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Editorial notes

CSCL: A Learning and Collaboration Science?

Michael Baker and Peter Reimann

Introduction

Our participation in the CSCL conference in June 2024¹, that took place in Buffalo, USA within the framework of the International Society of the Learning Sciences Annual Meeting (<https://2024.isls.org/>), led us to reflect on the orientations of CSCL. In these brief editorial notes, we describe two elements of a vision of CSCL research, with a view to stimulating the submission of squibs that further the debate in the research community. Firstly, our concept of collaboration is evolving; secondly, we need a unified language.

Four changes

Of the many changes that have taken place over the past thirty years, we would like to emphasise just four of them.

Firstly, collaborative pedagogies have become mainstream in many countries². Whilst that may be more or less true, depending on the country, we can at least assert that research papers in the field of CSCL no longer take pains to argue for the general interest of instigating learning situations where collective activities are organised involving learners and teachers, often with technology mediation. This means that research can focus on institutional organisation, design and understanding the processes involved. Thus, an increasing number of papers published in the journal describe advanced formal techniques for analysing group behaviours using existing platforms.

Secondly, technology for collaboration has become infrastructure (see Ludvigsen & Steier, 2019). Of course, bespoke online software for collaboration is still being developed, as it was from the beginnings of broadly available Internet and CSCL in the 1990s; but such software rarely makes its way out of the research lab and the duration of funded projects. There are

¹ See the following link for downloading the CSCL 2024 Proceedings: <https://2024.isls.org/proceedings/>

² See the early comparative study of Alexander, 2001.

exceptions of course, of which an emblematic example is the CSILE/KnowledgeForum® (Scardamalia et al., 1994). But the main effect for CSCL research, of the now prevalent use of platforms such as Moodle, is to put the emphasis on designing the organisation of groups of students and teachers, with their complex sequences of tasks, rather than on the characteristics of the software itself.

Thirdly, what counts as learning has changed. Certainly, individual knowledge gains are still evaluated, as they must be in order to give students grades. But the emergence of large learning collectives, or even communities, puts the emphasis on the dynamic reconfigurations of such large groups, that can be seen as species of learning where the subject who learns is the collective itself.

Finally, — and this emerges from the above — collaboration has changed scale. The foundational situation of collaborative learning is, historically, that of the small group (or even the dyad), where students work together in a largely synchronous manner in the classroom. And what might be termed the classical definition of collaboration was predicated on that situation (Roschelle & Teasley, 1995; Dillenbourg, 1999; Baker, 2015), in that it involves mostly synchronous agency towards a shared representation of a problem, over a limited timescale. Today, the prototypical case is rather that of the large collective, often blending online with face-to-face, synchronous with asynchronous work, over larger timescales, with the sporadic emergence of “zones of collaboration” (Fréard et al., 2012) within less closely-coupled collective work in epistemic communities. This is now increasingly recognized in the CSCL community. Thus Jeong et al. (2017) propose a broad and useful “A3C” framework for joint interactions in large online knowledge communities. The model integrates different forms of participation, from “attendance” (being a community member observing the ongoing knowledge building processes), to coordination, cooperation and finally collaboration. The paper by Yang (2024), intitled “Combining Danmaku and Discussion Boards: toward a scalable and sociable environment for mass collaboration” in this issue of the journal, draws on the A3C framework, combining it with analysis of the socio-emotional dimension of interaction, in order to analyse mass participation in a MOOC on basic maths. The online environment studied involves a “Danmaku” (a type of “shoot ‘em up” online game) community and a discussion board. It was found that the form of mass participation depended on the tools used — indirect crowd speech in the Danmaku environment *versus* direct communication and collaboration within threads of the discussion board.

Whilst these evolutions of the nature of collaboration concern the distribution and coordination of actions across tools in online epistemic communities, a further aspect that should change our view of collaboration concerns what it is *about*, the task, its (in)tangible nature. There are important differences between collaborating in understanding elementary maths, in debating causes of climate change and in actually making together a new innovative and tangible artifact. The latter issue is addressed by the paper, published in this issue, of Davies, Seitamaa-Hakkarainen and Hakkarainen (2024) entitled “Knowledge creation through maker practices and the role of teacher and peer support in collaborative invention projects”. The paper also deals with the important issue of teacher and/or peer tutor support for maker-based collaboration.

Intermediary conclusion: the conceptualization of collaboration in CSCL is evolving. To state the matter provocatively, the meaning of the acronym CSCL should perhaps be Computer

Supported *Collective Learning*. To go even further: could there be a meaningful and useful *collaboration science*? We discuss an approach to avoiding a theoretical Tower of Babel in such a framework, involving creating a common unified language.

The Collaboration Sciences

CSCL is not the only research domain concerned with collaboration and knowledge work — see, for example, small group (communication) research, CSCW, co-design, networked learning, and collaborative creativity. Could there be a domain, a superclass of CSCL, called the *Collaboration Sciences*? A class that is related to but not identical to the Learning Sciences (LS)? Might not CSCL, thus conceived, share goals and methods with the LS and also have shared goals and methods within the Collaboration Sciences?

By blending Learning and Collaboration Sciences, CSCL would gain a broader perspective on learning under the conditions of technology-mediated collaboration, including forms of group learning that are not designed for in advance. As a Collaboration Science, CSCL would examine groups as learning entities and, more generally, as interacting (communicating) entities. One such lens is group dynamics, the "scientific study of the behaviours, processes, and phenomena that emerge in social groups, including their formation, interaction patterns, structures, performance, and changes over time." (Forsyth, 2010). Also relevant is research on group and team communication (Beck et al., 2021), group and organizational learning (Argote & Levine, 2020), and cognitive and neuro-science research concerned with social learning (Tamir & Thornton, 2018). The contribution of Zamecnik et al. (2024) to this issue, "The perception of task cohesion in collaborative learning teams," is an example for the group dynamics perspective applied to CSCL. The authors build on the concept of cohesion, introduced by one of the founders of social psychology: Leon Festinger. Cohesion has two dimensions: task cohesion and social cohesion. The study puts into relation learning team members' interactions with a survey-based measure of task cohesion and finds relations between the strength of perceived task cohesion and team performance.

But the risk of an orientation for CSCL that is even broader than the LS (!) could lead to a theoretical Tower of Babylon. In their review and analysis of CSCL theories, Gerry Stahl and Kai Hakkarainen (2021) noted a "... *confusing* variety of incommensurate, competing theories..." with roots in "... constructivist, socio-cultural, social-psychological, and information processing frameworks." (p. 26, our italics). This variety in frameworks and theories is mirrored by the many methodologies and methods used in the field. Whilst there is value in theoretical and methodological variety for a field as interdisciplinary as CSCL — not one theory/methodology "to rule them all" (Rummel, 2018) — the risk is fragmentation: multi-instead of inter-disciplinary research. How can we increase unity while providing room for multiple frameworks and theories? An answer to this conundrum that may be worthy of consideration is to strive for a *unified language* in which *different theories* can be expressed.

A Unified Language

The success of such a *formalization* strategy can be seen in science and engineering, where mathematics is the unifying language. Other forms of formalization are logics (Bringsjord, 2008) and specifications for programming a computer (Cooper & Guest, 2014).

Whilst very rare in CSCL and the Learning Sciences in general — we are still only aware of one instance in CSCL, Abrahamson & Wilensky (2005) — formalization of theory (for instance, in form of a computer model) is frequently practiced in other collaboration sciences (for instance: Cushman & Gershman, 2019; van Eijndhoven et al., 2023; Sun, 2008). We treat computational modelling as a form of theory building, different from theory testing through statistical or computational data modelling (see also Wise & Schwarz, 2017)

However, it could be that CSCL is a research area where formalisation and simulation do not add value (the pitfall of reductionism). Perhaps CSCL is similar to social psychology in this respect: There is no shortage of theory and empirical data but an almost complete absence of a mathematically and/or computationally formalized theory. Hence, we must ask: When and how does formalisation add value to a scientific enterprise? The short answer is that formal modelling makes us think deeply about our theories and what we are going to model (a phenomenon, process, or capacity). Engaging in the development of even a partial model can highlight gaps and lack of clarity in the theory. It also contributes to *open theorising*, making our theoretical assumptions and commitments explicit (Guest & Martin, 2021). In addition, formalised theories tend to be highly compact and are easily exchanged between researchers because of their explicit semantics; they travel easily (von Hippel, 1994).

An Example: Shared Meaning-making

Let us take as an example a phenomenon that is arguably highly pivotal to CSCL: shared meaning-making (Roschelle & Teasley, 1995). How do students know what meaning others in their group give to a word? The problem is hard because concepts are not identical to words: a word can be seen as a coin, where one face is the acoustic or visual image and the other a concept (de Saussure, 1916/1995), each face being indissociable from the other. While students can readily register the use of words uttered by a peer — say, in the context of a science class — the conceptual meaning of words remains hidden. Thus, students must engage in 'mind reading' (mental state inference, or “mentalizing”: C.L. Baker et al., 2017): What does the other mean when using the word "force"? Mentalising, to have a chance to be correct, needs to take into account the context in which the utterance is made and all of the signals the speaker provides: Not only what is said but also para-verbal and non-verbal signals. In addition, the hearer will need to rely on world and cultural knowledge, such as about the practice in which the hearer and speaker are engaged. This *common ground* might have to be dialogically established beforehand, and the shared meaning to be negotiated in dialogue, once meaning gaps are identified or suspected.

Can mentalising be formalised? The answer is yes if we consider it as a form of reasoning under uncertainty. Reasoning under uncertainty can be formally modelled as a probabilistic inference in a Bayesian framework; and there is good reason to believe that the brain implements this kind of reasoning (Knill & Pouget, 2004). The brain has evolved in an environment where decisions must be made constantly without full information. The rational basis for good guessing is being guided by probabilities about which world structures are most likely a priori (Griffiths et al., 2008, p. 60). Suppose we attempt to infer the probability of some (meaning covering) concept given some utterance, $P(\text{concept} | \text{utterance})$. The first argument of the predicate is calculated by multiplying the prior probability of the meaning $P(\text{concept})$ and the likelihood that the concept would generate the utterance $P(\text{utterance} | \text{concept})$, followed by normalising so the resulting probabilities sum to 1. Applied to answering "What

is the most likely meaning when a peer says *force*", listeners must have their own conceptualisations of force (not necessarily in propositional format) to compute the likelihood of an alignment with the speaker's conception. A more knowledgeable listener (for instance, a teacher: Shafto et al., 2014) would know multiple conceptualizations of "force" and thus be able to identify which of them is held by the speaker, if any.

What Can CSCL Research Gain?

What do we gain from such formalisations? It should be clear from the above that any particular explanation of how a student inferred what another student meant by certain words or actions requires specifying what background knowledge is available to the listener and how it gets connected in inferences by the listener. A solely verbal formulation of these components and their relations would quickly become unmanageable. Formalising the model allows for managing the information, thereby making explicit assumptions; it is a form of open theorising. Furthermore, since a Bayesian Network is a specification language and a computational mechanism simultaneously, models formalized in this language are generative. By computing the inferences the model licenses, data get generated that can be compared with empirical data and those generated by other computational models, Bayesian or other (e.g., connectionist networks, Rumelhart et al., 1987). As important, the theory's implications can be explored by posing "what if" questions to the model. Many philosophers of science consider the extent to which a theory enables counterfactual reasoning pivotal for its explanatory power (Woodward, 2003; Ylikoski & Aydinonat, 2014).

These benefits are not confined to theories of meaning-making or, more generally, group communication. Another example for an important area of CSCL research is self- and social regulation of collaboration (Järvelä & Hadwin, 2014). From a Bayesian perspective, meta-cognitive regulation involves strategic decision-making: the rational choice of learning activities. Since the performance of a Bayesian model on a task defines rational behaviour for that task — it is the mathematically optimal choice (Jacobs & Kruschke, 2011) — it provides a yardstick for comparing human performance with optimal performance. Without such a yardstick, we can interpret performance differences between individuals or groups only relative to each other.

The fourth paper in this issue, "Collaborative Problem-Solving in Knowledge-Rich Domains: A Multi-Study Structural Equation Model", by Brandl et al. (2024), touches on the formalisation theme in two ways. For one, this work is grounded in Klahr & Dunbar's (1988) theory of inductive learning as a search in two problem spaces, which itself is formalised as a computer model (specifically, a production system). The second connection is through the paper's focus on medical diagnostic reasoning: It synthesises data from three former studies on collaborative diagnostic reasoning, using multivariate statistics. Diagnostic reasoning is one of the main applications of Bayesian Network methods (Polotskaya et al., 2024). Since neither production system nor Bayesian Network modelling is applied in Brandl et al. (2024) (and the underlying research program), let us indicate how this research could be further advanced by formalisation. A first step could build on the fact that the Bayesian framework provides a reference point for optimal task behaviour. While Brandl et al. find, for instance, positive correlations between content knowledge and the quality of evidence elicitation, claims to effectiveness become stronger once the role of evidence elicitation for *optimal* task performance is known. In the absence of which, we are stuck with relative accounts. Once we

know what is computed and why it needs to be computed — what David Marr calls computational analysis (Shagrir, 2010) and John Anderson calls rational analysis (Anderson, 1991) — with Bayesian Networks providing the technique, one can progress to Marr's algorithmic (e.g., production system models) and implementation (neuro-cognitive) levels.

The Bayesian framework can also be unifying in the sense that it connects CSCL with foundational theories in Cognitive Science, such as the *Predictive Brain* (Clark, 2013) and the *Free Energy Principle* (Friston et al., 2023). This is all valuable for CSCL research, but do we have something to contribute to the cognitive and collaboration sciences? We see one form of CSCL's contribution in work such as Brandl and colleagues' (ibid.), where the classical individual cognitive task of diagnostic reasoning has been transformed into a collaborative task. This constitutes a new challenge for collaboration science and provides data for model development and testing. More generally, collaborative diagnostic reasoning is an instance of the fact that in collaborative settings, learners are exposed to multiple learning resources (the peers), creating the need for conceptualising information integration and coherence building. Another contribution from CSCL to other fields could be knowledge building. While there are many Bayesian models of human learning, the collaborative construction of new knowledge is different (Scardamalia & Bereiter, 2014). It requires the inclusion of epistemic norms such as coherence and newness as part of the priors. This, along with the potential of BNs to model active learning and discover causal relations, might be a starting point for a new kind of learning within the Bayesian framework. As another important research challenge to the collaboration sciences, we propose the question of how to theorise and formalise the role of technology in social collaboration.

Before closing, it needs to be mentioned that Bayesian Networks not only offer answers to questions of induction; they are also of practical value in the design of group and learning support systems. They have been frequently used to build student models (Millán et al., 2010) and for assessment (Almond et al., 2015). What is a well-established technique in the cogent fields of AI in Education and Educational Measurement and Assessment can also serve as a means to formalise collaborative learning theories. The fact that its methodological basics can be learned in a couple of weeks (e.g., in a university course) and that the method is supported by many software tools, including several R packages, makes it a comparatively low threshold and definitely a high ceiling.

In conclusion, employing the Bayesian framework as a formal language for expressing theoretical ideas is within reach for CSCL researchers. Along with other formal approaches, such as Agent-based Modelling (Wilensky & Rand, 2015), it has the potential to advance the field and counteract epistemic fragmentation.

Closing

In these editorial notes, with reference to the four papers published in this issue of the journal, we have allowed ourselves to mediate on two ideas that may be of interest to CSCL: the broadening of the foundational concept of collaboration, and the possible role of formalisation in providing a common language that would offset a possible Tower of Babel in our interdisciplinary field. Our hope is that these remarks will stimulate reflection and discussion, within the journal in the form of squibs, and at the upcoming CSCL conference.

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