborative learning tasks and the elaboration of conceptual knowledge. *Learning and Instruction*, *10*(4), 311–330. https://doi.org/10.1007/s40815-016-0287-5

van Boxtel, C., van der Linden, J., Roelofs, E., & Erkens, G. (2002). Collaborative concept mapping: Provoking and supporting meaningful discourse. *Theory Into Practice*, *41*(1), 40–46. https://doi.org/10.1207/s15430421tip4101_7

Weinberger, A., Stegmann, K., & Fischer, F. (2007). Knowledge convergence in collaborative learning: Concepts and assessment. *Learning and Instruction*. https://doi.org/10.1016/j.learninstruc.2007.03.007

Wunnasri, W., Pailai, J., Hayashi, Y., & Hirashima, T. (2018a). Reciprocal Kit-Build concept map: An approach for encouraging pair discussion to share each other's understanding. *IEICE Transactions on Information and Systems*.

Wunnasri, W., Pailai, J., Hayashi, Y., & Hirashima, T. (2018b). Reciprocal Kit-Building of concept map to share each other's understanding as preparation for collaboration. In *Proceeding of the 19th International Conference on Artificial Intelligence in Education, London, United Kingdom*.

Yoshida, K., Osada, T., Sugihara, K., Nino, Y., Shida, M., & Hirashima, T. (2013). Instantaneous assessment of learners' comprehension for lecture by using kit-build concept map system. In *International conference on human Interface and the Management of Information* (pp. 175–181).