Frontline Learning Research
An official journal of EARLI

Frontline **L**earning **R**esearch 6 (2014) 25-33
ISSN 2295-3159

Constructing nomological nets on the basis of process analyses to strengthen CSCL research

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Article received 26 May 2014 / revised 6 August 2014 / accepted 29 September 2014 / available online 23 December 2014

Abstract

Due to the nature of collaborative learning, realising perfectly controlled experiments often requires an unreasonable amount of resources and sometimes it is not possible at all. Against this background, I propose to augment as good as feasible experimental design with a nomological net of relations between instructional support (intervention), learning processes and learning outcomes. Nomological networks are known from construct validity. In construct validity, the relations between variables (e.g. group differences, correlation matrices) are used to provide evidence for the validity of a measure. By adding multiple process and outcome variables together with the corresponding relations between intervention, process and outcome, the validity of causal relations found can be strengthened. I suggest adopting quality criteria from good research designs to evaluate the nomological nets. The resulting net needs to be (1) theory grounded, (2) situational, (3) feasible, (4) redundant, and (5) efficient. By making these nomological nets explicit and by designing them according to the presented criteria, CSCL research becomes more potent: the risk of inconclusive results is reduced while results that form a consistent nomological net can be interpreted with a stronger confidence, even if the experimental design has some flaws. If this becomes standard in CSCL research, it can be expected to contribute significantly better to knowledge accumulation in this area of research.

Keywords: Construct Validity; Nomological Net; Research Design; Computer-supported Collaborative Learning (CSCL)

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Doi: http://dx.doi.org/10.14786/flr.v2i4.112

1. The role of process analyses in CSCL research

Approaches to computer-supported collaborative learning (CSCL) are mainly based on three assumptions. First, collaborative learning outperforms (under particular circumstances, e.g. with specific support) other methods when it comes to learning outcomes. Usually, specific collaborative activities like argumentation (e.g. Clark, D'Angelo, & Menekse, 2009), transactive co-construction (e.g. Molinari et al., 2013; Weinberger & Fischer, 2006), reciprocal teaching (Palincsar & Brown, 1984) and collaborative concept mapping (van Boxtel, van der Linden, Roelofs, & Erkens, 2002) are considered to be positively related to individual cognitive processes of learning.

Second, computer support enables both certain learning activities (e.g. simulation-based inquiry learning; de Jong & van Joolingen, 1998) and more direct support for certain activities (e.g. scaffolds as an inherent, but adaptive, component of the learning environment; cf. Koschmann, 1994). Technology enables natural systems and phenomena that would otherwise be invisible and therefore impossible to be experienced (e.g. the heart of an engine or magnetism on an atomic level; cf. Fischer, Lowe, & Schwan, 2008). Technology also enables us to facilitate learning processes by different means, e.g. by making various resources accessible (e.g. Osborne & Hennessey, 2003), scaffolding specific individual processes like the construction of single arguments (Stegmann, Wecker, Weinberger, & Fischer, 2012), or offering ways to communicate and collaborate (Wegerif, 2002).

Third, the combination of collaborative learning and technology can have positive interaction effects that go beyond the simple combination of main effects. On the one hand, the quality of collaborative learning processes is lifted through adaptive scaffolds that positively moderate the positive effects of collaborative learning. On the other hand, the effects of technology functions (like access to various resources) on learning outcomes are boosted through collaborative learning (cf. Weinberger, Stegmann, & Fischer, 2010).

Set against this background, CSCL research aims to provide knowledge about how technology can support collaborative learning processes (and thereby learning outcomes on an individual as well as a group level; cf. Stahl, 2006) most effectively. On the one hand, the problems that may arise through collaboration or the use of technology have to be minimised, while, on the other, the use of technology resources and collaborative learning processes has to be optimised. The effect of CSCL on learning outcomes is therefore mediated by processes that occur during the collaborative learning phase. This general model can be described in a triangle of hypotheses (cf. Wecker, Stegmann, & Fischer, 2012; Fig. 1): (a) instructional/technological support facilitates learning activities; (b) facilitated learning activities have positive effects on learning outcomes; and (c) mediated by learning activities, instructional/technological support has a positive effect on learning outcomes.

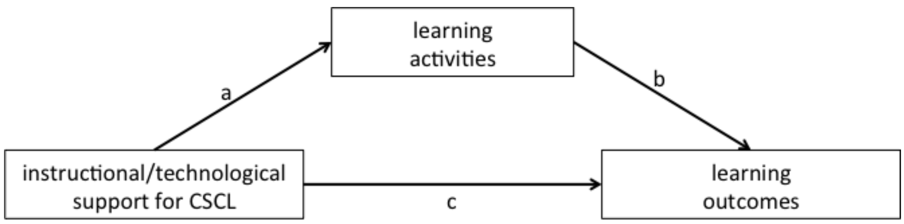

Figure 1: General triangle of hypotheses in CSCL research.

To test this triangle of hypotheses and to allow researchers to infer causal-effect relations, three conditions must be fulfilled (cf. Cook & Campbell, 1979): (a) when the causing variable varies, the affected variable must vary too (covariation); (b) the cause must occur before the effect occurs (temporal precedence); and (c) no plausible alternative explanations exist. While the first two conditions can be reached in CSCL research rather easily, the third condition is very difficult to reach. CSCL research often takes place in field-like settings and even studies with a rather higher level of control (e.g., Weinberger, Marttunen, Laurinen, & Stegmann, 2013) are much less controlled than classical psychological experiments.

The adherence to instructional advice, for example, is usually not enforced. Testing the effect of an intervention on learning activities is, therefore, experimentally a variation check, but semantically the test of whether the way the instruction is realised is able to induce the intended behaviour. Due to the nature of collaborative learning, realising perfectly controlled experiments requires an unreasonable amount of resources and sometimes it is not possible at all.

Just imagine a jigsaw experiment (for a detailed description of the jigsaw method see Aronson, 1978). In a jigsaw script, the content to be learnt is split into, for example, four subtopics. Groups of four prepare one of the four topics and finally four new groups are formed with one learner from each of the previous groups and learners teach their subtopic to the other group members. In this experiment, individual learning, unscripted collaborative learning and collaborative learning using the jigsaw method are compared. In the individual learning condition, 32 subjects are enough if a large effect with 80% power is expected. In the condition with unscripted collaborative learning in groups of four, the number of subjects might be optimally, due to nestedness of data, 128 learners in 32 groups. In the jigsaw condition, 512 subjects are required due to the fact that 16 subjects learn collaboratively together in 32 groups. According to Maas and Hox (2005), a number of more than 50 groups is needed for acceptable statistical multilevel analyses. With 64 groups across two conditions, this criterion is fulfilled. Finally, this simple one-factorial design with three conditions requires 672 subjects to find effects with large effect size. And still it would not be free of confounded factors, e.g. the type of support is confounded with group size. While a condition with unscripted learners in groups of 16 would be possible, a condition with jigsaw script with groups of four is not possible. This example illustrates the inherent problems of CSCL research in excluding plausible alternative explanations through experimental design. Against this background, I propose to augment as good as feasible experimental design with a nomological net of relations (hypotheses) between instructional support (intervention), learning processes and learning outcomes.

2. Criteria for nomological nets as the basis of high quality CSCL research

Nomological networks are known from construct validity (cf. Cronbach & Meehl, 1955). In construct validity, the relations between variables (e.g. group differences, correlation matrices) are used to provide evidence for the validity of a measure. I like to utilise this idea to validate the (causal) relation between interventions, mediators and outcome variables. The smallest nomological net possible comprises just two variables and one relation, but does not yet additionally validate a causal relation. The net, however, becomes stronger the more ties and knots are part of the net. The stronger the net, the stronger the confidence in the validity of causal relations between variables. The smallest net that can increase the confidence in a causal relation in CSCL research is the triangle of hypotheses described previously with three knots and three relations. By adding multiple process and outcome variables together with the corresponding relations between intervention, process and outcome, the validity of causal relations found can be strengthened. The development of such a nomological net requires some general quality criteria that allow evaluation of the net. I suggest adopting quality criteria from good research designs as described, for example, by Trochim and Land (1982). According to these authors, the nature of good designs is (1) theory grounded, (2) situational, (3) feasible, (4) redundant, and (5) efficient. In the following sections, I provide a short explanation of the criteria and some illustrating examples from CSCL research for each criterion.

2.1 Theory grounded

The nomological net needs to be theory grounded. For each of the relations, a directional effect needs to be explicable by a theory and may be backed up by previous empirical findings. The question, for example, concerning the extent to which learners mutually influence one another has attracted considerable attention in CSCL research. Particular focus has been placed on the degree to which groups of learners share a mutual understanding via social interaction. Accordingly, attempts have been made to quantify this process, which is referred to as knowledge convergence, based on analyses of text-based knowledge-building processes. Mäkitalo-Siegl and colleagues (2012) traced so-called knowledge pieces through collaboration.

The transfer of knowledge pieces from one learner to another was measured by comparing the knowledge pieces mentioned by single learners before, during and after collaboration. The relations in the corresponding nomological net would be that collaborative learners share more knowledge pieces during collaboration and that these shared knowledge pieces are known better by group members after collaboration.

Weinberger, Stegmann and Fischer (2007) presented an approach with additional quantitative measures of the convergence of prior knowledge, collaborative processes and acquired knowledge based on fine-grained (i.e. at the level of inferences) analyses of text-based data sources (pretest, text-based online discussion, post-test). The authors suggest using the variation coefficient of the number of different inferences within a group of learners (analogous to knowledge pieces) as an indicator of knowledge divergence. Applying these measures provided insight into the relationship between the processes and outcomes of collaborative knowledge construction (e.g., Weinberger, Stegmann, & Fischer, 2005; Zottmann, et al., 2013). The nomological net may comprise, for example, the relation that learners with high divergence during online discussions (i.e. contributing different as opposed to identical inferences) are more likely to share knowledge after collaboration than learners with high convergence during online discussions.

In real life, however, not all assumed relations show up as expected in empirical research. The strength of the net is, of course, stronger if all hypotheses made a priori test successfully. In practice, a net needs to be adopted post hoc to explain the results at hand. In these cases, additional explanatory variables and relations may be added to achieve a consistent net. The new relations need, of course, to be theory grounded as well. By adding further mediators, moderators and/or suppressors, the results can form a consistent net again. As a by-product, the adaption of a net is a further development of the initial theory.

2.2 Situational

The manipulated/measured variables as well as the relations between them need to be situational defined. The interventions, the process variables and, to a large extent, the outcome variables in CSCL research are highly situational, i.e. depend on the situation, content and context at hand. The intervention is usually one realisation out of an endless number of possible realisations of a specific theoretical principle (e.g. an implementation of the jigsaw method; cf. Wecker, 2013). The process and outcome variables may be termed rather general (such as “content quality”, “quality of argumentation”; cf. Stegmann, Weinberger, & Fischer, 2007), but the concrete operationalisation requires the inclusion of bottom-up criteria that derive from the (learning) material and raw process data. In most cases, especially in the case of process variables, general (i.e. less situational) measures of skills or competences (like those applied in PISA studies; cf. Kobarg, Prenzel, & Seidel, 2011) are not suitable, because they measure features (abilities) of persons, not activities. It is, therefore, necessary to apply measures with a high content validity. Such measures usually need to be developed individually for each situation. It is necessary to quantify the qualities of collaborative activities with respect to multiple quality dimensions. A detailed description of such a Multidimensional Approach for the Qualitative Coding of Online Discussions (MAQCOD) can be found in Stegmann and Fischer (2011).

Collaborative (learning) activities are, for example, often analysed in terms of the content quality or quality of the argumentation (e.g. Weinberger & Fischer, 2006). Depending on the dimension, the grain size of the analysis needs to be defined (cf. Strijbos, Martens, Prins, & Jochems, 2006). The quality of the argumentation, for example, could be defined for the entire discourse, single messages or even single arguments. Which grain size is most suitable depends on the theoretically defined relationship between the quality dimension to be analysed and the intended learning outcome. If, for example, the theoretical model assumes that formulating arguments with grounds and warrants is a core collaborative learning activity, single arguments rather than complete conversations need to be the focus. Along with grain size, the categories need to be defined. Single arguments can, for instance, be coded in terms of whether they are grounded or not. The definitions of the dimensions, grain size and categories per dimension need to be carefully documented. This may comprise: segmentation rules and examples for the application of these rules; the names of dimensions and categories; rules about when to assign a specific category; and examples when a category applies and when it does not. This documentation forms the basis for an objective, reliable and content-valid coding of learning activities and, thereby, for the inclusion of process variables in a nomological net.

2.3 Feasible

The inclusion of process variables in a nomological net requires that it is feasible to extract the variable from the recorded activities during CSCL. It is, for example, problematic to measure the depth of cognitive processing just by analysing written CSCL discourse data. Researchers may argue that a sophisticated, well-elaborated argument can be regarded as an indicator of deep cognitive processing. The argument, however, might be just “copied” from a different source (e.g. a learning partner or prior knowledge) without deep cognitive processing. Such a measure, therefore, does not have sufficient content validity to be included in a nomological net with the intended function. This is not an argument against the variable “depth of cognitive processing” in general. The requirement is to measure the variable in a content-valid way, i.e. as directly as possible. If data sources such as think-aloud protocols are available (e.g. Stegmann, Wecker, Weinberger, & Fischer, 2012), it might be adequate to include such a variable in a nomological net.

2.4 Redundant

Like in a cockpit of an aeroplane, central components of the nomological net might be redundant, i.e. implemented several times. In CSCL research, this redundancy is often regarded as a methodological challenge rather than a strength of the research design. An inherent feature of collaborative learning is the nestedness of learners in groups and in time. Learners are part of a group and thereby features of the group affect learning. In addition, the knowledge and skills of the single learner as well as of the group change over time (Wise & Chiu, 2011). The activities of learners in a group are affected not only by the initial features of the single learners and the collaborative learning phase, but also by the activities that the single learner and the group performed previously. Furthermore, instructional support such as collaboration scripts affects the relationship between previous and current activities.

The nestedness of learners in groups and in time is not only an issue if researchers aim to understand why learners learn in a certain way; learners and groups also change over time. The Script Theory of Guidance (SToG; Fischer, Kollar, Stegmann, & Wecker, 2013), for example, assumes that instructional support for collaborative learning needs to be adapted consecutively to ensure the optimal fit between the skills of the single learners/the group and the instructional support. As a result, a nomological net may include relations that reflect such ideas but add time as a moderator of the effect of an intervention on the process of collaborative learning.

As already raised in the jigsaw study example, (quantitative) research on CSCL often requires many more participants due to the issue that learners who learned in groups cannot be regarded as independent observations. From the viewpoint of the nomological net, the relation, for example, of an intervention at group level on a specific process is redundant within a group. For an intervention that aims to facilitate, for example, argumentation sequences (e.g., Stegmann, Weinberger, & Fischer, 2011; Jeong, Clark, Sampson & Menekse, 2010), a positive relation between the intervention and the number of argument-counterargument-syntheses sequences may be added to the nomological net at group level. On an individual level (i.e. the level of group members), positive relations between the intervention and the number of contributed counterarguments and syntheses may be added to the net. Furthermore, scaffolds examined in CSCL research often focus on specific processes that occur multiple times during collaborative learning. If an intervention such as a collaboration script aims to support the quality of each single argument (cf. Stegmann, Wecker, Weinberger, & Fischer, 2012) with respect to grounds and warrants, the effect is expected to show up on the level of each argument (as the probability that a claim is supported by ground and/or warrant), on the level of each individual learner (as the share of grounded/warranted claims contributed by an individual), and on the group level (as a higher argumentative quality of the discussion).

2.5 Efficient

An important aspect, finally, is the efficiency of the testing of the relations specified in the nomological net. Efficiency is in general determined by two factors: the usefulness of a result and the extent of resources required to reach the result. This criterion seems to be contradictory to the examples for the previously described criteria. These criteria require rather qualitative analyses of processes on multiple levels including time series. Many more resources (i.e. technology to record data, space to archive the data, manpower to develop coding manuals and to analyse data) need to be spent. In CSCL research, however, the digital learning environment in which learning activities under examination usually take place can reduce the amount of resources. Especially assessing and analysing data are supported by technology. Technologies like iBeacon or active RFID chips allow learners to be traced as well as the interaction between them and artefacts to learn from in the context, for example, of museums. Eberle and colleagues (2013), for example, traced the activities of conference participants using active RFID chips to examine the relation between interaction between conference participants, planned future collaboration right after the conference and collaborative publications two years after the conference. In scenarios with computer-mediated communication, the communication can easily be recorded.

The opportunity to log data in technology-enhanced learning environments can easily produce a large amount of data that exceeds the limits for meaningful human analyses. The development in the area of machine learning technology, however, enables researchers to train algorithms to – supervised or unsupervised – analyse digital data according to multiple dimensions such as quality of argumentation, content quality or emotions. To apply these algorithms to data at hand, in a first step, features of the learning processes need to be extracted. In the case of written discourse data, for example, the number of specific words or word pairs, the punctuation or the line length are extracted. This step can be easily performed using tools such as TagHelper (Rosé et al., 2008) or lightSIDE (Mayfield & Rosé, 2012). In a second step, these features are used in conjunction with a human coding that serves as training material to build models that are able to measure the respective quality. Recently, Mu and colleagues (2012) presented the ACODEA framework, which may serve as a blueprint on how to apply this technology in CSCL research. The empirical results presented by Mu and colleagues (2012) show that this procedure enables objective analyses of texts that were not previously used for training to be conducted. The results obtained were at the same level as those produced by human coding, and were in some cases even better than those produced by inter-human objectivity.

While the described application of technology in the research process contributes to a reduction of required resources, I further argue that the usefulness of the results is increased by testing a comprehensive nomological net in comparison to results not embedded in a net. Testing the three types of hypotheses of the general triangle of hypotheses (cf. Fig. 1) increases the probability that a study will produce useful results (and not just because three times more hypotheses are tested). If all of the three hypotheses are significant, this can be regarded as a validation of the underlying theoretical model. However, if one or two of the three hypotheses fail (e.g. the relationship between learning activities and learning outcomes), but the others are significant, the findings provide a starting point for explanations that may improve the initial theoretical model. It is only if all of the hypotheses fail to be significant that the empirical results will be completely inconclusive regarding generalisability and causal relations. Nevertheless, a more in-depth analysis of learning activities and post hoc adaption of the nomological net still provides insights into the mechanisms of learning, regardless of significant effects on learning outcomes.

3. Conclusion

The general structure of CSCL research can be described using the introduced triangle of hypotheses. Therefore, nomological nets are an inherent feature of CSCL research. By making these nomological nets explicit and by designing them according to the presented criteria, the research becomes more potent: the risk of inconclusive results is reduced while results that form a coherent nomological net can be interpreted with a stronger confidence even if the experimental design has some flaws. This, however, is by no means an argument to conduct studies with an easily improvable experimental design or to skip experimental variation completely. An as good as possible experimental design is the basic prerequisite for the nomological net to contribute to strengthening the confidence in causal interpretations of effects. The suggestion to use a nomological net as described is, nevertheless, not limited to quantitative research approaches. Some if not all relations might be examined with qualitative methods. The effect on the confidence in the interpretation is the same as in quantitative methods: it increases. Actually, I would expect quantitative and qualitative methods to be used in a complementary way to form nomological nets in CSCL research. The explication of the nomological net, therefore, should become obligatory in reports and presentations on research in CSCL. Studies that aim to provide evidence for causal relations need to report effects on processes and outcomes, not either or. The processes have to be analysed in a way that ensures content validity. The (statistical) analyses have to make use of the multilevel structure of the process data. New technologies have to be applied to cope with the vast amount of data. If this becomes standard in CSCL research, it can be expected to contribute significantly better to knowledge accumulation in this area of research.

Keypoints

- Realising perfectly controlled experiments often requires unreasonable amount of resources and sometimes it is not possible at all.
- By adding multiple process and outcome variables together with the according relations between intervention, process and outcome into a nomological net, the validity of causal relations found can be strengthened.
- The resulting nomological net needs to be (1) theory grounded, (2) situational, (3) feasible, (4) redundant, and (5) efficient
- Incorporating nomological nets reduce the risk of inconclusive results while results that form a consistent nomological net can be interpreted with a stronger confidence, even if the experimental design has some flaws.

References

Aronson, E. (1978). *The jigsaw classroom*. London: Sage.

Clark, D. B., D'Angelo, C. M. & Menekse, M. (2009). Initial structuring of online discussions to improve learning and argumentation: Incorporating students' own explanations as seed comments versus an augmented-preset approach to seeding discussions. *Journal of Science Education and Technology*, *18*, 321-333. doi:10.1007/s10956-009-9159-1

Cook, T. D., & Campbell, D. T. (1979). *Quasi-experimentation: Design and analysis for field setting*. MA: Houghton Mifflin.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological bulletin*, *52*(4), 281. doi:10.1037/h0040957

De Jong & van Joolingen (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*, 68, 179-201. doi:10.3102/00346543068002179

Eberle, J., Stegmann, K., Lund, K., Barrat, A., Sailer, M., & Fischer, F. (2013). Fostering learning and collaboration in a scientific community – evidence from an experiment using RFID devices to measure collaborative processes. In N. Rummel, M. Kapur, M. Nathan, & S. Puntambekar, S. (Eds.), *To See the World and a Grain of Sand: Learning across Levels of Space, Time, and Scale: CSCL 2013 Conference Proceedings Volume 1 — Full Papers & Symposia* (pp. 169-175). International Society of the Learning Sciences.

Jeong, A., Clark, D. B., Sampson, V. D., & Menekse, M. (2010). Sequential analysis of scientific argumentation in asynchronous online discussion environments. In S. Puntambekar, G. Erkens & C. Hmelo-Silver (Eds.), *Analyzing Interactions in CSCL: Methodologies, Approaches and Issues*. Berlin: Springer. doi:10.1007/978-1-4419-7710-6_10

Fischer, F., Kollar, I., Stegmann, K., & Wecker, C. (2013). Toward a script theory of guidance in computer-supported collaborative learning. *Educational Psychologist*, *48*(1), 56-66. doi:10.1080/00461520.2012.748005

Fischer, S., Lowe, R. K., & Schwan, S. (2008). Effects of presentation speed of a dynamic visualization on the understanding of a mechanical system. *Applied Cognitive Psychology*, *22*(8), 1126-1141. doi:10.1002/acp.1426

Kobarg, M., Prenzel, M., & Seidel, T. (2011). *An international comparison of science teaching and learning. Further results from PISA 2006*. Münster: Waxmann Verlag.

Koschmann, T. D. (1994). Toward a theory of computer support for collaborative learning. *The Journal of the Learning Sciences, 3*(3), 219-225. doi:10.1207/s15327809jls0303_1

Maas, C. J. M., & Hox, J. (2005). Sufficient samples sizes for multilevel modeling. *Methodology*, *1*, 86–92. doi:10.1027/1614-1881.1.3.86

Mayfield, E., & Rosé, C. P. (2012). LightSIDE: Open Source Machine Learning for Text Accessible to Non-Experts. In M. D. Shermis & J. Burstein (Eds.), *Handbook of Automated Essay Grading* (pp. 124-135). New York: Routledge.

Mäkitalo-Siegl, K., Stegmann, K., Frete, A., & Streng, S. (2012). Orchestrating computer-supported collaborative learning: Effects of knowledge sharing and shared knowledge. In S. Abramovich (Ed.), *Computers in education* (pp. 75-91). Commack, NY: Nova Science Publishers.

Molinari, G., Chanel, G., Betrancourt, M., Pun, T, & Bozelle, C. (2013). Emotion Feedback during Computer-Mediated Collaboration: Effects on Self-Reported Emotions and Perceived Interaction. In N. Rummel, M. Kapur, M. Nathan, & S. Puntambekar, S. (Eds.), *To See the World and a Grain of Sand: Learning across Levels of Space, Time, and Scale: CSCL 2013 Conference Proceedings Volume 1 — Full Papers & Symposia* (pp. 336-343). International Society of the Learning Sciences.

Mu, J., Stegmann, K., Mayfield, E., Rosé, C. & Fischer, F. (2012). The ACODEA framework: Developing segmentation and classification schemes for fully automatic analysis of online discussions. *International Journal of Computer-Supported Collaborative Learning*, *7*(2), 285–305. doi:10.1007/s11412-012-9147-y

Osborne, J., & Henessy, S. (2003). *Literature review in science education and the role of ICT: promise, problems and future directions*. Bristol: NESTA Futurelab. Retrieved from http://www.futurelab.org.uk/resources/publications_reports_articles/literature_reviews /Literature_Review380

Palincsar, A. S., & Brown, A. L. (1984). Reciprocal teaching of comprehension-fostering and comprehension-monitoring activities. *Cognition & Instruction*, *1*(2), 117-175. doi:10.1207/s1532690xci0102_1

Rosé, C. P., Wang, Y. C., Arguello, J., Stegmann, K., Weinberger, A., & Fischer, F. (2008). Analyzing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning*, *3*(3), 237-271. doi:10.1007/s11412-007-9034-0

Stahl, G. (2006). *Group cognition*. Cambridge, MA: MIT Press.

Stegmann, K. & Fischer, F. (2011). Quantifying qualities in collaborative knowledge construction: the analysis of online discussions. In S. Puntambekar, G. Erkens & C. Hmelo-Silver (Eds.), *Analyzing interactions in CSCL: methods, approaches and issues* (pp. 247-268). New York: Springer. doi:10.1007/978-1-4419-7710-6_12

Stegmann, K., Weinberger, A., & Fischer, F. (2011). Aktives Lernen durch Argumentieren: Evidenz für das Modell der argumentativen Wissenskonstruktion in Online-Diskussionen [Active learning by argumentation: Evidence for the model of argumentative knowledge construction in online discussions.]. *Unterrichtswissenschaft*, *39*(3), 231–244.

Stegmann, K., Wecker, C., Weinberger, A. & Fischer, F. (2012). Collaborative argumentation and cognitive elaboration in a computer-supported collaborative learning environment. *Instructional Science*, *40*(2), 297-323. doi:10.1007/s11251-011-9174-5

Stegmann, K., Weinberger, A., & Fischer, F. (2007). Facilitating argumentative knowledge construction with computer-supported collaboration scripts. *International Journal of Computer-Supported Collaborative Learning*, *2*(4), 421-447. doi:10.1007/978-0-387-36949-5_12

Strijbos, J.-W., Martens, R. L., Prins, F. J., & Jochems, W. M. G. (2006). Content analysis: What are they talking about? *Computers & Education*, *46*(1), 29-48. doi:10.1016/j.compedu.2005.04.002

Trochim, W., & Land, D. (1982). Designing designs for research. *The Researcher*, *1*(1), 1-6.

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. doi:10.1207/s15430421tip4101_7

Wecker, C. (2013). How to support prescriptive statements by empirical research: Some missing parts. *Educational Psychology Review*, *25*(1), 1-18. doi:10.1007/s10648-012-9208-9

Wecker, C., Stegmann, K., & Fischer, F. (2012). Lern- und Kooperationsprozesse: Warum sind sie interessant und wie können sie analysiert werden? [Learning and Cooperation Processes in Case-Based Learning. Interesting Issues and Analysis Approaches] *REPORT: Zeitschrift für Weiterbildungsforschung*, *35*(3), 30-41. doi:10.3278/REP1203W

Wegerif, R. (2002). *Thinking skills, technology and learning: a review of the literature for NESTA FutureLab*. Bristol: NESTA Futurelab. Retrieved from: http://www.futurelab.org.uk/resources/publications_reports_articles/literature_reviews/Literature_Review394

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

Weinberger, A., Marttunen, M., Laurinen, L., & Stegmann, K. (2013). Inducing socio-cognitive conflict in Finnish and German groups of online learners by CSCL script. *International Journal of Computer-Supported Collaborative Learning*, *8*(3), 333-349. doi:10.1007/s11412-013-9173-4

Weinberger, A., Stegmann, K., & Fischer, F. (2005). Computer-supported collaborative learning in higher education: Scripts for argumentative knowledge construction in distributed groups. In T. Koschmann, D. D. Suthers & T.-W. Chan (Eds.), *Computer Supported Collaborative Learning 2005: The Next 10 Years! Proceedings of the International Conference on Computer Supported Collaborative Learning 2005* (pp. 717-726). Mahwah, NJ: Lawrence Erlbaum. doi:10.3115/1149293.1149387

Weinberger, A., Stegmann, K., & Fischer, F. (2007). Knowledge convergence in collaborative learning: Concepts and assessment. *Learning and Instruction*, *17*(4), 416-426. doi:10.1016/j.learninstruc.2007.03.007

Weinberger, A., Stegmann, K., & Fischer, F. (2010). Learning to argue online: Scripted groups surpass individuals (unscripted groups do not). *Computers in Human Behavior*, *26*(4), 506-515. doi:10.1016/j.chb.2009.08.007

Wise, A. F., & Chiu, M. M. (2011). Analyzing temporal patterns of knowledge construction in a role-based online discussion. *International Journal of Computer-Supported Collaborative Learning*, *6*(3), 445-470. doi:10.1007/s11412-011-9120-1

Zottmann, J., Stegmann, K., Strijbos, J. W., Vogel, F., Wecker, C., & Fischer, F. (2013). Computer-supported collaborative learning with digital video cases in teacher education: The impact of teaching experience on knowledge convergence. *Computers in Human Behavior*, *29*(5), 2100-2108. doi: 10.1016/j.chb.2013.04.014