

Interdependence as a Treatment Effect: An Example From Group Awareness Research

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Abstract: Interdependence of data within collaborative learning is often viewed as a mere statistical phenomenon. However, interdependence may provide valuable information about the collaboration process. Thus, we report data of an exemplary study ($N = 82$) about the impact of metacognitive group awareness information on collaborative learning to illustrate how this information may add to data interpretation. Our analyses indicate that interdependencies after collaboration may be part of the treatment effect and point towards differential collaboration strategies.

Introduction

One great challenge for quantitative research in CSCL is the interdependence of individual data when learners interact in dyads or groups. Usually, dealing with hierarchical data is done in a stepwise procedure: first, the actual data is tested for statistical interdependence and – depending on the outcome – the data is analyzed accounting for interdependence if necessary (Cress, 2008). If there is no interdependence, independence may be assumed, and corresponding statistical analyses can be used. However, collaboration processes usually rely heavily on interaction between group members and should thus foster non-independence on some levels. Additionally, treatments varied experimentally are often specifically designed to foster collaboration and thus explicitly target interaction between subjects. Thus, we cannot assume interdependence to be a mere effect of the overall collaboration task, but it might be part of the treatment effect and thus more heavily apply to groups of learners within one experimental condition. In this paper, we will describe exemplary data to show how a treatment targeting interaction between individuals learning in a dyadic setting may affect interdependence differently and how this information can enrich our analyses.

Empirical study: Group awareness tools to foster collaboration

Group awareness tools are designed to inform learners about aspects of group members or the group in order to implicitly guide their learning processes (Bodemer, Janssen, & Schnaubert, in press). Thus, they affect collaboration in a way that is thought to be beneficial for individual learning. Empirical research uses a great variety of target concepts of such tools, and especially tools providing cognitive group awareness information may support relevant learning processes (cf. Janssen & Bodemer, 2013). For example, they may visualize individual needs or conflicting assumptions, thus fostering partner modelling central for collaboration processes (Dillenbourg, 1999). Thereby they may help learners to structure and coordinate joint learning processes (Clark & Brennan, 1991) and to tail their conversation to the needs of the individuals (Clark & Murphy, 1982). In our study, we aimed at investigating whether metacognitive group awareness information has an additional benefit to cognitive group awareness information. We hypothesized that learners receiving information on metacognitive confidence regarding specific assumptions learn more during collaboration than learners who do not receive this information due to improved collaboration processes and that they gain more confidence in the process, since insecurities signaling individual need for clarification may explicitly be addressed during collaboration.

To test our hypotheses, we evaluated data of an experimental study with 41 dyads of learners randomly assigned to two (between-dyad) research conditions varying the availability of metacognitive confidence information during collaboration (MC+ vs. MC-). Dependent variables were assessed pre and post collaboration (within-subject). All participants each read a text on diabetes mellitus and answered questions regarding the topic individually, and then came together in dyads to discuss the topic guided by the questions on a multi-touch tabletop. Afterwards, they answered the questions again individually. They gave a confidence rating with each answer, but the display of this information during collaboration depended on experimental condition. Our dependent variables were (a) the number of learning tasks each individual solved correctly pre and post collaboration to assess knowledge gain (performance) and (b) the number of confidently solved items per person pre and post collaboration to assess changes in confidence levels (confidence). While the treatment was implemented on dyad level during collaboration, outcome measures were assessed individually. Because we worked with partially-dependent data for our analyses on learning outcomes (individuals nested within dyads), we computed intra-class-correlation coefficients (ICC; Shrout & Fleiss, 1979) for each experimental condition.

To analyze the data, we conducted two-factorial MANOVAs with repeated measures on one factor with dyads and individuals as units of analyses, and additionally analyzed the data via a dyadic multi-level model using linear mixed modeling with restricted maximum likelihood estimation. We found a multivariate main effect of time and an interaction effect. Univariate ANOVAs confirmed main effects of time with performance and confidence levels rising significantly from pre to post and a significant interaction effect with MC+ learners' performance increasing more from pre to post than the performance of learners in MC-.

While these results largely corresponded with our expectations, taking a closer look at ICC values produced some unexpected results: We found that after collaboration, the two conditions (MC+ vs. MC-) differed considerably in their statistical interdependence, leading us to assume different collaboration processes. While learners within dyads in MC+ were more interdependent with regard to resulting confidence levels (ICC = .56) than learners in MC- (ICC = .26, n.s.), the latter were more similar regarding performance levels (ICC = .67) than learners in MC+ (ICC = .31, n.s.). Thus, providing metacognitive information may have shifted attention to different aspects of the learning processes and may have resulted in different collaboration efforts. While it was assumed that learners gain from metacognitive information performance-wise, the assumption was based on improved collaboration processes where learners more efficiently exchange information or co-construct knowledge (Dillenbourg, 1999). However, this should have resulted in higher dependencies regarding performance, which was not the case. Rather, it could be that visualizing metacognitive information may have given the learners less need to negotiate their understanding of the content, since displayed uncertainties might be a way to maintain differences while reducing cognitive conflict.

Conclusion

While statistical interdependence is often seen as a nuisance due to constraints they put on the usage of standard statistical analyses, it is worth noting that various collaborative learning scenarios explicitly target dependencies of learners who interact whilst influencing the learning partners' cognitive processes (Dillenbourg, 1999). Hence, the focus of this paper was to exemplarily show how ICCs may add valuable information that may easily be lost when merely compensating for interdependence rather than interpreting it. Interdependence is not a mere statistical phenomenon, but a result of common exposure to situational factors (shared experiences) or of reciprocal influence and thus interaction (Cress, 2008). Especially the latter is in the core of collaborative learning, where peers interact while pursuing a learning goal (Suthers, 2012) and thus, low ICCs may often not be in line with the (more or less explicit) theoretical assumptions made about collaborative processes. It is thus not surprising, that treatments designed to foster collaborative learning processes may differentially influence interdependence, since they affect the interaction processes between learners within a learning group.

References

- Bodemer, D., Janssen, J., & Schnaubert, L. (in press). Group awareness tools for computer-supported collaborative learning. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International Handbook of the Learning Sciences*. New York, NY: Routledge/Taylor & Francis.
- Clark, H. H., & Brennan, S. E. (1991). Grounding in communication. In L. B. Resnick, J. M. Levine, & S. D. Teasley (Eds.), *Perspectives on socially shared cognition* (pp. 127–149). Washington, DC: American Psychological Association.
- Clark, H. H., & Murphy, G. L. (1982). Audience design in meaning and reference. *Advances in Psychology*, 9(C), 287–299. [https://doi.org/10.1016/S0166-4115\(09\)60059-5](https://doi.org/10.1016/S0166-4115(09)60059-5)
- Cress, U. (2008). The need for considering multilevel analysis in CSCL research—An appeal for the use of more advanced statistical methods. *International Journal of Computer-Supported Collaborative Learning*, 3(1), 69–84. <https://doi.org/10.1007/s11412-007-9032-2>
- Dillenbourg, P. (1999). What do you mean by “collaborative learning”? In P. Dillenbourg (Ed.), *Collaborative learning: Cognitive and computational approaches* (pp. 1–19). Oxford, UK: Elsevier.
- Janssen, J., & Bodemer, D. (2013). Coordinated computer-supported collaborative learning: Awareness and awareness tools. *Educational Psychologist*, 48(1), 40–55. <https://doi.org/10.1080/00461520.2012.749153>
- Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, 86(2), 420–428. <https://doi.org/10.1037/0033-2909.86.2.420>
- Suthers, D. D. (2012). Computer-supported collaborative learning. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning*. New York, NY: Springer.