NETWORK VISUALIZATIONS AS GROUP AWARENESS TOOLS FOR COMPUTER-SUPPORTED COLLABORATIVE LEARNING ON SOCIAL MEDIA

Von der Fakultät für Ingenieurwissenschaften,

Abteilung Informatik und Angewandte Kognitionswissenschaften

der Universität Duisburg-Essen

zur Erlangung des akademischen Grades eines

Doktor der Naturwissenschaften (Dr. rer. nat.)

genehmigte Dissertation von

Marielle Dado

aus Manila

1. Gutachter: Prof. Dr. Daniel Bodemer

2. Gutachter: Prof. Dr. Jun Oshima

Tag der mündlichen Prüfung: 13.09.2018

To Mike

ABSTRACT

English

Computer-supported collaborative learning (CSCL) provide rich contexts for learners to interact with each other and with various technological, instructional, and knowledge artifacts (e.g., web apps, learning resources) to jointly accomplish a learning goal. Social media platforms, especially social networking sites (SNS), help foster these interactions through features for communication and resource sharing. Yet they tend to lack some features for meaningful CSCL discussions, such as contextual cues that help learners know more about their co-learners. One way to overcome this is through group awareness tools that visualize key social and cognitive information about group members (e.g., activity, level of knowledge) to help groups establish a common frame of reference.

The four studies included in this work contribute to research about group awareness tools by exploring their usefulness during CSCL on social media. In particular, they explored how network visualizations, which represent relations between actors in a social network, can be used as group awareness tools that depict relations between learners and artifacts in CSCL environments. Network visualizations are used in social network analysis (SNA) to measure and represent structural relations. Although a promising method, SNA is relatively less-established in CSCL compared to learning analytics, a related field that uses techniques to perform analysis on learning-related data and transforms them into applications to impact learning.

Studies 1 and 2 are literature reviews of SNA as a technique to reveal important actors and relations in CSCL. Their results show that studies have limited their understanding of CSCL to direct interaction (i.e., communication) between learners. As

such, they do not take into account mediated interactions between learners and artifacts in their environment. It had further emerged that messages exchanged between learners are a prominent knowledge artifact in CSCL environments. Based on these results, Studies 3 and 4 investigate network visualizations as applications in CSCL, namely as group awareness tools that visualized knowledge artifacts (i.e., terms from learners' messages) as cognitive information in a network graph (i.e., SNA as an application). These tools were evaluated in field studies to support collaborative argumentation on SNSs. The results suggest that although the tools led learners to exchange arguments with non-friends and develop awareness of multiple perspectives, these did not necessarily lead to multiple-perspective taking. The networked arrangement of group information emphasized similarities in cognitive information. This finding is different from other group awareness tools that tend to highlight dissimilarities, which learners could discuss in order to reduce any disparities. Future CSCL studies that use SNA should thus consider exploring learner-artifact interactions in order to better contextualize the relations beyond direct communication. Moreover, future studies should look into combining the tools with argumentation scripts that help learners consider the merits of discussing dissimilar cognitive information.

German

Computerunterstütztes kollaboratives Lernen (CSCL) bietet Lernenden vielfältige Möglichkeiten, sich untereinander auszutauschen und mit verschiedenen technologischen, didaktischen und wissensbezogenen Artefakten (z.B. Webanwendungen oder Lernressourcen) zu interagieren, um gemeinsam ein Lernziel zu erreichen. Social-Media-Plattformen, insbesondere Social-Networking-Sites (SNS), unterstützen solche Interaktionen, indem sie Funktionen für die Kommunikation und das Teilen von Ressourcen bereitstellen. Dennoch fehlen ihnen Funktionen, die lernförderliche CSCL-Diskussionen hervorrufen, beispielsweise die Bereitstellung kontextueller Hinweise, die den Lernenden helfen, mehr über ihre Mitschüler zu erfahren. Hierbei können Group Awareness Tools Abhilfe schaffen, die wichtige soziale und / oder kognitive Informationen über Gruppenmitglieder (z.B. Aktivitäten oder Wissensstände) visualisieren

und damit eine Basis für die gemeinsame Planung und Durchführung von Interaktionen schaffen.

Die vier Studien in dieser Arbeit tragen zur Erforschung solcher Group Awareness Tools bei, indem sie die Nützlichkeit besagter Tools beim computerunterstützen kollaborativen Lernen in sozialen Medien untersuchen. Insbesondere wurde untersucht, wie Netzwerk-Visualisierungen, die Beziehungen zwischen Akteuren in sozialen Netzwerken repräsentieren, für Group Awareness Tools adaptiert werden können, um Zusammenhänge zwischen Lernenden und Artefakten in CSCL-Umgebungen zu verdeutlichen. Netzwerk-Visualisierungen werden in der sozialen Netzwerkanalyse (SNA) genutzt, um strukturelle Zusammenhänge zu erfassen und darzustellen. Obwohl sie eine vielversprechende Methode ist, ist die SNA im Bereich CSCL weniger etabliert als im artverwandten Bereich Learning Analytics, der SNA zur Analyse lernbezogener Daten und zur Umsetzung lernförderlicher Anwendungen nutzt.

In den Studien 1 und 2 werden Literaturrezensionen von CSCL-Studien vorgestellt, in denen SNA als Methode eingesetzt wird, um wichtige Akteure und deren Beziehungen im Kontext von CSCL aufzudecken. Hierbei zeigt sich eine Beschränkung der analysierten Studien darauf, dass CSCL allein als direkte Interaktion (d.h. Kommunikation) zwischen Lernenden verstanden wird. Damit berücksichtigen diese Studien keine Wechselwirkungen zwischen Lernenden und den Artefakten in ihrer Umgebung. Zudem hat sich herausgestellt, dass Aussagen, die Lernende in CSCL-Umgebungen miteinander austauschen, ein bedeutsames, wissensbezogenes Artefakt sind. Diese Ergebnisse wurden genutzt, um Group Awareness Tools zu designen, die Wissensartefakte (d.h. Begriffe aus Aussagen von Lernenden) als kognitive Informationen in einem Netzwerkgraph visualisieren. In den Studien 3 und 4 wurden diese Tools anhand von Feldstudien evaluiert, um das kollaborative Argumentieren auf SNS zu unterstützen. Die Ergebnisse deuten darauf hin, dass die Werkzeuge zwar dazu führten, dass Lernende Argumente mit anderen austauschten, die nicht ihre Freunde sind, und Kenntnisse verschiedener Perspektiven ausbildeten, dies aber nicht unbedingt zu einer Einnahme verschiedener Perspektiven führten. Die vernetzte Anordnung

von Informationen über die Gruppe betonte zudem Ähnlichkeiten bezüglich kognitiver Informationen. Dieses Ergebnis unterscheidet sich von den Ergebnissen zu anderen Group Awareness Tools, die auf eine Hervorhebung von Unähnlichkeiten abzielen, die von Lernenden zur Verringerung ihrer Ungleichheiten diskutiert werden können. Zukünftige CSCL-Studien, die SNA verwenden, sollten daher Lerner-Artefakt-Interaktionen untersuchen, um Zusammenhänge von Interaktionen, die über die direkte Kommunikation hinausgehen, besser zu ergründen. Zusätzlich sollten zukünftige Studien Group Awareness Tools mit Argumentationsskripten kombinieren, die den Lernenden helfen, die Vorzüge von Diskussion über abweichende kognitive Informationen.

TABLE OF CONTENTS

Page

ABSTRACT iii

LIST OF INCLUDED PAPERS ix

1 Research Summary and Background 1

1.1 Computer-supported collaborative learning 2

1.1.1 Levels and units of analysis in CSCL 3

1.1.2 Artifacts in CSCL environments 5

1.1.3 Summary 7

1.2 Social media as a platform for CSCL 7

1.2.1 Social networking sites as an educational tool 8

1.2.2 Social networking sites for CSCL and argumentation 9

1.2.3 Challenges of using SNSs as an educational tool 11

1.2.4 Summary 13

1.3 Group awareness for CSCL on social networking sites 14

1.3.1 Social group awareness in SNSs 14

1.3.2 Cognitive group awareness in SNSs 15

1.3.3 Group awareness and argumentation in SNSs 16

1.3.4 Summary: Group awareness for CSCL on SNSs 18

1.4 Network visualizations as group awareness tools 18

1.4.1 The potential of social network analysis in CSCL 19

1.4.2 Social network analysis and learning analytics 21

1.4.3 Future directions of group awareness based on social learning analytics 23

1.4.4 Summary 25

1.5 Summary of included studies 25

Page

1.5.1 Studies 1 and 2: Establishing the relevance of SNA in CSCL . . 27

1.5.2 Studies 3 and 4: Network visualizations as group awareness tools depicting social and cognitive information 32

1.6 Synthesis and conclusion 40

2 Study 1: A review of methodological applications of social network analysis in computer-supported collaborative learning 47

3 Study 2: On the adoption of social network analysis methods in CSCL research - A network analysis 70

4 Study 3: Social and cognitive group awareness to aid argumentation about socially acute questions on social media 79

5 Study 4: Group awareness to aid argumentation on social media among linguistically diverse students 88

6 Bibliography 131

LIST OF INCLUDED PAPERS

Study 1

Dado, M. & Bodemer, D. (2017). A review of methodological applications of social network analysis in computer-supported collaborative learning. *Educational Research Review*, 22, 159–180. doi:10.1016/j.edurev.2017.08.005

Study 2

Dado, M., Hecking, T., Bodemer, D., & Hoppe, H. U. (2017). On the adoption of social network analysis methods in CSCL research: A network analysis. In Smith, B. K., Borge, M., Mercier, E., and Lim, K. Y. (Eds.) *Making a Difference: Prioritizing Equity and Access in CSCL, 12th International Conference on Computer Supported Collaborative Learning (CSCL) 2017*, Volume 1 (pp. 287-294). Philadelphia, PA: International Society of the Learning Sciences

Study 3

Dado, M., & Bodemer, D. (2018) Social and cognitive group awareness to aid argumentation about socially acute questions on social media. In J. Kay and R. Luckin (Eds.) *Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences (ICLS) 2018*, Volume 1 (pp. 456-463). London, UK: International Society of the Learning Sciences.

Study 4

Dado, M. & Bodemer, D. (under review). Group awareness to aid argumentation on social media among linguistically diverse students. Manuscript submitted for publication to *Instructional Science*.

1. RESEARCH SUMMARY AND BACKGROUND

The rise of technology integration in learning settings has led to the study of computer-supported collaborative learning (CSCL). Computers provide rich contexts for learners to interact with each other and engage with various learning artifacts (e.g., digital resources, web apps, instructional videos etc.) to jointly accomplish a learning goal (Stahl et al., 2014). Social media platforms help foster these relations through features for communication and resource sharing (e.g., posting messages and uploading images on a forum), enabling learners to establish social networks among themselves (K.-Y. Lin & Lu, 2011). However, social media was not created with learning activities in mind, and thus tend to lack contextual cues and affordances that enable successful collaboration between learners (Jeong & Hmelo-Silver, 2016). For instance, social media platforms may not have technological features that allow users to know more about other users, such as what they are doing and what their level of knowledge is, and how the activity is progressing. One way to overcome this challenge is through group awareness tools (Bodemer & Dehler, 2011) that visualize key social and cognitive information to help learners establish a common frame of reference that could be the basis for productive collaborative learning activities.

The present work aims to contribute to the current body of knowledge about group awareness tools by exploring their usefulness during CSCL activities on social media. In particular, it explores how network visualizations, which visually represent relations between actors in a social network, can be used as group awareness tools that depict relations between learners and artifacts in CSCL environments. In doing so, network visualizations can represent social and cognitive information about group members, which could be useful for the group as they interact and communicate towards a common learning goal.

To this end, there are 4 studies included in the present work. Studies 1 and 2 (Chapter 2 and 3) explore how current CSCL studies have used social network analysis (the discipline from which network visualizations are derived) to reveal important actors and relations in CSCL. Social network analysis is a promising method of analyzing CSCL relations, yet it is relatively less-established compared to its use in learning analytics, a related field that applies techniques (e.g., social network analysis) to perform analysis on learning-related data and transforms them into applications to impact learning. Thus, the first two studies establish social network analysis as an appropriate technique for uncovering important CSCL relations that impact learning. Results from these studies were then used in Studies 3 and 4 (Chapters 4 and 5) to develop a group awareness tool that visualizes relations between learners and artifacts to aid argumentation activities on a social networking site.

The sections in this chapter provide a deeper insight into the literature about CSCL (Section 1.1), social media (Section 1.2), group awareness (Section 1.3), social network analysis and learning analytics (Section 1.4) that have informed the objectives and rationale behind the four studies. This is followed by a summary of the included studies and how their results contribute to fill in known research gaps. This chapter concludes with an outlook of future directions for CSCL and group awareness on social media.

1.1 Computer-supported collaborative learning

The term "computer-supported collaborative learning" (CSCL) refers to both the process of and the interdisciplinary research field concerned with groups of people mutually engaged towards a common learning goal with the help of computers (Lipponen, 2002). Despite this simple definition, the inclusion of information and communication technologies adds some complexity to what encompasses "learning". Thus, this section attempts to elaborate on the definition of CSCL by taking into consideration (1) levels and units of analysis and (2) artifacts present in CSCL environments.

1.1.1 Levels and units of analysis in CSCL

Learning in CSCL can take place at various levels (Kirschner & Erkens, 2013). When a new skill is developed or new knowledge about a subject matter is acquired, learning is said to have occurred on a cognitive level. When group functioning has shown marked improvement, learning on a social level is said to have occurred. Finally, learning at a motivational or affective level takes place when changes in attitudes, values, and beliefs are observed. Collaborative learning implies the involvement of more than one learner: small groups (e.g., dyads, triads), bigger groups (e.g., class), or even large-scale online communities (e.g., school level). Gains in learning among groups can thus be observed; nevertheless, learning gains can also be examined on an individual level (Ludvigsen, 2016). For example, a study by Golanics & Nussbaum (2007) investigated argumentation based on the quality of individual arguments and the extent to which group discussion reflected critical and constructive engagement with those arguments. In this case, argumentation quality was assessed among individuals at a cognitive level and among group members on a social level.

CSCL is an interdisciplinary research field primarily guided by learner-centered frameworks ranging from socio-cognitive constructivism, which focuses on active cognitive processing in individual and group settings, to socio-cultural approaches, which emphasize the role of the social environment in understanding learning (Jeong et al., 2014). In all of these frameworks, it is acknowledged that the quality of the collaborative process (e.g., discourse, self-reflection) provides a useful context for understanding the results of a learning activity (Spada et al., 2005). Consider, for instance, a study by Hmelo et al. (2000) that found that a high prior knowledge group and a low prior knowledge group each arrived at solutions to a problem that were equal in quality. However, the high prior knowledge group was able to solve the problem quicker, whereas the low prior knowledge group was rather disorganized with pooling their resources together. Without taking group differences in coordinating and planning into account, important distinctions between how high and low prior knowledge

students learn together would be overlooked. Thus, it is crucial to pay attention not only to the outcomes of a learning activity, but also to the processes that led to it. In this manner, appropriate interventions that target relevant learning processes can be developed to ensure successful learning. In this example, providing scaffolds was found to be effective in helping the low-prior knowledge group structure their collaborative activities (Hmelo et al., 2000).

To capture a more well-rounded picture of learning that includes both processes and outcomes, CSCL studies often triangulate multiple data sources using a variety of analytical methods (Jeong et al., 2014). For example, to study how roles influence group performance and collaboration, Strijbos et al. (2007) used Likert scale evaluation questions to measure individual characteristics (e.g., attitudes) and perceived group dynamics (e.g., group cohesion) as well as quantitative content analysis of email communication. Computer environments also store digital trace data, such as log files of communication and clickstream data, that record user actions that may signal the occurrence of certain learning processes. For example, records of how long a student viewed a particular thread on a discussion forum may have implications on how much that student has thoroughly read information about the topic (Wise et al., 2014). As a result, CSCL expands the definition of what learning entails, from simply knowledge/skill mastery and acquisition, to include improvements in social interactions or meta-aspects of cognitive, social and motivational variables(Law, 2005).

In CSCL, interactions between students are of key importance; teachers, on the other hand, are no longer the sole keepers of knowledge but are rather "conductors" that orchestrate the learning activities (Dillenbourg et al., 2009). Learners are said to have engaged in high-level interactions when there is evidence of collaborative knowledge construction in their discourse. Collaborative knowledge construction is often defined as a process whereby multiple learners create and expand upon a shared knowledge base by collectively seeking and making sense of information (Beers et al., 2005; Fischer et al., 2002). This process begins when individuals express (i.e., "externalize") what they know, which in turn causes (i.e., "elicit") other group members

to express what they know. From here, learners begin to negotiate meaning: explain how they understood the contributions of their group members, offer feedback, clarifying and verifying information until a common understanding of or common frame of reference for the activity has been reached (Beers et al., 2005). From a constructivist paradigm, learners must relate new information with their prior ideas or beliefs, which could lead to substantial restructuring of knowledge on an individual and group level (van Aalst, 2009). Socio-cultural theories further emphasize the importance of participation in this restructuring (Hmelo-Silver, 2003). In both cases, evidence of these dynamics are often found in the messages exchanged between learners. Among the discourse moves that promote collaborative knowledge construction are repeating or interpreting information, asking task-relevant questions, sharing and comparing information, questioning information, explaining, and offering solutions and strategies (Wever et al., 2006).

1.1.2 Artifacts in CSCL environments

Working with and through technologies provides learners with opportunities not only to communicate with each other, but also to immerse themselves in a number of artifacts that may influence individual and group learning. These artifacts include the technological platforms that facilitate communication and collaboration between learners (e.g., web applications and discussion forums). CSCL technologies can be described in terms of "affordances", which refers to design features of any given tool that enable certain actions: one can "afford" to do something with the help of a tool (Norman, 1999). According to Jeong & Hmelo-Silver (2016), core affordances of CSCL tools enable learners to: (1) engage in a joint task, (2) communicate, (3) share resources, (4) engage in productive collaborative learning processes, (5) engage in co-construction, (6) monitor and regulate collaborative learning, and (7) find and build groups and communities (p. 249).

Instructional artifacts, such as domain topics, lessons, guidance, visualizations, scaffolds or script, may help provide a structure for learners to carry out their collaborative activities (Stahl et al., 2014). Scripts, for instance, provide a sequence of activities, procedures, or roles that learners can follow throughout the collaborative learning activity in accordance to the affordances of technological artifacts (Kollar et al., 2006). Representational guidance tools are another kind of instructional artifact, which provide groups of learners with a visual representation of knowledge that is relevant or emerges from the collaborative activity (Suthers, 2003). These tools offer "guidance" by serving as an externalized "group memory" that learners can use as a common reference point for discussing and orienting group activities. For instance, Suthers et al. (2008) found that among pairs using knowledge maps together when problem solving, students were more likely to converge on the same conclusion and scored significantly higher on a knowledge test.

The term "artifact" can also refer to the product of collaborative knowledge construction. These are known as knowledge artifacts, which is the goal of the activity and also functions as a reference point for further interaction, even as it emerges as the group product (Stahl et al., 2014). For example, learners who are tasked to create concept maps together must discuss each draft before achieving the optimal final concept map (Suthers et al., 2010). Knowledge artifacts produced as a result of high levels of knowledge construction are generally considered of higher quality. For example, in a study by van Aalst & Chan (2007), learners created an electronic portfolio by adding and linking notes containing facts about the topic. They found that providing reflective explanations to their collaborators about why they linked certain notes together were related to a higher quality contributions to the portfolio, as well as superior performance in the exam.

1.1.3 Summary

To summarize, CSCL can be described as the use of technology to engage in joint activities to achieve shared learning goals. Learning can be observed among groups as well as in individuals within these groups—whether in the outcomes that serve as evidence of knowledge/skill acquisition or improved collaboration; or in the social, motivational or affective processes that led to these outcomes. Learners primarily interact by communicating with other collaborators in an effort to construct new knowledge. However, they also interact with various artifacts, which serve as a platform (i.e., technological artifacts), guide (i.e., instructional artifacts) or reference point (i.e., knowledge artifacts) for establishing and negotiating common ground among learners (Paavola & Hakkarainen, 2009). Therefore, learners in CSCL engage in *direct interaction* as well as *mediated interaction* via these artifacts towards the same shared understanding of the learning goals. In the next section, social media, particularly social networking sites, are discussed as a potential technological artifact for CSCL, facilitating the exchange of knowledge artifacts via asynchronous communication.

1.2 Social media as a platform for CSCL

Social media is an umbrella term referring to computer-mediated technologies that facilitate interaction and communication between users in the construction, co-construction, or dissemination of multi-modal user-generated content (Dabner, 2012). Some examples of social media platforms are social networking sites (e.g., Facebook), blogs (e.g., Wordpress), wikis (e.g., Wikipedia), video-sharing sites (e.g., YouTube), image-sharing sits (e.g., Instagram) and micro-blogging sites (e.g., Twitter). It is closely associated with the concept of "Web 2.0", which describes web platforms that host a dynamic flow of content created and uploaded by its users—as opposed to "Web 1.0" sites that feature content curated by a select group of people (Cormode & Krishnamurthy, 2008). As the name implies, social media is "social" in the sense

that it encourages users to participate in content generation and to interact with each other, such as through comments, messages, ratings, and recommendations, depending on the features of the platform (Kaplan & Haenlein, 2010). For this reason, there has been growing interest in the use of social media for educational purposes, specifically for collaborative learning between learners. In the following subsections, the appropriateness of using social networking sites, one particular type of social media, as an educational tool is discussed, along with some of the opportunities and challenges of adopting these platforms for CSCL.

1.2.1 Social networking sites as an educational tool

Social networking sites (SNS) are Internet-based platforms for users to establish and maintain connections with each other and, as a result, create networks or communities of people (K.-Y. Lin & Lu, 2011). They can be categorized according to their intended purpose (Thelwall, 2009). Socializing SNSs are used for personal networks of friends who have existing relations in the offline world; examples of this type of SNS are Facebook and Google+. Networking SNSs connect users for non-social, usually professional, purposes. For instance, LinkedIn and ResearchGate are SNSs for work and business contacts, the latter being specifically tailored for academics and researchers. Finally, social navigation SNS help users find specific information or resources, such as Goodreads which allows users to catalogue and recommend books to their friends. All of these types follow a similar format whereby users: (1) each have a profile with which to connect with each other; (2) share information to their network by creating posts; (3) interact with each other asynchronously (by commenting on each other's posts), synchronously (i.e., chat), indicating approval by clicking a "like" button, depending on the features of specific platforms. Thus, SNS allows people to stay connected with other people who share similar interests, backgrounds, or with whom they have real-life connections.

Surveys have suggested that socializing is the main reason why people choose to use SNS (K.-Y. Lin & Lu, 2011). Students use SNSs to connect with their classmates and fellow students on an informal basis, for instance to make it easier to disseminate information about social events on university campuses (Madge et al., 2009). Because of this, educators hope to leverage these social relationships that are built and maintained on SNSs (Manca & Ranieri, 2013). Because they are often used by students outside of the classroom, SNSs may provide a valuable environment for combining formal learning activities and informal social networking opportunities (Greenhow & Lewin, 2016). In this regard, SNSs can be used as a platform to extend classroom learning by discussing real-world applications of theories learned in class (Chen & Bryer, 2012) or to connect students with external resource speakers (Cain & Policastri, 2011) and other students from other regions or cultures (C.-M. Wang, 2012). Others have proposed that the group or community pages that can be created on certain SNSs for specific interests or purposes (e.g., Facebook Groups, Google+ Community) could be used as learning management systems (LMSs) for posting/receiving announcements, organizing activities, sharing resources and conducting online discussion (Manca & Ranieri, 2013; Q. Wang et al., 2011). Although traditional LMSs enable information and resource-sharing, they do not necessarily promote social connections or communications between students (Dabbagh & Kitsantas, 2012). Indeed, educators who are interested in social construction of knowledge are drawn by SNSs' potential to enable peer learning (Churcher et al., 2014) and communities of practice (Gunawardena et al., 2009).

1.2.2 Social networking sites for CSCL and argumentation

Given that collaboration and knowledge construction between learners are core goals of CSCL (Stahl et al., 2005), it is unsurprising that there is considerable interest in using SNSs to foster collaborative learning and discussion among communities of learners (Greenhow & Askari, 2017). For example, in a study by Liao et al. (2015),

university students used Google+ for jigsaw-style discussion activity in which groups of 3 shared each other's own observations of fish in various habitats; this lead to improvements on a social (e.g., greater interaction with peers), motivational (e.g., enhanced learning intention) and attitudinal (e.g., greater confidence and satisfaction in groupwork) level. In another study (P.-C. Lin et al., 2014), discussions on Facebook groups were combined with a simulation tool for collaborative problem solving for network trouble-shooting: students discussed possible solutions based on their individual attempts on the simulator, before agreeing on the most suitable solution. The activity led to improved trouble-shooting skills (i.e., cognitive-level learning), which was attributed to the cognitive diversity reflected in Facebook discussions. SNS discussions have also been shown to benefit English-as-a-Foreign language students, for instance increased participation and sense of autonomy among English learners engaged in collaborative writing (Razak & Saeed, 2014) and improved grammar and syntax in writing assignments along with a greater sense of trust and enjoyment after peer assessment (Shih, 2011).

One area of CSCL activity that would be particularly suited for SNSs discussions is collaborative argumentation or argumentative knowledge construction, whereby learners engage in specific discourse activities that lead to knowledge on both argumentation and the domain that is being discussed (Weinberger & Fischer, 2006). A typical argumentation sequence consists of arguments constructed by individual learners, counterarguments that challenge the initial arguments, and replies or rebuttal to those counterarguments (Leitão, 2000). Most educational applications of SNSs utilize its asynchronous communication functionality (Manca & Ranieri, 2013), which is ideal for argumentation activities because it gives learners time to process their peers' counterarguments, prepare their own rebuttals, and finally refine their initial arguments in light of the counter-information they received (Scheuer et al., 2010). Argumentation activities work well with when ill-structured topics or problems because they can be explored from multiple perspectives, which increases the chances of learners proposing and deliberating on their points of view (Noroozi et al.,

2012). For instance, controversial topics that have implications on various fields of knowledge would require exchange of information and opinions pertaining to different domains, thus facilitating knowledge acquisition (Mason & Scirica, 2006). Greenhow et al. (2015) investigated a Facebook debate about climate change among high school and college students and found that students crafted arguments on scientific and social implications of climate change in order to challenge the assumptions of their peers and attempt persuade them to consider alternative perspectives. In a similar Facebook activity about a controversial topic (migration), Asterhan & Hever (2015) found that students tended to perform better in knowledge tests when they were exposed to alternative perspectives compared to one-sided arguments. Given that educators are motivated to use SNSs as an extension of classroom learning (Chen & Bryer, 2012), SNSs are a promising environment for students to exchange multiple perspectives about controversial and ill-structured topics, thereby allowing students to learn about the real-world implications of the concepts they learned in class.

1.2.3 Challenges of using SNSs as an educational tool

Despite of its appropriateness as an educational tool, it should not be taken for granted that SNSs are primarily designed for recreational and commercial purposes, which means that it may lack some structural features for meaningful CSCL discussions (Friesen & Lowe, 2012; Llorens Cerdà & Capdeferro Planas, 2011). To be sure, most of these affordances mentioned by Jeong & Hmelo-Silver (2016) (refer to Section 1.1.2) are present in SNSs, such as synchronous and asynchronous communication between users, the formation of communities and groups, and—as evidenced in previous studies—engagement in joint tasks and resource sharing. Nevertheless, unlike threaded online discussion forums typically used for educational purposes, SNSs discussions have a "flat-structured" arrangement: posts appear all in one page in chronological (or reverse chronological) order, with replies to each post appearing un-nested below each post (Kirschner, 2015; Llorens Cerdà & Capdeferro Planas,

2011). Such an arrangement makes monitoring and regulating collaborative learning difficult, as it is not easy to find one's own postings, let alone others'. For example, in a study by Q. Wang et al. (2011), students had "to explicitly mention the names and posts they referred to when they replied to existing messages", which they noted felt "unnatural" and made monitoring and regulating group activities "complicated and troublesome" (p. 436). Rambe (2012) similarly found that although Facebook's format "democratized" communication within learner groups, making interaction enjoyable and allowing for information exchange", there were nevertheless "limited opportunities for deeper reflexive engagement with concepts, and connection between theory and practical issues" (p. 143). Using SNSs for educational purposes has been described as a "double-edged sword" that can serve as both an informative medium and a distraction, thus could potentially help or hinder learning (Smith, 2016). In a field experiment comparing online discussions on Facebook and a traditional LMS forum, Hou et al. (2015) found that although students were more engaged in discussions on Facebook than in the forum, there were also more off-topic discussions and less evidence of more advanced knowledge construction phases and deeper cognitive processes (i.e., limited to knowledge sharing and understanding, respectively). Veletsianos & Navarrete (2012) similarly found that most discussions on SNS do not exhibit knowledge construction, instead focusing on completing the assignments posted on the platform. It appears, as noted in Meishar-Tal et al. (2012), that the structure of SNSs encourages active participation, yet it makes orientation, retrieval of information, and ultimately productive communication behaviors difficult. If learners are expected to negotiate meaning by elaborating and adding upon each other's ideas (Beers et al., 2005) or to exchange and consider multiple perspectives during argumentation (Weinberger & Fischer, 2006), then a flat-structured arrangement would make it difficult to do so since it is not easy to see which posts or comments (and the ideas contained within) are referred to in the replies. Overall, research has shown that social interactions and relationships can be fostered on SNSs (Manca & Ranieri, 2013; Tess, 2013). However, the design of SNSs may hinder the productivity of those

interactions, making crucial information that would aid in knowledge construction rather difficult to access, which could lead to off-task behaviors.

1.2.4 Summary

When used as a CSCL tool in the classroom, SNS platforms could function as technical artifacts through which learners exchange and discuss knowledge artifacts (e.g., information, field observations, learning materials) towards consensus-building or the development of further knowledge artifacts. As such, collaborative argumentation is an especially appropriate activity for SNSs because they possess affordances that facilitate argumentative sequences (constructing initial arguments, constructing rebuttals or counterarguments, revising one's initial argument) that lead to an exchange of multiple perspectives. Nevertheless, the lack of certain affordances in SNSs specific to learning presents a challenge to learners with regards to finding crucial information for meaningful argumentation, as well as staying focused and on-task. These challenges do not negate the usefulness of SNSs for CSCL activities, but rather indicate that SNSs should be carefully adapted for this purpose, given that SNSs were created initially for informal social connections. One suggestion to overcome these limitations is to combine SNSs with other tools (C.-M. Wang, 2012). Some educators have already used other social media platforms and other tools in parallel with SNS discussions, such as Twitter or smartphone messaging (Manca & Ranieri, 2013). However, these combinations seem to target improvements in social interaction, rather than ensuring that quality discussions are taking place. Since socio-motivational level learning is disproportionally fostered in SNSs (Greenhow & Lewin, 2016; Rambe, 2012), there is potential in integrating instructional artifacts that could facilitate better cognitive level learning. The next section discusses one type of instructional artifact called group awareness tools, which can visualize both social and cognitive aspects of a collaborative learning scenario with the aim of guiding learners towards behaving in

ways that foster better learning processes and outcomes, especially in environments where contextual cues are limited.

1.3 Group awareness for CSCL on social networking sites

Group awareness is a concept referring to learners' awareness of important information about their group and its members (Bodemer & Dehler, 2011). Broadly speaking, in a computer-mediated setting this information could be social (e.g., who is in the group and what are they doing) and cognitive (e.g., what is the current level of knowledge of other group members; Janssen & Bodemer, 2013) in nature. Tools that aim to increase group awareness visually depict such information to compensate for the lack of contextual cues when interacting via computers (Buder, 2011). With this information, group awareness tools provide learners with a common frame of reference about their collaborators' social and cognitive information, enabling them to use that information to monitor and adjust their own behaviors, ideally in ways that promote better collaborative interactions and learning outcomes (Bodemer et al., 2018). This section discusses in more detail how the two broad categories of group awareness and reviews current research findings and gaps on group awareness and collaborative argumentation.

1.3.1 Social group awareness in SNSs

Social group awareness refers to the perception that one is working with "real" people in a virtual setting (Janssen & Bodemer, 2013). For instance, SNSs allow users to create personal profiles on which they can display personal information; displaying one's photo particularly helps reduce the anonymity and increases the likelihood of interaction (S. S. Wang et al., 2010). However, knowing who is who is not enough to foster learning. Educators tend to create private SNSs groups for their classes; in this case, the students already know each other (Manca & Ranieri, 2013). Thus, social group awareness tools should also display indicators of the behavior of other members

of the group (Bodemer & Dehler, 2011). Positive changes in learning-related behaviors are particularly observed when social group awareness tools allow for individual users to compare how they behave relative to their peers'. For example, in the Participation Tool by Janssen et al. (2011), students were represented in spheres: larger spheres and those located closer to the center indicated that the student it represents contributed more to the discussion. Seeing this visualization compelled learners to discuss any disproportionate effort, resulting in more equal participation. Qualitative information about participation can also be displayed: for instance, Phielix et al. (2010) used a tool that visualized how each student rated their peers' friendliness, reliability, productivity, cooperation, and the quality of their contributions. Students were then able to compare their self-ratings with the ratings they received from their peers, which led to less conflicts within the group and fostered a sense of group cohesiveness.

1.3.2 Cognitive group awareness in SNSs

Cognitive group awareness (alternatively known as knowledge group awareness) refers to awareness of the knowledge of other group members (Bodemer & Dehler, 2011). Like social group awareness tools, a group awareness tool could enable comparison of one's level of knowledge against that of their peers'. For example, concept maps can function as a cognitive awareness tool that displays one's knowledge structures; Engelmann & Hesse (2011) found that comparing concept maps would enable one to see and discuss what their partners know that they themselves do not, and vice versa, which subsequently increased the quality of group output. Visually displaying qualitative evaluations of knowledge may also lead to positive effects. For instance, a tool by Dehler-Zufferey et al. (2010) depicted self-ratings of each group members' understanding of the lesson; this resulted in learners providing explanations based on how the recipient perceived their expertise, ultimately leading to increased performance in an inferential knowledge test. These examples show that, much like social group awareness tools, cognitive group awareness tools influence not

only content-related learning but also social interaction, particularly communication behavior. That is because cognitive group awareness is highly related to the concept of common ground, in that the information provided by the cognitive awareness tools can serve as a point of discussion in an effort to establishing mutual understanding (Engelmann & Hesse, 2010). Thus, comparison of one's knowledge or cognition to that of their peers' could bring attention to one's knowledge gaps or unshared information, consequently leading to behaviors that aim to reduce these disparities, such as more question-asking and giving targeted explanations (Dehler-Zufferey et al., 2010; Engelmann & Hesse, 2011).

Certain Web 2.0 platforms, such as social question-and-answer sites like the Stack Overflow network, employ gamification techniques that work in a similar fashion as cognitive group awareness tools. To engage users and ensure quality contributions, Stack Overflow users are allowed to give points to quality questions and answers, which are then awarded to the contributors as"badges" that are displayed next to their usernames (Vasilescu et al., 2014). Earning more badges and points are often taken as cues of the expertise of the user, which have been shown to motivate users to contribute more and to pay attention to the quality of their contributions (Cavusoglu et al., 2015). The badge system is particularly useful for platforms dedicated to knowledge sharing and is a convenient way of identifying the most knowledgeable members of the community. However, as mentioned earlier, popular SNSs were not constructed for learning or knowledge sharing purposes, but rather for social interaction in informal settings. Thus, unlike social group awareness, there are even fewer features on SNSs that display cognitive group awareness information.

1.3.3 Group awareness and argumentation in SNSs

Studies that have investigated group awareness tools in the context of argumentative knowledge construction on SNSs have mainly focused on social and attitudinal aspects of group members. In a series of controlled laboratory experiments of an

argumation activity using a Facebook-like platform, Tsovaltzi and colleagues looked into the effects of social group awareness by informing learners, prior to writing their initial arguments for a collaborative discussion, that their arguments will be commented and amended by other learners. In one study (Tsovaltzi et al., 2014), this information resulted in higher quality arguments when combined with argumentation scripts, but on its own there were no observed learning gains in content knowledge. Another study (Tsovaltzi et al., 2015) similarly found no gains in learning nor did social group awareness lead to considering multiple perspectives. Social group awareness in these studies are limited in scope (i.e., awareness of the mere presence of others in the online environment versus information about the group members' behavior, as discussed in Section 1.3.1), which may have resulted in these detrimental effects to learning.

Puhl and colleagues conducted studies on a group awareness tool integrated on Facebook that displayed communication attitudes of learners, who rated various communicative scenarios that fell on either multi-perspective/flexible attitude or goal-oriented/structured attitude (active) dimension. Each learner then has 2 rating scores, which were then plotted on a 2-dimensional space, with the x- and y-axes representing the cognitive and behavioral dimensions, respectively. Thus, each point represented one learner; learners positioned closer to each other on the 2D space had similar communication attitudes. Learners who viewed this tool acquired more domain-specific knowledge and change in multi-perspective/flexible attitude towards communication (Puhl et al., 2015a,b). In another study (Tsovaltzi et al., 2017), the tool in combination with argumentation scripts resulted in more interactions; however, communication attitudes did not become more similar during the course of the discussion when learners were only exposed to the group awareness tool.

1.3.4 Summary: Group awareness for CSCL on SNSs

As discussed in Section 1.2, educators are attracted to the affordances of SNSs that enable social interaction, yet these platforms lack affordances that enable deeper learning processes. Although some features in SNSs enable social awareness, such as displaying the names and other basic information of community members, little else is known about the actions that they take on the platform that may have implications on their collaborative activities. Promising results have been found in studies that investigated group awareness in SNSs by developing additional tools that can be integrated in the SNSs. However, these studies have so far only targeted awareness of social-level and attitudinal-level aspects of collaborative learning. There have been no group awareness tools that aim to overcome the "flat-structured" layout of SNSs that makes finding relevant information from discussion posts difficult. Providing cognitive-level information, such as topics discussed in posts, might help mitigate such problems and keep learners' behaviors on-task. To this end, the following section details how network visualizations (also known as network graphs or sociograms) can be used in group awareness tools to visualize relations between collaborators based on their social and cognitive information, potentially improving social and cognitive gains in collaborative argumentation.

1.4 Network visualizations as group awareness tools

Network visualizations are derived from social network analysis (SNA), a term that refers to theories, perspectives and methods for measuring and representing structural relations (Carolan, 2014; Knoke & Yang, 2008). This section begins with an overview of SNA and the relevance of relational structures in CSCL. This is followed by a discussion on the applications of SNA in social learning analytics, its similarities to group awareness, and on this basis how network visualizations can be used as group awareness tools.

1.4.1 The potential of social network analysis in CSCL

Any given social network is composed of actors and the relations between them. Any entity that *acts* or is *enacted upon* is an actor in the network; in educational settings, actors can refer to students and teachers, as well as the technological, instructional and knowledge artifacts that are used for learning purposes. The mode of a network refers to the number of types of actors present: one-mode networks are those that only have one type (e.g., a classroom network with only students as actors), whereas two-mode or multi-mode networks have two or more types (e.g., a classroom network with students and the learning materials they use). When visualized, each actor is represented as a single node (i.e., a point or shape). Relations are represented as ties (i.e., lines) that connect two actors that have an established relationship between them. Common relations in educational settings include interaction/communication (e.g., talking to each other in class) affiliations (e.g., belonging to the same class), or social relationships (e.g., friendships). Given these elements, SNA can be described as the study concerned with relational structures between actors and the implications of these structures on these actors.

SNA and CSCL operate under the common assumption that one's relations are important for understanding observed behavior. Thus, SNA is an appropriate method for analyzing the relations that emerge, evolve, and give rise to knowledge and learning during CSCL (Lipponen et al., 2004). The potential influence of relational structures on actors can be quantified using local and global measures (also known as metrics or indices). Local measures quantify how individual actors are embedded in the network. Centrality measures, the most basic set of local measures, is calculated based on the number of relations of an actor and is taken as indication of an actor's prominence in a network (Knoke & Yang, 2008). Having many direct (high degree centrality) or close (high closeness centrality) relations to other actors means that a highly central actor could have greater access to information, resources or opportunities compared to less central actors. Similarly, an actor that is connected to other actors that are

not highly connected (high betweenness centrality) is an important as a mediator, providing access to information between groups who otherwise would be isolated from each other. Global measures quantify patterns of relations the whole network. Density is the most basic global SNA measure, calculated by dividing the number of relations in the whole network by the number of possible relations. A highly dense network implies that the many actors have established relations with each other, implying more group cohesion or unity.

In any given CSCL activity, there are several learners communicating with each other whilst interacting with various technological, instructional and knowledge artifacts in the environment. Data about these relations can be collected by directly asking learners (e.g., "Who did you talk to in class today?") or by looking into digital trace data (e.g., by looking at the chat logs to see which learner spoke to whom, Carolan, 2014). Whereas interaction analysis in CSCL is traditionally carried out by coding and counting units of discourse data (e.g., messages) that reflect certain collaborative activities, SNA provides a means for visually and mathematically representing the frequency, intensity, strength and direction (i.e., whether a relation is reciprocated) of these relations. For example, centrality measures could identify which learners are "popular" insofar as they have established relations with a large number of their peers. However, typical code-and-count interaction analysis and SNA need not be at odds with each other; in fact, they can both be applied to complement each other, as is conventional practice in CSCL (Jeong et al., 2014), thereby further enriching understanding of the context in which CSCL learning operates.

To illustrate, de Laat et al. (2007) used SNA to explore participation in an online discussion forum at the beginning, middle, and end of a 10-week period. In addition, the researchers conducted content analysis of the messages exchanged during these 3 time periods to identify whether they reflected learning (e.g., discussing content) or tutoring (e.g., facilitating discussion) activities. By generating network visualizations of the communication established on the forum, they were able to see that some learners were very actively initiating messages, whilst others were simply receiving them.

Through content analysis, it was further shown that the two most active learners in the beginning phase talked about different things: one had more learning-related messages in the beginning, more tutoring-related messages in the middle phase and remained a highly central actor until the last phase. In this manner, SNA provides educators and researchers with a meaningful "snapshot" of CSCL interactions that takes spatio-temporal dimensions (i.e., changes or addition closely related in time or position in the collaboration space) into account (Law et al., 2011). Combining this information with content analysis provides further context to the relative contributions of individual actors to the collaborative process.

1.4.2 Social network analysis and learning analytics

Despite its potential relevance, the application of SNA in CSCL contexts is still at its infancy. According to a methodological review of 400 studies from leading CSCL journals, the number of studies that applied SNA was considered negligible, or too low to be reported (Jeong et al., 2014). Thus, in order to find out how SNA can be used better in CSCL, it would help to explore how related fields in which SNA techniques are more established. One such field is learning analytics, which is concerned with "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013). Tracing its roots back to business intelligence, learning analytics emerged from a desire by educational institutions from the teaching, research, commercial and governmental sectors to extract value from the large amount of data accumulated by computers to optimize opportunities for learning (Ferguson, 2012). This led to the development of learning software (e.g., dashboards) that provide visualizations of the activities of learners to help instructors gain a better overview of course activity, reflect on its progress and identify issues, and ideally make changes in their practices based on these insights (Verbert et al., 2013). Thus, it can be said that learning analytics has the dual components of *technique*

(i.e., conducting analytics) and *application* (i.e., using techniques to impact learning, Chatti et al., 2012; Siemens, 2013). For example, a tool called Course Signals identifies which students are at risk of failing the course based on their task performance and previous academic history (technique) and signals them on a dashboard using red or orange symbols for high risk or potential risk students, respectively, allowing teachers to write personalized emails to specifically address the topics that place the students at risk of failure (application).

As helpful as insights into academic performance are, some have raised concerns that learning analytics focused mostly on summative feedback (Ferguson, 2012). Social learning analytics is a subfield developed in response to this dominance of summative assessment, shifting the focus instead to "elements of learning that are relevant...in a participatory online culture" (Shum & Ferguson, 2012, p. 5). One of these elements are relations between learners, resources and ideas, hence SNA is among the established types of analysis in social learning analytics. As a technique, SNA is used to quantify relationships that are present in a learning platform, for instance to analyze "patterns" of peer support in a MOOC based on discussion forum postings on peer assignments (Kellogg et al., 2014). As an application, SNA visualizations are used in some social learning analytics dashboards to depict information about direct communication between learners to indicate engagement (e.g., messaging). For example, the "Social Networks Adapting Pedagogical Practice" (SNAPP) dashboard extracts data from a discussion forum (posts and replies) in real-time and visualizes the post-and-response patterns of learners as a network graph (Bakharia & Dawson, 2011). With this visualization, instructors can infer which students are most or least active on the forum and provide timely interventions to address unproductive behaviors. Other dashboards could also visualize relations of students other than communication. Ángel Hernández-García et al. (2015) used a similar tool called Gephi not only to visualize post-and-reply networks, but also "read" networks which depict a relation between two learners when one has read the post of the other. They found that the read networks to be denser than the reply networks, which allows

teachers to identify which students are "lurkers" (those who read many posts but do not often post a reply). Finally, social learning analytics tools can also visualize interactions between students mediated through artifacts. SocialLearn is one such tool, which visualizes networks between learners that interact with the same learning topics (Schreurs et al., 2013).

1.4.3 Future directions of group awareness based on social learning analytics

Learning analytics applications and group awareness tools share many of the same characteristics. Both aggregate and visualize information that is valuable for informing educational interventions and improving learning processes and outcomes. One major difference is that learning analytics is typically designed for teachers to make informed decisions about their own teaching, whereas group awareness tools is designed primarily for learners to regulate their own learning behaviors. Because of this, group awareness tools place a greater emphasis on allowing students to compare their information against other group members, which students could focus on when making decisions about their behaviors. Finally, as the name implies, group awareness tools depict information about activities and behaviors of individuals working in groups. Thus, group awareness tools are particularly designed to benefit collaborative learning processes and outcomes. Learning analytics tools traditionally focus on individual learners and their behaviors without paying much attention to the social aspects of learning, at least until social learning analytics began to develop.

In spite of these differences, research in learning analytics, particularly social learning analytics, hints at future directions for group awareness tools. Specifically, SNA and the network visualizations in social learning analytics dashboards, which are usually designed to help educators consider participatory aspects of learning, could instead be integrated in group awareness tools for students. Some studies have attempted to use social network analysis measures and visualizations as feedback for

learners in collaborative groups. For example, Lambropoulos et al. (2011) augmented a traditional LMS with 7 tools for "social awareness", including a network graph depicting learners as nodes connected when a learner has replied to another learner in the LMS forum. Although their results showed that "active participation" increased, the researchers did not attribute the results specifically to one the 7 tools. One of those tools was a "participation graph", a bar chart that shows how many days each learner has logged onto the discussion forum. It is therefore unclear whether, and if so how, the network visualization contributed to better social awareness. J.-W. Lin et al. (2015) evaluated a "social awareness tool" that showed whether a particular co-learner is a close friend (e.g., based on questionnaire answers), as well as how many help messages the co-learner has received and replied to (i.e., in-degree and out-degree centrality). The results show that learners provided with this tool interacted more than learners that did not; however, there were no differences between the two groups on message quality. Cadima et al. (2010) used network graphs to visualize the density of the communication networks of a learning group. This allowed the researchers to identify certain students as being knowledge bridges: the sole common actor connecting 2 large groups of interconnected learners. Learners were asked to rate in the questionnaire whether they were more aware of the cohesiveness of their group, although the effect of the graphs on learning was not quantitatively evaluated.

These studies show that information from SNA is promising for building group awareness. However, the aforementioned studies have focused primarily on visualizing communication between learners on the online environment. In doing so, these studies have limited the kinds of relations that learners must be aware of during CSCL. Similarly, a preliminary literature review of SNA in "e-learning" studies (Cela et al., 2015) founded that SNA has been used to examine "patterns of interaction for collaborative learning". However, communication between learners is the only relation that is explored. It appears that only social relations between learners have been investigated, leaving out artifacts and the interactions that learners have with them from analysis. The dominance of communication networks can be attributed to the

ease in which communication log files are stored (Cela et al., 2015). However, communication is not the only way learners acquire knowledge in collaborative settings. Log files only contain discrete instances of communication occurring between learners, without information about its content or quality. In SNA, non-human agents such as technological, instructional and knowledge artifacts are considered as valid actors in a network; interactions of learners with objects in the environment are treated analytically in the same way as human-human interactions (Jones, 2015). Therefore, integrating the various artifacts that learners interact with in CSCL settings could provide more information about the content of the interaction that took place.

1.4.4 Summary

Network visualizations, based on social network analysis, can be used to represent relations between various actors in CSCL environments: from human agents such as learners and teachers that communicate with each other on a discussion forum, to artifacts that mediate interaction between learners. Although SNA is a relatively new method in CSCL, its use in the related field of learning analytics, particularly social learning analytics, hints at possible applications of network visualizations as group awareness tools for learners. The challenge, however, is identifying which kinds of relations should learners be aware of in order to better regulate their learning behaviors. There appears to be a large focus on representing communication relations between learners, even though there is a diversity of relations and actors in CSCL.

1.5 Summary of included studies

The previous section (Section 1.4) introduced SNA as a potentially relevant method in CSCL, especially considering the parallels between between group awareness tools and social learning analytics dashboards. Specifically, SNA visualizations can be useful as group awareness tools that depict relations between learners and artifacts in a CSCL activity. The fact that such learner-artifact relations are often overlooked

(Section 1.4.3) indicates that teachers, let alone learners, may not always consider how interaction with or mediated by various artifacts influences learning. When used as group awareness tools, network visualizations could potentially bring awareness to other ways in which learners interact and relate to each other beyond direct communication. This could be particularly useful for CSCL activities in SNSs, a promising CSCL platform that disproportionately fosters social aspects of learning (Section 1.3.4). Awareness of cognitive aspects, on the other hand, are impeded due to certain technical features (i.e., "flat-structured" arrangement of posts) that make it difficult for learners to access information that could promote learning and productive discussions (Section 1.2.4).

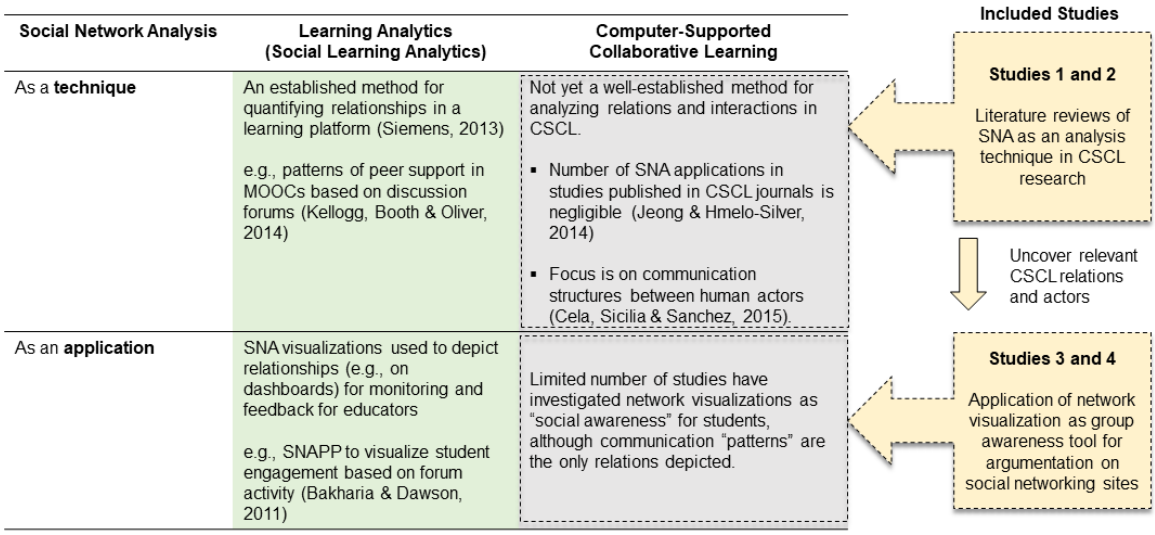


Fig. 1.1. Comparison of SNA in learning analytics and CSCL and how the included studies address research gaps

Against this background, the studies included in the present work explore the relevance of SNA in CSCL, particularly of network visualizations as a group awareness tool for SNSs. Figure 1.1 demonstrates how the four included studies address specific research gaps. As discussed in Section 1.4.2, the dual components of learning analytics means that applying SNA as a *technique* leads to *applications* that impact

learning, particularly as feedback tools for educators (Siemens, 2013; Chatti et al., 2012). However, SNA is not as well-established as a technique in CSCL as it is in learning analytics. Therefore, before a SNA-based group awareness tool can be designed and evaluated for CSCL activities on SNSs, the relevance of SNA in CSCL as an analysis technique must be investigated more deeply. For this purpose, Studies 1 and 2 were conducted as systematic reviews of research about SNA as an analysis technique for collaborative learning through computers. By gaining an understanding of which CSCL relations and actors have been investigated using SNA, particularly those that have been under-researched (likely non-communication relations and artifacts as actors), these studies helped identify the kinds of relations that learners should be aware of in order to better regulate their learning behaviors. Thus, the results of Studies 1 and 2 serve as the foundation for the design of the group awareness tools in Studies 3 and 4, which was evaluated in a collaborative argumentation activity on SNSs. In line with practices in CSCL research (as discussed in Section 1.1), Studies 3 and 4 investigated the influence of the learners' interactions with each other and with CSCL artifacts on learning on various levels (social, cognitive, affective). Furthermore, to gain insights on the learning process through which awareness was developed, digital trace data from the interactions (e.g., clicking and view times) of students with the tools' elements were collected and analyzed.

The following subsections summarize key contributions of these four studies to the present work. The research gaps in Figure 1 are then revisited in light of these findings.

1.5.1 Studies 1 and 2: Establishing the relevance of SNA in CSCL

CSCL and SNA share the premise that "relationships matter", which makes SNA an appropriate method for revealing important relational structures that emerge from CSCL. However, as was hinted in Section 1.4.3, previous work suggests that when discussing "relations" and "interactions" in CSCL, studies usually refer to how learners

communicate with each other via computers. They rarely take into account that students also engage with various technological, instructional, and knowledge artifacts in their environment, which could have meaningful implications for learning (refer to Section 1.1.2). It is also unclear how SNA is used to quantify learning outcomes in CSCL . Therefore, in Study 1, 89 CSCL studies that have applied SNA as an analysis method were analyzed with the following research questions in mind: (1) do current applications of SNA in CSCL research reflect the diversity of CSCL actors and interactions that influence learning?; and (2) how are SNA measures related to CSCL learning outcomes on the cognitive, social, and motivational levels?

The inclusion criteria for analysis were as follows: studies must (1) use primary data; (2) be an empirical study set in an instructional course/program up to the postgraduate level; (3) use SNA techniques, explicitly mentioned in the Methods section; (4) report SNA findings in the Results section; and (5) analyze collaborative learning activities between learners using computers. The included papers were all full-text studies published as journal articles, book chapters, conference papers, and proceedings by search online databases using the following keywords: "social network analysis" AND "computer-supported collaborative learning" OR online OR computer OR collaborat* OR learning. This means that unlike the review by Jeong et al. (2014), Studies 1 and 2 include studies that were published in other sources besides major CSCL journals. Content analysis was conducted to categorize the studies based on their (1) general methodology (research design, learning setting, sample size, educational level of sample, collaborative learning activity, and non-SNA methods); and (2) SNA features (actor type, relational tie type, SNA measures, and additional analysis methods on SNA data).

The results of the review indicate that, indeed, most CSCL studies incorporating SNA focus on "patterns of interaction" by analyzing one-mode networks of communication between learners. Centrality and density were the most commonly used metrics, which means that CSCL interactions were mostly defined by the amount of communication messages exchanged between learners. Only 11 of the 89 papers

(12%) incorporated technological, instructional and knowledge artifacts as actors or alongside learners in a two-mode network. For instance, generating a network with learners and threads in the discussion forum as actors, connected together when learners choose to post in a thread, allowed researchers to infer which topics learners were most interested in (Lotsari et al., 2014). Using key terms from discussion forum posts as network actors also helped determine what topics students were discussing the most (Sha et al., 2010). Furthermore, only a fraction of studies related SNA results with the cognitive, social or motivational process and outcomes; most studies simply described network characteristics based on the metrics used. However, as most studies analyzed communication between learners, the few studies that applied statistical correlations between SNA and CSCL measures found that learners who are actively communicating on the CSCL platform (i.e., highly central actors) tend to be highly motivated learners and ultimately earn higher marks (Claros et al., 2016).

Study 2 further investigated the notion of "patterns of interaction" in CSCL as measured by SNA through network text analysis. The 150 most prominent (i.e., frequently occurring) terms were extracted from the abstracts and Results sections of 90 CSCL studies that applied SNA in their methods (including studies in Study 1). After combining synonyms and spelling variations, 101 terms were analyzed and placed in one of four categories: (1) CSCL activities (45 terms); (2) CSCL methods (11 terms); (3) CSCL contexts (23 terms); or (4) SNA terms (22 terms). Then a concept network was extracted, with the CSCL and SNA terms as actors linked together if they appeared in the same publication. By extracting terms from a corpus of CSCL publications and constructing a network based on how these terms are related to each other, Study 2 presents a conceptual structure of SNA as a technique in CSCL research.

The network of SNA and CSCL terms was analyzed in three ways. First was a frequency count of the occurrences of the 22 SNA terms in the publications. Similar to the findings in Study 1, the terms "degree centrality" and "centrality" appeared most often in the studies (70 out of the 90 papers). Second, the 3 closest CSCL terms (of

each type: activities, methods and contexts) for each SNA term were identified based on geodesic distance, resulting in characteristic CSCL "profiles" for each SNA concept. Appearing in nearly every profile were the CSCL activity terms "group work", "interaction" and "communication"; the CSCL context terms "course", "message" and "class"; and the CSCL methods "interaction pattern", "correlation" and "questionnaire". These results once again confirm that communication between groups of learners is a primary research aim in the studies. Lastly, bipartite modularity maximization was performed to reveal cohesive clusters, which are subgroups or "clouds" of terms that are more densely connected to each other than the average in the network. From this analysis, it emerged that two clusters were highly connected to all other terms in the network: one that contained terms of the most common SNA metrics (e.g., "centrality", "density") and one that contain CSCL concepts related to communication (e.g., "message", "post") and interaction between learners (e.g., "interaction", "discussion", "groupwork"). These clusters therefore constitute the "conceptual core" that define how SNA is used in CSCL research: researchers seek to understand "interaction patterns" in CSCL by applying basic SNA indices.

Contributions of Study 1 and Study 2

With Study 1 and Study 2, it can be said that SNA is growing in relevance in CSCL research. Researchers have used SNA to quantify relations between learners based on instances of communication, as well as to infer how these relations influence learning processes and outcomes. However, the way it has been applied in existing studies has been limited and somewhat inaccurate. Study 1 shows that SNA in CSCL do not take into account the diversity of CSCL actors and the interactions that transpire between them. Although only limited number of studies demonstrated how relations between learners can be mediated by artifacts, Study 2 revealed that the terms "message" and "post" are among the most prominent CSCL context terms and the most highly connected terms in the network overall. This indicates that

messages serve as relevant knowledge artifacts that embody knowledge construction from the discussion and mediates further interaction between learners as they build upon each other's ideas (Stahl et al., 2014). Thus, by excluding such artifacts from SNA, it appears that current CSCL research are likely overlooking important mediated relations between learners. Moreover, as Study 2 reveals, "interaction patterns" in CSCL are often operationalized based on centrality and density. These measures do not necessarily reveal patterns in a sense that they are recurring constellations of communication behavior that persist over time and consistent in other context, but rather quantify discrete exchanges between learners specific to that particular time and learning situation (e.g., the amount of messages were sent/received are not the same in every discussion). It appears, then, that there is mismatch between the intended result that CSCL researchers have when using SNA in their analysis and what SNA can actually reveal about CSCL relations.

Mediated learner-knowledge artifact relations in a group awareness tool

The results of Studies 1 and 2 provide a basis for *using SNA as an analysis technique in CSCL*, as well as identifying limitations in its current usage. With these results in mind, it would be interesting to *explore how network visualizations can be used as an application* in such a way that maximizes the potential of SNA to include the diverse relations and actors in CSCL. The limited studies that incorporated artifacts, particularly knowledge artifacts such as messages or topics, demonstrate that it is possible to not only derive the amount of communication from SNA, but also the content of that communication, giving more insight into what was actually learned. In this case, *knowledge artifacts visualized in a network can be considered as cognitive information* about the learners, which could be shared (or not) between learners depending on whether they engage in the same artifacts.

The fact that only a small number of studies have included such artifacts in their analysis of CSCL suggests that awareness of their impact on learning and learning

behaviors is similarly limited. Therefore, Studies 3 and 4 in the present work aim to extend current CSCL research by using network visualizations as a group awareness tool, similar to its use in social learning analytics dashboards (see Section 1.4.2). Taking insights from the results of Studies 1 and 2, the design of the group awareness tool in Studies 3 and 4 goes beyond simply visualizing communication or "interaction patterns" between learners, instead making learners aware of their relations to each other as mediated by artifacts.

1.5.2 Studies 3 and 4: Network visualizations as group awareness tools depicting social and cognitive information

Based on the results of Studies 1 and 2, group awareness tools were designed in which social and cognitive information were depicted in a network visualization. In Study 3 and Study 4, these tools were then evaluated in collaborative argumentation activities on SNSs (Google+ and Google Classroom, respectively) in authentic learning settings, namely in the Economics classes of international school students pursuing the International Baccalaureate diploma. The topics discussed in these activities are known as socially acute questions (SAQs) which are controversial dilemmas that are frequently encountered (i.e., acute) in society and debated by experts in various sectors and disciplines (Simonneaux, 2011). In Study 3, students engaged in argumentation about migration from developing to developed countries (a "socio-sociological" issue); in Study 4, the topic was about the effects of economic policies about climate change (a "socio-scientific" issue). As introduced in Section 1.2.2, collaborative argumentation is often conducted in a sequence of activities, whereby learners (1) state their initial arguments about a topic (Session 1); (2) are given the opportunity to propose counterarguments to their peers' initial arguments (Session 2); and (3) rethink and refine their initial arguments in light of the perspectives they were exposed to in the discussion (Session 3) (Leitão, 2000). Successful learning from collaborative argumentation requires that learners build on each other's arguments and integrate

multiple perspectives about the topic, instead of simply agreeing or accepting each other's arguments (Weinberger & Fischer, 2006).

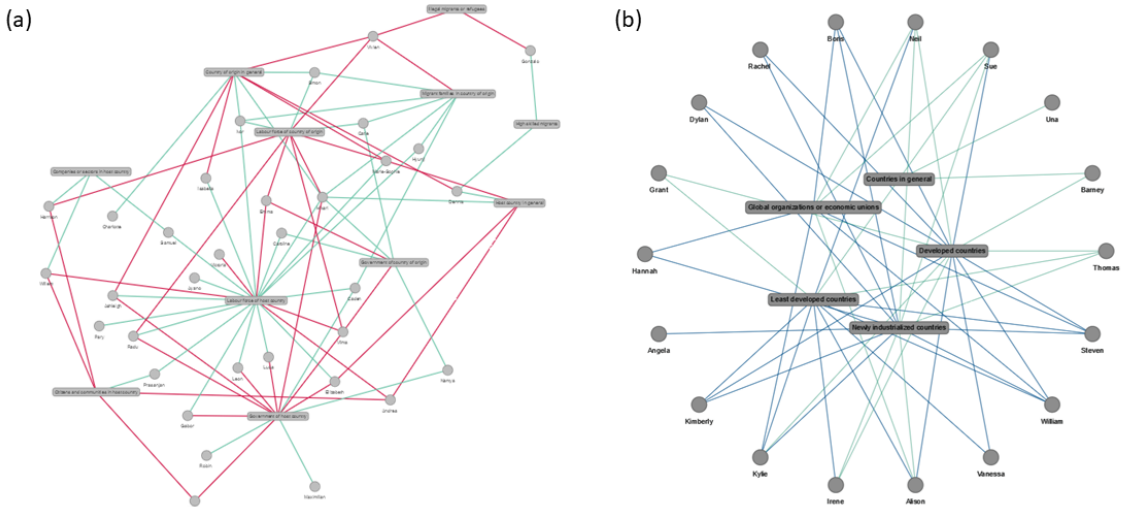


Fig. 1.2. The group awareness tools evaluated in Study 3 (a) and Study 4 (b)

During argumentation about SAQs, students must consider the points of view of the different stakeholders affected by the issue (Simonneaux & Simonneaux, 2009). Thus, *the different stakeholders mentioned by students in their discussion forum posts can be taken as a knowledge artifact and represented as cognitive information.* With this in mind, group awareness tools were designed to visualize how students' initial arguments are positioned with respect to their peers' arguments (see Figure 1.2). The network visualizations were composed of 2 types of nodes (1) students (circles); and (2) economic stakeholders affected by the issue that students mentioned in their initial arguments (rectangles). An edge was drawn between these 2 node types when a student mentioned that stakeholder in their initial arguments in the first argumentation sequence. Each edge was color-coded according to the perspective or stance expressed by the student. In Study 3 (see tool in Figure 1.2a), students could take the stances of "migration is / is not beneficial" for the stakeholders they mentioned. In Study 4 (see tool in Figure 1.2b), students had to explain how stakeholders are impacted

by the issue from an economic growth perspective or an environmental perspective. In this manner, social information was present in the circular nodes representing the students, whereas two types of cognitive information from students' initial arguments were shown: (1) stakeholders mentioned by students in their arguments, represented as rectangular nodes; and (2) the perspectives taken by that student about that particular stakeholder, indicated by the colored edges.

The activities in both Studies 3 and 4 were structured in 3 sessions corresponding to the argumentation sequence of Leitão (2000): students first had to post their initial arguments on the SNS, then share counterarguments or perspectives by leaving comments on each others' posts, then finally revise their initial arguments if their perspectives have changed since the start of the activity. In both studies, students were presented with the group awareness tool at the beginning of the second session. This is because the tool was designed to influence communication behavior on the basis of social and cognitive information, specifically how students select which of their peers to respond to in the second phase of the argumentation activity. Otherwise, the flat-structured arrangement of information on the SNSs would make it challenging for students to build on and exchange perspectives with each other. The networked arrangement of the tool allows for a general overview of the different stakeholders and perspectives mentioned, thereby raising the awareness of students about the multiple perspectives in the discussion. Furthermore, the tool was interactive, enabling students to click and drag nodes and edges in any arrangement they wished. This allowed students to have a closer look into the details of the visualization. Similar to other group awareness tools that present group information in a 2-dimensional space (as mentioned in Section 1.3.3, Puhl et al., 2015b), the networked arrangement could help learners become aware not only of the stakeholders and perspectives, but also similarities and differences between their own cognitive information and those of others based on (1) their connections (or the lack thereof) to the same stakeholders and (2) the similarities or differences in edge color which express the perspective of the student. The clicks and drags were also logged in order to make inferences about the

type of information that students allocated most of their attention to. Thus, similar to other group awareness tools (refer to Section 1.3), the information in this tool can be used as a common frame of reference when selecting which arguments to engage with in the second session, as well as common ground for initiating counterarguments and rebuttals.

Study 3 adopted a quasi-experimental between-groups design with 29 Year 12 students in 2 Economics classes. One class (n=15) served as the control group, whereas another class (n=14) was known as the group awareness tool (GAT) group, since they were able to access the tool in the second argumentation session. The SNS platform used in this study is Google+, created by Google, which follows a flat-structured format. As mentioned earlier, students followed the argumentation sequence stated in Leitão (2000) by answering the question "To what extent do you agree with the statement: Migration from developing to developed countries leads to economic development?". The overall research question for this study was: "Can a group awareness tool depicting (1) students (social information); (2) discussion topics and (3) opinion stances (cognitive information) foster argumentation and learning on a social media platform?". It was hypothesized that students the GAT group would be more likely than the control group to (1) post counterarguments on posts that reflect a different stakeholder or perspective than their own (communication behavior); (2) be more likely to revise their initial arguments by integrating multiple perspectives from the discussion (integration of multiple perspectives); (3) perform better in a related knowledge test (learning outcomes); (4) exhibit a greater shift in opinion on the various stakeholders (shift in opinion); (5) demonstrate better awareness of multiple perspectives (awareness of multiple perspectives).

In terms of communication behavior, the results show that students in both groups tended to respond to peers that expressed the same perspective as theirs on at least one stakeholder. Furthermore, the control group was more likely to respond to peers within their own class and those whom they consider their friends—despite having an equal number of friends in either class. Perhaps owing to the tendency of peo-

ple to change opinions when exposed to the opinions of people with whom they are personally close (Friedkin & Johnsen, 1997), the control group also integrated multiple perspectives more than the GAT group. The GAT group, on the other hand, was more likely to respond to friends and non-friends, classmates and non-classmates alike. However, they did not exhibit better learning outcomes, greater shifts in opinion, or more awareness of multiple perspectives. One reason behind this result could be the low interactivity on the tool (e.g., few click/drag actions were logged). This implies that the GAT group only perceived a general overview of the students, stakeholders and perspectives in the activity, without deeply processing the similarities and differences in cognitive information. However, this might have been enough for students to notice the presence of peers they might not know so well yet. Thus, the social information in the group awareness tool might have increased familiarity with students that they are not personally close to, helping them to consider their arguments of peers they might have otherwise overlooked.

Study 4 was also a field experiment in the same school, with the same teacher and school subject (Economics) as in Study 3. There are notable differences and similarities in the research design of Studies 3 and 4. Changes in the (1) independent variables and (2) SAQ as argumentation topic were made given the differences between the participants of the two studies. Study 4 involved 19 Year 11 students in one Economics class. Students in the class were linguistically diverse and, as noted by the teacher, the students with lower English proficiency tended to have a more difficult time following instructions in class, resulting in relatively poor academic performance. Thus, Study 4 included both between- and within- group comparisons. Between-groups comparisons were conducted between students taking the English A class (n=9, for native speakers/highly efficient English users) and students taking the English B class (n=10, for users of English as a Second or an Additional Language, ESL/EAL). Within-groups comparisons were conducted based on the two argumentation sequences administered to all students in the study; the group awareness tool was administered only in the second argumentation sequence. As for SAQ for this study,

a socio-scientific SAQ was selected about economic policies related to climate change, as this topic is relevant to the Microeconomics unit in the Year 11 IB curriculum (whereas socio-sociological SAQs are more relevant for the Developmental Economics unit in the Year 12 curriculum, as in Study 3). In the first argumentation sequence (no-GAT sequence), students responded to the question "To what extent do you agree with this statement: 'Tradable permits are the best solution for reducing global carbon emissions'?" In the second sequence (with-GAT sequence), students responded to the question "To what extent does solving global warming require international cooperation?".

Study 3 also differed in terms of the (1) SNS platform and (2) appearance of the GAT due to on practical considerations. The platform used in Study 4 was Google Classroom's Question function which also arranges information in a flat-structured manner. Users of this feature cannot view or comment on the responses until they have submitted their own. The comment function could be disabled by the teacher, which was useful for the study as participants were only allowed to reply to each other in Session 2. Thus, Google Classroom allowed more control over its functionalities during each session. The appearance of the GAT was modified in order to counter the low interactivity observed in Study 3. This low interactivity could have been the result of the complexity of network visualizations that students may be unfamiliar with. Therefore, in Study 4 the nodes and edges were arranged in a circular manner and unselected elements are rendered in grey to simplify interpretation and improve readability.

As with Study 3, awareness, communication behavior, integration of new perspectives, and learning outcomes were assessed in Study 4. Anxiety towards writing in English (Cheng et al., 1999) was also included as a dependent variable because ESL/EAL students tend to experience language-related anxiety, especially when during argumentation (Cheuk, 2016). Since there are no previous studies about ESL/EAL students and group awareness, selected *a priori* hypotheses were defined for variables that could be influenced by English proficiency or academic aptitude. They are: (1)

students in both English classes will exhibit greater awareness in the with-GAT sequence; (2) English A and English B students will differ in integration of multiple perspectives; (3) English A will perform better in the knowledge test overall, but English B scores will improve after the intervention and (4) English B will score higher in the anxiety measure overall, but will decrease after the intervention.

The results of Study 4 reveal that in terms of awareness, although exhibiting equally low awareness after the no-GAT sequence, English B students were able to exhibit greater awareness of stakeholders and perspectives than English A students in the with-GAT sequence. This could be due to English B students spending more time looking at the tool and clicking/dragging its elements, as evidenced by the logged interactions. However, students regardless of English class or the argumentation sequence chose to communicate respond to peers that expressed the same perspective as theirs on at least one stakeholder as well as with their friends and with peers in the same English class. This result is corroborated by an analysis of the logged actions on the tool: students were more likely to click the node of a peer that is connected to the same stakeholder. Furthermore, the logged data shows that English B students were less likely to notice peers with whom they did *not* share cognitive information. In terms of integration of multiple perspectives, students regardless of English class either dismissed or integrated new perspectives in both sequences. English A performed significantly better than English B students in the pre- and post-knowledge test. English B had significantly higher anxiety scores overall, which did not decrease after the intervention.

Contributions of Study 3 and Study 4

The results of Studies 3 and 4 provide insights about how network visualizations influence learning on social, cognitive and affective levels, as well as insights into the process by which learners developed awareness using the tools. In terms of learning on a social level, in both studies students chose to respond to peers that possessed

the same cognitive information as them (i.e., peers with whom they have a mediated relationship through the same knowledge artifacts). In Study 3, students that were not exposed to the tool responded mainly to friends and classmates, whereas those that received the tool responded equally to friends/non-friends and classmates/non-classmates alike. In terms of learning on a cognitive level, in Study 3 learners that did not receive the tool integrated multiple perspectives more. In Study 4, belonging to a certain English class nor exposure to the group awareness tool influenced multiple perspective taking. Finally, with regards to learning on an affective level, Study 4 found that ESL/EAL students experienced more anxiety throughout the intervention, despite being exposed to the group awareness tool. All of these results persisted regardless of how long students interacted with the tool (Study 3 participants spent 3.72 minutes on average whereas Study 4 participants spent an average of 9 minutes). Even English B students in Study 4, who exhibited greater awareness of multiple perspectives, performed similarly to their English A peers, who exhibited lesser awareness. This means that greater awareness of multiple perspectives did not necessarily lead to behaviors that promote multiple-perspective taking.

The digital trace data provides hints that could explain these results. Particularly in Study 4, students mostly clicked on the nodes that represented cognitive information (stakeholders) that they shared in common with other peers. This knowledge artifact is evidently the most salient cue in the network visualization: according to Suthers (2001), nodes are easier to perceive visually than edges. It would involve more visual search operations to detect differences in perspectives denoted by edge color, as well as identify peers with whom they did not share a stakeholder, since students would need to find peer nodes with whom they did *not* have a mediated connection with through a common stakeholder. Thus, due to the complexity of the visualization, perhaps students noticed only nodes and existing edges (the most salient cues), which represent shared cognitive information. This could perhaps explain why English B students in Study 4 did not perform any different than their English A peers, despite

exhibiting greater awareness of multiple perspectives: English B students experienced more difficulties in identifying unshared cognitive information.

1.6 Synthesis and conclusion

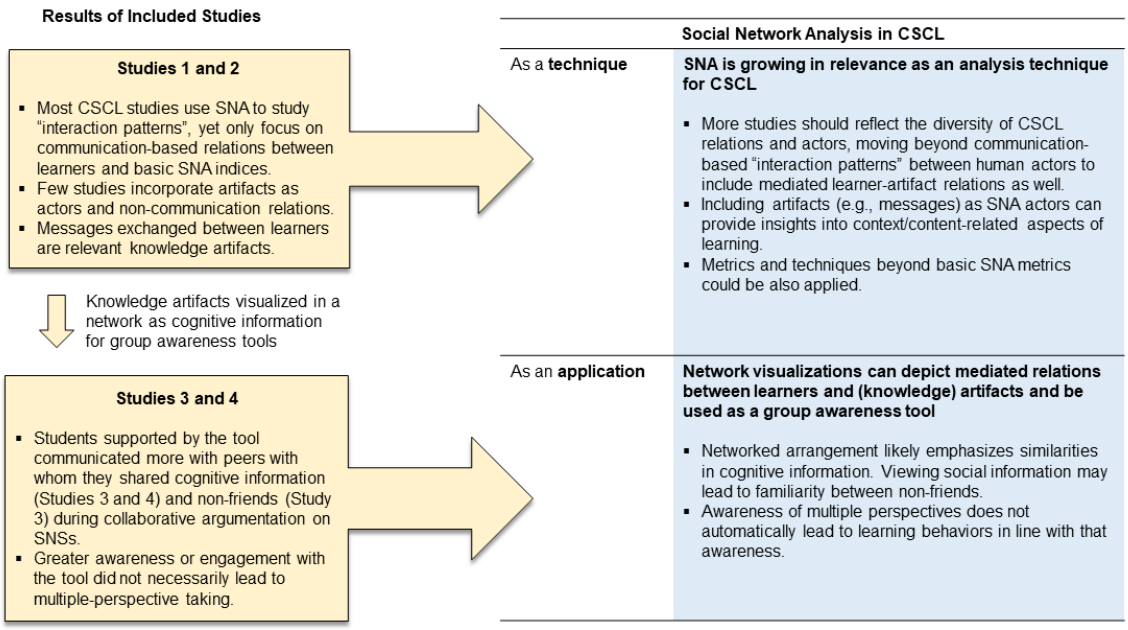


Fig. 1.3. Summary of key findings of included studies with reference to SNA in CSCL as a technique and application

Synthesis

Figure 3 synthesizes the key findings of the four studies in the present work and presents what these results imply about SNA as a technique and application in CSCL.

Studies 1 and 2 highlight both the relevance of SNA in CSCL research, as well as some limitations in the ways in which researchers have used this technique. CSCL takes place in context-rich, dynamic and highly interactive environments (Kreijns et al., 2003). Yet majority of studies that have analyzed these environments using SNA

do not reflect this complexity, despite the adaptability of SNA and network visualizations to incorporate different artifacts as actors and depict non-communication relations. Messages between learners have emerged as particularly relevant knowledge artifacts. Yet only a small number of studies were able to demonstrate how artifacts—whether instructional, knowledge and technological—can provide context- and content-rich information about CSCL environments. In doing so, Studies 1 and 2 expand the understanding of CSCL "interaction patterns" beyond communication-related ties and basic indices to include mediated learner-artifact relations.

In addition to revealing insights into SNA as a technique for CSCL, the results of Studies 1 and 2 were used to inform the design of a group awareness tool that visualizes key group information in a network graph. The small number of CSCL studies that incorporated knowledge artifacts demonstrate how these could embody learners' cognitive information, such as keywords of concepts that learners know. Whereas communication networks only represent the amount of contact exchanged between learners (i.e., number of messages sent and received), two-mode learner-knowledge artifact networks show the content of that exchange. It would then be possible to see how learners are related to each other via the knowledge artifacts that they have in common, as well as to infer which learners do not share the same cognitive information. Therefore, in order to meaningfully adapt SNA as an application to impact CSCL, learner-artifact networks could be used as group awareness tools that enables reflection not only on the basis of social information (as a communication network would provide) but also on cognitive information.

In Studies 3 and 4, the tools were implemented to support collaborative argumentation on SNSs. This was done because of growing interest in appropriating social media for educational purposes, despite certain features that may impede meaningful learning. This includes the flat-structured arrangement of discussion that makes it difficult to find and build upon the ideas and arguments proposed by one's co-learners. As such, group awareness tools that show social and cognitive information may help learners orient their behaviors on SNSs in a meaningful way. The results of Studies

3 and 4 suggest that although the group awareness tools led students to exchange arguments with non-friends (as in the GAT group in Study 3) and develop awareness of cognitive information (as in English B students in Study 4), these behaviors did not necessarily lead to multiple-perspective taking. Process data from Study 4 further found that higher ability students were more likely to notice dissimilarities in cognitive information, although they spent less time looking at the tool overall and did not demonstrate multiple-perspective taking either. Since the group awareness tool depicted mediated relationships via knowledge artifacts (i.e., stakeholders mentioned in initial arguments), the similarities in cognitive information were the most salient elements of the tool. This means that unlike in other group awareness tools, the group awareness tools do not emphasize dissimilar cognitive information, even if this can be derived by observing the difference in edge colors that indicate perspectives or the absence of edges that link two peers to a shared knowledge artifact.

Limitations

There are a number of limitations in the present work. One limitation in Studies 1 and 2 is that the studies included in the literature reviews are set in formal learning environments up to the postgraduate level. Therefore, the studies included in the literature reviews do not include informal learning contexts or professional development settings that may be characterized as networked learning. Furthermore, these reviews aim to *introduce* SNA as a method in CSCL rather than definitively *prescribe* measures to quantify learning processes or outcomes. As noted earlier, SNA measures simply take into account discrete instances of relations specific to particular scenario and do not necessarily persist in other situations. For example, having a high outdegree centrality may be desirable among students (indicating active discussion, Claros et al., 2016), but not among teachers (as this could indicate that teachers are more active in the discussion than the students, Zafar et al., 2014). Thus, researchers are cautioned to carefully consider the context in which they wish to analyze using SNA.

Network graphs, a field of research on its own (Becker et al., 1995), are novel and relatively complex visualizations in group awareness research. Readability of network visualizations vary depending on the network size (i.e., number of nodes), edge crossing (i.e., the extent to which edges overlap), and layout algorithm, to name a few (Dunne & Shneiderman, 2009). These factors were taken into account in Studies 3 and 4 to a limited degree: for instance, a circular layout was adopted in the tool for Study 4 in order to minimize edge crossings. This means that the results of Studies 3 and 4 may not hold true for other learner groups, as the visual complexity of the group awareness tool greatly depends on the group's context. Furthermore, it is beyond the scope of these studies to prescribe a specific constellation of readability factors that would be optimal to promote group awareness. It is therefore crucial to provide learners with a "training" phase to help them get acquainted with network visualizations and to teach them how to interpret it correctly before using it as a group awareness tool, as was done in these studies.

Studies 3 and 4 were set in authentic classroom settings, which enabled the investigation of collaborative argumentation on a real SNSs. Nevertheless, certain potentially confounding variables could not be accounted for. For instance, the influence of holding a minority or majority perspective was not investigated systematically as in other group awareness studies (e.g., Buder & Bodemer, 2008), as it was not to possible to foresee the participants' arguments and the spread of perspectives prior to the interventions. Moreover, the group awareness tools were hosted on an external website rather than integrated in the SNS, which means whether any process loss occurred and, if so, what effect did it have were not measured. Nevertheless, the methodologies in Studies 3 and 4 were designed with ecological validity in mind (Jeong et al., 2014). Lack of technical expertise and knowledge on how to use computer-based learning platforms meaningfully are some of the major barriers against technology integration in the classroom (Kopcha, 2012). On the other hand, as discussed in Section 1.2.1, educators are intrigued by educational potential of SNSs precisely because of its accessibility and ease of use among students. As such, rather than constructing

an SNS with an integrated group awareness tool for purposes of a true experiment, the Google social media suite was used because this was readily integrated in the participants' class activities and existing technical set-ups. Hence, the findings could be used to inform future research and practice-based interventions involving readily available commercial SNSs for educational purposes. Furthermore, the results between Study 3 and Study 4 may not be directly comparable given the differences in the research design, particularly the SNS platform, independent variables, argumentation topic and the appearance of the GAT, despite the necessity of adapting these design considerations given contextual differences between the studies. Thus, these studies could be best interpreted as investigations of network-based GATs on similar SNS platforms for collaborative argumentation with SAQs (socio-sociological and socio-scientific), yet with different populations (students with similar language proficiency vs. linguistically diverse students).

Future directions and conclusion

Relationships between learners and the artifacts in the learning environment are key to understanding how learning occurs in CSCL settings. The aim of the present work was to investigate whether awareness of such relations influences CSCL by using network visualizations as group awareness tools. To achieve this, the utility of social network analysis in CSCL was explored, taking cues from social learning analytics and its use of social network analysis as a technique and application. Unpacking how SNA is used as a technique in CSCL has shown that conceptualizations of CSCL "interaction patterns" are limited to direct communication. This does not usually include mediated relations between learners and artifacts, thereby highlighting a critical research gap. Communication is undoubtedly important in CSCL, but it is by no means the only way that learners relate with each other, nor are learners the only relevant actors in a CSCL network. Thus, future CSCL studies that use SNA as a technique should consider exploring how learners interact with technological,

instructional, and knowledge artifacts in order to better contextualize the relations beyond direct communication that transpire as learning occurs. A network that depict whether learners engage with the same artifact, for instance the same discussion thread or talk about the same topic, provides more information about the knowledge being exchanged that a network that only shows which learner messaged whom.

This work has further demonstrated that presenting knowledge artifacts as cognitive information enriches learning activities in SNSs—an environment that lacks content-related cues, yet is often appropriated for educational purposes. Nevertheless, the networked arrangement of group information emphasizes similarities rather than dissimilarities in cognitive information. Thus, future studies should look into combining the tools with argumentation scripts that help learners consider the merits of exchanging unshared cognitive informatio. Previous studies on group awareness tools and argumentation have additionally investigated its effects when combined with collaboration scripts (Puhl et al., 2015a; Tsovaltzi et al., 2015). In many of these cases, the combination of explicit (scripts) and implicit (group awareness tool) guidance led to more knowledge acquisition and argumentation quality. Even when students developed greater awareness, given the complexity of the tool students may have failed to act on that information during the activity. Thus, it might help to include a script that could explicitly guide learners to consider unshared information as they proceed with their argumentation tasks.

Key terms from messages were selected as the knowledge artifact to be visualized in the group awareness tool because messages emerged as a prominent artifact in CSCL studies. Nevertheless, there are also technological and instructional artifacts in CSCL, such as threads (i.e., technical artifacts) or lecture slides (i.e., instructional artifacts). Future studies should explore whether these artifacts can similarly be integrated as cognitive information and whether learners' awareness of their mediated relationships through these artifacts could influence their learning. Such group awareness tools could also be investigated in other types of CSCL activities. For example, webquests are inquiry-based learning activities that explicitly encourage

learners to collaboratively solve problems by combining information from various web sources, such as websites and articles (Leite et al., 2015). In this case, a networked learner-artifact group awareness tool may be important because engagement with these instructional artifacts are critical to the success of the activity.

In conclusion, the results of the present work establish a foundation for SNA techniques and applications in CSCL that reflect the diversity of actors and relations in CSCL environments. This work also sets the precedent for using knowledge artifacts as cognitive information in group awareness tools. As social media continues its strong presence in the social lives of learners, incorporating network visualizations as group awareness tools could help them become aware of the many ways in which they relate to each other beyond simply sending messages, thereby fostering social interaction and knowledge construction.

2. STUDY 1: A REVIEW OF METHODOLOGICAL APPLICATIONS OF SOCIAL NETWORK ANALYSIS IN COMPUTER-SUPPORTED COLLABORATIVE LEARNING

Educational Research Review 22 (2017) 159–180

Contents lists available at ScienceDirect

Educational Research Review

journal homepage: www.elsevier.com/locate/edurev

Methodological Reviews

A review of methodological applications of social network analysis in computer-supported collaborative learning

Marielle Dado*, Daniel Bodemer

University of Duisburg-Essen[1], *Lotharstraße 65, D-47057 Duisburg, Germany*

ARTICLE INFO

Article history:
Received 27 January 2017
Received in revised form 3 July 2017
Accepted 20 August 2017
Available online 26 September 2017

Keywords:
Computer-supported collaborative learning
Social network analysis
Collaborative learning
Learner interaction

ABSTRACT

Social network analysis (SNA) is a promising research method for analyzing relational ties in computer-supported collaborative learning (CSCL)—activities in which learners interact towards a common learning goal with the aid of computers—because they share the same underlying assumption that learning and behavior are influenced by one's relations. This methodological review examines whether CSCL research (n = 89) (1) reflects the diversity of actors (learners and artifacts) and relational ties that are important in CSCL environments; and (2) relates these relational ties as measured by SNA indices to CSCL learning outcomes. The results suggest that SNA applications in CSCL (1) do not reflect this diversity of CSCL actors and relational ties, investigating only one-mode networks of learners connected by communication-based relational ties; and (2) are limited to a descriptive reporting of SNA results. Future directions for CSCL are focused on filling these gaps by (1) integrating technical, instructional and knowledge artifacts as SNA actors, and (2) relating SNA findings to cognitive, social and motivational CSCL outcomes using statistical analysis.

1. Introduction

Studying learner interactions and relations is the key to understanding how learning occurs in computer-supported collaborative learning (CSCL) settings. As technologies for CSCL become more advanced, there is a greater call for analysis methods that can derive insights about learner interactions from large amounts of computer-generated data, such as log files, messages, and other artifacts (Jeong, Hmelo-Silver, & Yu, 2014). Techniques from computer science and learning analytics could be a step in the right direction in addressing these issues (Martin & Sherin, 2013). One such technique is social network analysis (SNA), an application of graph theory which allows for the analysis of patterns of relationships between actors that interact with each other (Sie et al., 2012; Wasserman & Faust, 1994). SNA has had a long history predating the use of computers; nevertheless, promising SNA findings have already led to meaningful insights and future directions in educational research and technology-enhanced learning (Cela, Sicilia, & Sanchez, 2015). However, the ways in which SNA has been and could be valuable in CSCL research has not yet been explored systematically. The present review examines trends in the applications of SNA as a research method for analyzing learner interactions during CSCL.

* Corresponding author.
E-mail addresses: marielle.dado@uni-due.de (M. Dado), bodemer@uni-due.de (D. Bodemer).
[1] Institute for Research Methods in Psychology – Media-Based Knowledge Construction.

http://dx.doi.org/10.1016/j.edurev.2017.08.005
1747-938X/

1.1. Summary of important SNA concepts

In SNA, the relationships that link individual actors in a community are of central importance. In educational settings, these *actors* could be learners, groups of learners and teachers, as well as non-human agents such as classes, courses, learning materials, or features of the learning environment that persons interact with or participate in Carolan (2014). Social networks can be composed of actors of the same type (e.g., learners) or of two or more types (e.g., learners and learning materials), these are called one-mode and two/multimodal networks, respectively. An actor is connected to another actor by the presence of at least one type of *relation* between them; some common relational ties in education include interaction and communication (e.g., talking or sending messages to each other), association (e.g., taking the same courses), and social relations (e.g., friendships). In computer-mediated learning settings, information about these relations can be collected by asking actors about their relationships within the network (e.g., "Who did you talk to in class today?") or from digital trace data (e.g., a chat log that shows who talked to whom). Given these elements, *SNA is concerned with the structure of relational ties between a group of actors* and the implications of these structural patterns on learners' behavior and attitudes. SNA allows for the study of relationships among actors that interact with one another and/or their environment in a particular way.

Relational data can be measured on several levels (Carolan, 2014). Local (egocentric) level analysis emphasizes how individual actors are embedded in the network in relation to other actors (e.g., "Who is the most active learner in the discussion forum?"). Global level analysis provides a "snapshot" of the network structure by describing the patterns of relations in the network (e.g., "How engaged are the learners in discussions with each other?"). Networks can be further analyzed by detecting subgroups of actors that are connected to each other at a high rate (e.g., "Do learners communicate with certain learners more than with others?") and positions of actors that occupy the same place or have similar patterns of relations with others (e.g., "Which learners have yet to establish a relationship with each other?").

SNA data may be represented in two ways: visually using node-link representations and mathematically. Graphical representation of networks is achieved using network graphs, known as sociograms, whereby actors are represented as nodes and the relational ties as lines connecting nodes to each other, which may be weighted depending on the strength or frequency of the relationship. This provides an intuitive display of the patterns of relationships in a group. Based on the number of actors and number, strength or frequency of relations in the network, different *local* and *global measures* or indices can be calculated to succinctly quantify characterize network relations. Some of the most common SNA measures, particularly in the social sciences, are centrality as a local measure and density as a global measure (Knoke & Yang, 2008). Centrality is calculated based on the number of relational ties an actor has: a highly central actor is one that is directly connected to many actors (degree centrality), has the shortest connections to many actors (closeness centrality), or serves as a mediator between two groups of actors (betweenness centrality). It is often used to determine the most prominent and important participants in the network (Carolan, 2014). The density of the network refers to the total number of ties in the network divided by the number of all possible ties (Carolan, 2014). The density value ranges from 0 to 1; the closer the value is to 1, the denser and more cohesive are the nodes in the network.

1.2. The role of SNA in CSCL research

1.2.1. Definition of CSCL

CSCL can be described as activities in which two or more learners interact and are mutually engaged towards the accomplishment of a common learning goal with the support of information and communication technologies (Lipponen, 2002; Suthers, 2012). The emphasis on *mutual engagement* helps to distinguish CSCL from other technology-enhanced learning such as e-learning, commonly defined as the use of technology to deliver information for learning purposes (Sangrà, Vlachopoulos, & Cabrera, 2012). Although e-learning platforms may have interactive elements, e-learning activities themselves do not have to be collaborative in nature in order to result in effective e-learning outcomes (Sun, Tsai, Finger, Chen, & Yeh, 2008). For example, e-learning interventions may include videos explaining a topic followed by a quiz to test the learner on the videos' content, which can be completed successfully without interacting with other learners (Lahti, Hätönen, & Välimäki, 2014). Moreover, the role of computers in CSCL is supportive in that it facilitates interaction and stimulates learning, which does not exclusively mean information delivery. This means CSCL interactions may occur face-to-face (e.g., working together using a multitouch table), remotely (e.g., online distance courses) or a combination of both (e.g., blended classrooms, Jeong et al., 2014).

CSCL extends where the definition of e-learning stops at "deliver information for learning purposes" by encompassing activities designed to foster productive learner interactions in an effort to establish a shared understanding of the learning task (Dillenbourg, Järvelä, & Fischer, 2009). Different forms of CSCL interactions exist (Suthers, Dwyer, Medina, & Vatrapu, 2010). Effective *direct* interaction, whether through synchronous or asynchronous communication, is necessary to achieve joint information processing during collaboration (Rummel, Deiglmayr, Spada, Kahrimanis, & Avouris, 2011). However, learning also occurs when learners engage in *mediated* or indirect interaction via engaging in shared artifacts and objects relevant to the learning tasks. These artifacts may be technological (e.g., web applications through which learners

communicate) or instructional (e.g., studying course content, exchanging helpful learning resources) in nature; or may be knowledge artifacts which are the product of the collaborative activity (e.g., developing a joint concept map, or collaboratively writing an article; Stahl, Ludvigsen, Law, & Cress, 2014). Artifacts serve as a common ground for learners in a group, facilitating direct interaction and forming the basis for their shared understanding of the learning goals or the co-construction of the group product (Stahl, 2006).

CSCL is also the name of the interdisciplinary research field concerned with evaluating both individual and shared learning outcomes due to learner interactions with the support of computers (Lipponen, Hakkarainen, & Paavola, 2004). These outcomes occur on a *cognitive/metacognitive* level (acquiring new knowledge), but also on *social/metasocial* (e.g., better team functioning) and *motivational/affective* levels (e.g., coping and regulation; Kirschner & Erkens, 2013). These learning outcomes are difficult to abstract from each other, as the result of learning at one level influences the outcome at another level. For this reason, CSCL research commonly involves triangulation of multiple data sources using different analytical methods to gain a more detailed picture of the learning that occurred (Jeong et al., 2014). For example, multiple-choice questions and essays may be used to assess content learning, along with a content analysis of learner discussions to investigate how group dynamics may have informed knowledge acquisition.

In sum, CSCL could be conceived as an *approach* to e-learning that emphasizes meaningful interactions between learners, both directly through communication and mediated by artifacts, as a prerequisite for learning (Jeong & Hmelo-Silver, 2016; Stahl, Koschmann, & Suthers, 2006). Learning can occur on the cognitive, social, or motivational levels, which is often measured and triangulated based on a variety of data sources and analysis methods.

1.2.2. Potential uses of SNA for analyzing CSCL interactions

The common assumption of SNA and CSCL that "relationships matter" is what makes SNA an appropriate method for revealing relational structures that arise from CSCL interactions. CSCL makes clear and deliberate links between learning, social activity, and the use of computer technologies; learners develop into social networks by engaging, communicating, and sharing knowledge with each other via computers (Haythornthwaite, 1999). More than simply transmitting information, however, is the notion that learning in CSCL is "distributed" over individuals and artifacts their environment, meaning that knowledge emerges from the relations that transpire during interaction, and is "situated" in these networks of distributed activities of participation (Lipponen et al., 2004). SNA provides researchers with measures and visualizations that explicitly take into account relational phenomena associated with members of a group, thereby capturing distributed and situated learning.

Although existing methods for analyzing CSCL interactions include qualitative and quantitative techniques, most of them utilize verbal or text-based data from communication between learners, such as dialogue transcripts, chat logs or discussion forum posts (Puntambekar, Erkens, & Hmelo-Silver, 2011). However, there is growing demand in CSCL research for methods that can efficiently and meaningfully analyze large amounts of digital trace data from CSCL settings, a relatively untapped data source given the dominance of qualitative code-and-count analyses of discourse data in CSCL research (Jeong et al., 2014). Digital trace data can be a source of non-verbal interaction between learners and various artifacts in the learning environment (e.g., editing a wiki), which could result in patterns that are meaningful for understanding verbal data (Suthers & Medina, 2011). SNA can harness a large amount of digital data consisting of thousands and even millions of users (actors) from computer log files that register user behavior (ties), allowing researchers to infer collaborative learning processes in very large groups (Nurmela, Lehtinen, & Palonen, 1999).

The visual component of SNA can be applied to research on visualizing interactions in CSCL. Law and colleagues (Law, Yuen, Wong, & Leng, 2011) have distinguished two main categories of visual representations: linear, which present information in sequence, usually chronologically; and non-linear, to which SNA sociograms belong which, present information independent of time, "[providing] meaningful snapshots of CSCL discourses" (p. 60). Visual representations are useful for detecting and interpreting complex patterns in CSCL environments. Moreover, since individual learning is nested in group processes, data from CSCL allows for variation in the unit of analysis that suits the levels of analysis of SNA: from individuals (egocentric level analysis) to dyads, small groups and communities (global level analysis; Lipponen et al., 2004). The application of SNA in CSCL would enable an analysis of the interplay of individual and group processes, without neglecting the influence of one unit of analysis in favor of another—a common problem encountered in other quantitative methods (Cress, 2008).

1.3. Current trends and limitations of SNA in online learning: what do they mean for CSCL?

Despite its apparent advantages, the use of SNA in CSCL have not yet been studied extensively (Jeong et al., 2014). A preliminary review of SNA in 37 "e-learning" papers (Cela et al., 2015) outlined a number of trends in the current research body related to online learning. The results indicate that SNA is most commonly applied to study collaborative learning between learners in online discussion forums based on their communication patterns (e.g., posting messages), thus involving only one-mode networks. The most common SNA measures are centrality and density indexes, and SNA is often combined with qualitative content analysis to provide a deeper understanding of the nature of learner relations within the network.

These results point to the potential usefulness of SNA to study direct communication between learners collaborating via computers. However, as noted previously in Section 1.2, the main search term used, "e-learning", refers to the medium through which information is transmitted for learning purposes. Thus, the findings of the review, specifically with regards to

(1) the relational ties and network modes being studied, and (2) analysis methods used in conjunction with SNA results, give a limited insight into the relevance of SNA in CSCL.

1. *Relational ties and network modes*: Focusing only on communication patterns limits the understanding of important relational mechanisms and interactions in CSCL (Wellman et al., 1996). The dominance of communication-based relations has been attributed to convenient access to computer data sources, such as log files, that store this information. However, Enriquez (2008) points out that log files would not be able to detect potentially important relational ties, such as discussion forum "reading ties" which are established whenever a learner reads a forum topic but does not post a reply. This act of reading may have resulted in the acquisition of new knowledge, but this is overlooked when only verbal data is considered. Communication patterns may not fully encompass the degree to which learning in a CSCL activity has truly occurred or whether a relation has indeed been established.

Similarly, focusing only on one-mode learner-learner networks may ignore the artifacts that facilitate or co-constructed during the collaborative activity (Stahl et al., 2014). Two-mode networks (e.g., networks with more than one type of node, such as learners and the learning materials they engaged with) may be applied to reveal indirect/mediated interaction between learners based on their engagement in technological/instructional/knowledge artifacts or common activities. These artifacts are essential for mediating communication and interaction between participants of a CSCL activity. When SNA is applied, these non-human agents are treated analytically in the same way as human-human interactions (Jones, 2015), which provides more information on the interaction that took place. For instance, Oshima and colleagues (Oshima, Oshima, & Matsuzawa, 2012) note that if analyzing communication is the goal of the SNA in a CSCL environment, learner-learner networks do not provide any information on the content of the discussions, thus not capturing how knowledge advances during collaboration in the same way that, for example, a network of learners and shared key terms in the discussion would.

2. *Analysis methods*: Analysis of SNA results are often limited to descriptions of network properties by visual inspection of sociograms and reporting the values of the SNA measures (Carolan, 2014). For example, the density of a network is often reported as a value between 0 and 1, or a description of the connectedness of nodes in a sociogram. However, SNA results in and of themselves do not indicate whether the interaction led to learning. Content analysis may compensate for this problem, but this can only be applied to text data (e.g., communication transcripts), which sets limits as to what can be inferred about the collaborative process from the SNA data. Since a highly dense, one-mode communication network does not bear information on *what* was discussed, it is not possible to infer whether the information exchange is associated with learning gains. As noted earlier, learning outcomes in CSCL are found at various levels, which necessitates a multimethod approach to research. SNA measures may be further analyzed in conjunction with quantitative indicators of these cognitive, social and/or motivational outcomes collected from other research methods (e.g., correlating density with final grades). Doing so extends the findings of SNA beyond description and onto inferences about impact of relational ties on learning outcomes (Carolan, 2014).

In sum, SNA is a promising technique for revealing relational structures that arise from CSCL interactions. Although direct communication between online learners has been widely examined using SNA (Cela et al., 2015), it is currently unclear whether (1) SNA has been applied to analyze indirect/mediated interactions between learners via artifacts in their environment, and (2) whether the analysis methods have been used to supplement SNA results to gain more insight into the impact of interactions on learning. In order to maximize its analytical potential in CSCL research, SNA should also include non-human agents such as learning artifacts, and relational ties that are "more than [indents] in a thread … [but rather] a shared article, experience, story, lessons, etc.…that may constitute the collaborative practices and process of learning" (Enriquez, 2008, p. 125). Furthermore, more efforts should be exerted not only into using different SNA measures and procedures, but also performing further analysis with SNA data to move beyond simply describing the network to explain how CSCL groups are influenced by their relationships.

1.4. Research questions

Previous evaluations of SNA in online learning (Cela et al., 2015) have demonstrated the usefulness of SNA as a means to describe direct communication networks between learners. However, established CSCL frameworks (e.g., Dillenbourg, Järvelä, Fischer, & T, 2009; Kirschner & Erkens, 2013) have noted that (1) beyond direct communication, there is a wealth of nonverbal interactions that occur in CSCL environments between learners and artifacts alike; and (2) interactions have implications on CSCL learning outcomes at different levels. Since a systematic investigation of SNA in CSCL has not been undertaken, the main objective of this methodological review is to examine whether current applications of SNA have incorporated these crucial aspects of CSCL activities. The following research questions address this goal:

RQ1: Do current applications of SNA in CSCL research reflect the diversity of CSCL actors and interactions that influence learning?

The first research question investigates whether current SNA applications in CSCL studies have taken into account that different direct and mediated interactions between learners and artifacts in the learning environment are essential for

establishing a shared understanding of CSCL learning tasks. To do so, it is necessary to outline which *CSCL actors* and *relational ties* have been studied using SNA.

RQ2: How are SNA measures related to CSCL learning outcomes on the cognitive, social, and motivational levels?

CSCL is an interdisciplinary, multimethod field that acknowledges that learning occurs at different levels due to relational ties established between actors in a network. The second research question investigates whether those relational ties as measured by SNA indices have any implications on CSCL cognitive, social, and/or motivational outcomes. Thus, to answer this question it is necessary to outline which *SNA measures* have been applied to analyze these actors and relational ties and which *analysis methods* have been applied to relate SNA measures with CSCL outcomes.

From the results of this review, it is possible to uncover how the research community views CSCL from a social network perspective, and the extent to which it aligns with established foundations of the field.

2. Methodology

2.1. Search and inclusion criteria

Relevant full-text studies published as journal articles, book chapters, conference papers, and proceedings were collected from October to November 2015 from the following databases: Springerlink (Disciplines: Computer Science, Social Sciences, Psychology, Education and Language), Elsevier Science Direct, EdITLib, IEEE Xplorer, ACM Digital Library, EBSCOHost (ERIC, PSYCInfo). Each database was searched using the following keywords: "social network analysis" AND "computer-supported collaborative learning" OR online OR computer OR collaborat* OR learning. Additional studies were collected through backward referencing and contacting researchers whose work appeared in the search results (e.g., newly published studies). Papers that were included in the review by Cela et al. (2015) were also included.

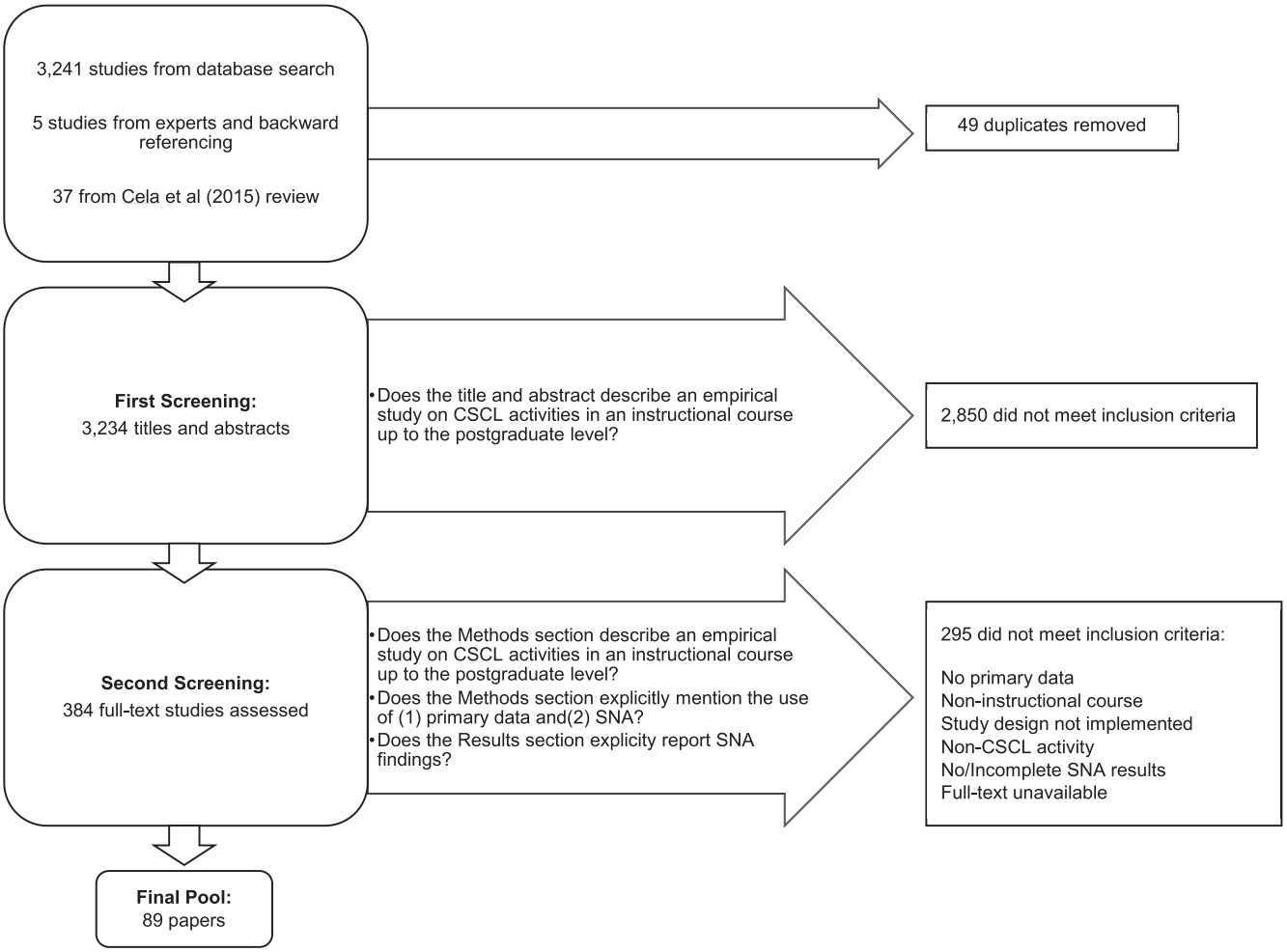


Fig. 1. Identification of included studies.

To be included in the analysis, studies must: (1) use primary data; (2) be an empirical study set in an instructional course/program up to the postgraduate level; (3) use SNA techniques, explicitly mentioned in the Methods section; (4) report SNA findings in the Results section; and (5) analyze collaborative learning activities between learners using computers. As stated in Section 1.2, an activity was considered a CSCL activity if two or more learners interact (directly or indirectly/mediated via artifacts) using computers for the purpose of accomplishing a learning goal that is shared by all group members (e.g., to develop a project or to discuss/understand a lesson). Three independent reviewers conducted all screening stages according the inclusion criteria. Discrepancies and citations that partially meet the criteria were re-screened by another reviewer and resolved by consensus.

Fig. 1 summarizes the screening procedure. From an initial pool of 3283 studies, 3234 titles and abstracts were screened. A study was considered for inclusion if the title or abstract described an empirical study on CSCL in an instructional course up to the postgraduate level. Through the first screening, 2850 papers that did not report on an empirical study, or reported on studies conducted in contexts beyond the scope of the review (e.g., professional learning settings) were discarded. Next, 384 full-text papers were assessed, of which 295 papers were discarded for a combination of the following reasons: in the Methods section, if there were no explicit mentions of the study on CSCL activities in an instructional course, the use of primary data, or SNA as an analysis method; or in the Results section, if no SNA findings were reported. In the case of two papers having the same data set, either the most recent publication was included in the final analysis (such as in the case of a study presented at a conference and published in the proceedings, then later published in a journal), or both were included if they reported different SNA applications and findings. This left 89 papers for the final analysis (see Appendix A). Of the 37 papers in the Cela et al. review (2015), only 14 met the inclusion criteria and were thus included for analysis (4 and 19 papers were discarded after the first and second screenings, respectively).

2.2. Data analysis

Content analysis was conducted to analyze the data in order to gain a qualitative description of the methodology of the CSCL studies. Content analysis was selected over other methods for two reasons. First, this review is the first synthesis of CSCL studies that include SNA and an extension of the preliminary analysis of Cela et al. (2015), thus requiring an exploratory and descriptive approach. Second, as is typical in CSCL research (Jeong et al., 2014), the research design of most of the included studies were qualitative, which does not allow for the calculation of an aggregated effect size as is typical in quantitative meta-analysis.

Each study was categorized based on descriptive information of their methodologies and the features of SNA procedures. There are two main categories: general methodology and SNA features. Table 1 provides a summary of the coding categories.

2.2.1. General methodology category

The general methodology category helps to give context to the papers included in this review. Research design and learning setting subcategories are adapted from Jeong et al. (2014); subcategories for collaborative activities and non-SNA methods were generated bottom-up from the available literature and refined through multiple coding iterations (as described in Krippendorff, 2012).

1. Research design: Research design refers to the overall approach, depending on the objectives of the study. It should be noted that design research papers include studies testing the effectiveness of the tool or intervention. In this case, the study would be coded as a design study rather than a descriptive or experimental study.
2. Learning setting: Learning setting refers to learning context in which the study was conducted.
3. Sample size and education level: Sample size refers to the number of participants in the study. This number may correspond to the number of nodes in the subsequent social network analysis. Educational level refers to the educational level of the students when the study took place.
4. Collaborative activity: This category refers to the collaborative activity whose processes and outcomes were analyzed using SNA. This means it is possible for a study to include multiple learning activities for learners, but the studies are coded only according to the activity on which SNA was applied. There may be some overlaps in these categories as all the collaborative activities involved some form of discussion; in this case, the main *purpose* of the discussion determines the category of the learning activity (e.g., a class working together on a wiki article via chat would be classified as a project/task-based activity rather than a discussion-based activity). In cases when the activity involved both general discussion and project/task-based discussions, those studies were categorized as having a project/task-based activity.
5. Non-SNA methods: This category refers to other methods that have been applied alongside SNA to gain deeper insights on the research question. Many studies include more than one method; in this case, the study would be coded multiple times.

2.2.2. SNA features category

The SNA features category encompasses details from the included papers that will help address the research questions stated in Section 1.4. The subcategories were developed bottom-up from the available literature (e.g., Carolan, 2014) and refined through multiple coding iterations (as described in Krippendorff, 2012). Many studies apply SNA multiple times; in this case, studies are usually coded multiple times within this category.

1. Node (actor) type: This category refers to the type of actor and/or object that is represented the social network analyses of the study.
2. Relational tie type: This category refers to the type of relation between nodes represented the social network analyses of the study.
3. SNA measures: SNA measures refer to the indices, methods, and algorithms based on network and graph theory that are applied to analyze network data.

Table 1
Coding categories for general methodology and SNA features.

Categories	Sub-categories	Description/Examples
General Methodology		
Research design	A. Descriptive studies	Processes and outcomes are examined without experimental manipulation.
	B. Field/Quasi-experimental studies	Causal relationships between are studied through experimental manipulation of variables.
	C. Design-based studies	CSCL tools or interventions that are grounded in theory and examined in practice settings.
Learning setting	A. Blended instruction	Instruction and learning activity takes place in integrated face-to-face and online settings
	B. Online learning	Instruction and learning activity takes place entirely online.
Sample size	A. $n \leq 50$	Number of participants in the study
	B. $50 < n \leq 100$	
	C. $100 < n \leq 200$	
	D. $n > 200$	
Education level	A. Primary/Secondary	Level of educational attainment of the participants
	B. University	
Collaborative learning activity	A. Discussion-based	Learners engaging in discussion on a particular topic, either unstructured or proposed by instructors or peers.
	B. Project or task based	Learners work together towards the completion of a project, task, or assignment.
	C. Peer feedback and assistance	Learners offer feedback or help on each other's work.
Non-SNA methods*	A. Content analysis	A method that makes inferences from texts through systematic text analysis or code-and-count techniques (Krippendorff, 2012)
	B. Questionnaires, rating scales and surveys	Instruments measuring specific learner characteristics.
	C. Natural language processing	Techniques that derive patterns from text (e.g., text mining)
	D. Interviews	Verbally administering questions to participants to gather information on their experiences of the learning activity (e.g., critical event recall)
	E. Performance measures	Instruments or metrics that measure learning outcomes (e.g., grades)
	F. Other qualitative methods	Qualitative methods present in only 1–3 studies
	G. Other quantitative methods	Quantitative methods present in only 1–3 studies
	H. None	
SNA Features		
Actor (node) type*	One-mode:	Network with only one node type, (i.e., actor-actor, object-object)
	A. Learners	
	B. Learners and instructors	
	C. Learners and learner groups	
	D. Objects/events/artifacts	
	Two-mode:	Network with two different node types, (i.e., actor-object)
	E. Learners and objects/events/artifacts	
Relational tie type*	A. Communication	Direct exchange of information between learners (e.g., forum messages)
	B. Project/task-related interaction	Non-communication actions/artifacts that lead to the completion of a project or task (e.g., shared keywords in a writing exercise; exchanging resources; reading output)
	C. Interaction with same objects	When learners interact with the same object in the learning environment (e.g., responding to the same thread)
	D. Self-reported interaction or social relation	Relations reported by learners via qualitative methods (e.g., questionnaire about preferred study partners)
	E. Relation between objects	Relations that tie objects together (e.g., threads with common participants)
SNA measures*	A. Local/individual measures	Measures used to describe an individual actor's personal network.
	B. Global network measures	Measures calculated from the entire network (e.g., density)
	C. Positions	Measures that determine actors' roles and positions with reference to other actors in the network (e.g., transitive triads)
	D. Subgroups and cliques	Algorithms that identify groups and positions from a complete network. (e.g., clique analysis); 2) general: learners were free to discuss course content or to coordinate their learning activities.
Additional analysis methods on SNA data*	A. Correlation analysis	Statistical methods that quantify the direction and strength of the linear association between the two variables (e.g., Pearson's R)
	B. Comparison of means	Parametric and non-parametric statistical methods that analyze the differences among group means (e.g., *t*-test, ANOVA).
	C. Multidimensional analysis	A method for visualizing data structures using space and distance by detecting meaningful underlying dimensions that reflect similarities and dissimilarities (using distances) among actors.
	D. Network simulation	Techniques for modelling behavior of a network to assess how it behaves under certain conditions.
		Statistical techniques for estimating the relationships among variables.

(*continued on next page*)

Table 1 (*continued*)

Categories	Sub-categories	Description/Examples
	E. Regression analysis/ mediation	
	F. Structural equation modelling	A combination of factor analysis and multiple regression analysis that is used to analyze structural relationships.
	G. Own metric	Metrics developed by researchers, calculated partially using SNA indices
	H. Other	Methods present in only 1 or 2 studies
	I. None (descriptive analysis only)	Reporting the values of SNA measures and/or visual inspection of the sociogram

Note. Unit of analysis are individual papers, but these may be coded multiple times in the categories marked with (*).

4. Additional analysis methods on SNA data: This category refers to additional methods that have been applied on the network data (i.e., the same data used for SNA) to augment SNA findings.

2.3. Coding and interrater reliability

As with Jeong et al. (2014), coding was conducted based on the descriptions provided in the papers or on contextual information from the text when precise terms were not specified. For example, a study would be coded as "blended learning" environment if the setting was described as having a face-to-face component alongside an online learning component. The unit of analysis was the individual papers, but multiple coding was possible in certain categories when papers contained multiple analyses. Two independent coders were involved in the coding procedure. The coders were trained by the first author. To ensure reliability, they first independently coded 33% of the sample. The Cohen's kappa values for the mutually exclusive categories are all above 0.80 (0.89 for research design, 0.98 for learning setting and number of participants, 0.88 for description of participants, 0.82 for the collaborative activity). For the categories that allow multiple coding, a Mezzich's kappa coefficient was calculated (Mezzich, Kraemer, Worthington, & Coffman, 1981). Mezzich's kappa is a modification of the Cohen's kappa formula, whereby partial agreement between raters is taken into account when calculating the observed agreement (i.e., sum of all partial agreement divided by total number of segments) and expected agreement (i.e., sum of all partial agreement divided by total number of code combinations formulated by both raters). The kappa for the non-mutually exclusive categories were also above 0.79 (0.79 for non-SNA methods, 0.91 for node type, 0.83 for relational tie type, 0.94 for SNA measures, 0.84 for additional analysis on SNA data). As these values were considered adequate (Cicchetti, 1994), the coders proceeded to code the full sample. All coding disagreements were discussed until consensus was reached.

3. Results

The Results section is divided into 3 subsections. The first subsection is a brief description of the included papers (based on the general methodology category in Section 2.2.1) to provide a context for understanding SNA applications in CSCL research. The second and third subsections consider the results from the SNA features category (Section 2.2.2) with reference to the two research questions stated in Section 1.4, namely: (1) whether current applications of SNA in CSCL research reflect the different actors and interactions that influence learning in CSCL (RQ1); and (2) what are the implications of SNA on CSCL outcomes (RQ2).

3.1. Descriptive information of included papers

Most of the included papers employed descriptive research design (n = 73, 82%); reported on studies conducted in blended learning environments (n = 58, 65%). Sample sizes are small, with most papers (n = 55, 62%) having a sample size of less than 50. Nearly all participants in the included papers have received or are currently pursuing a university degree (n = 80, 90%). These include professionals taking up online courses to earn additional higher education qualifications (e.g., Sundararajan & Moore, 2006). As for the collaborative learning activity, in most of the papers (n = 52, 58%) participants collaborated on specific projects or tasks. Examples include working on course assignments (e.g., Sundararajan & Moore, 2006), developing a knowledge artifact together (e.g., constructing an analog computer, Temdee, Thipakorn, Sirinaovakul, & Schelhowe, 2006), or jointly writing articles (e.g., Mansur, Yusof, & Othman, 2011). Content analysis was the most frequently used analysis method for supplementing SNA data (n = 29, 33%) in order to gain more qualitative insights into the written output from the collaborative activity or the discourse between learners, such as forum posts (e.g., Rienties, Tempelaar, Giesbers, Segers, & Gijselaers, 2014) and blog comments (Nguyen-Ngoc & Law, 2010). Questionnaires, surveys and rating scales were also administered in 23 papers (26%) in order to measure social (e.g., evaluate learners' experience of the collaborative activity; Agarwal & Ahmed, 2017) or motivational (e.g., Rienties et al., 2014) outcomes. The results of some of these questionnaires, along with performance measures (investigated in 11 or 12% of studies) which looked into how well learners performed during the collaborative activity, have been correlated with SNA data, as discussed in Section 3.3.

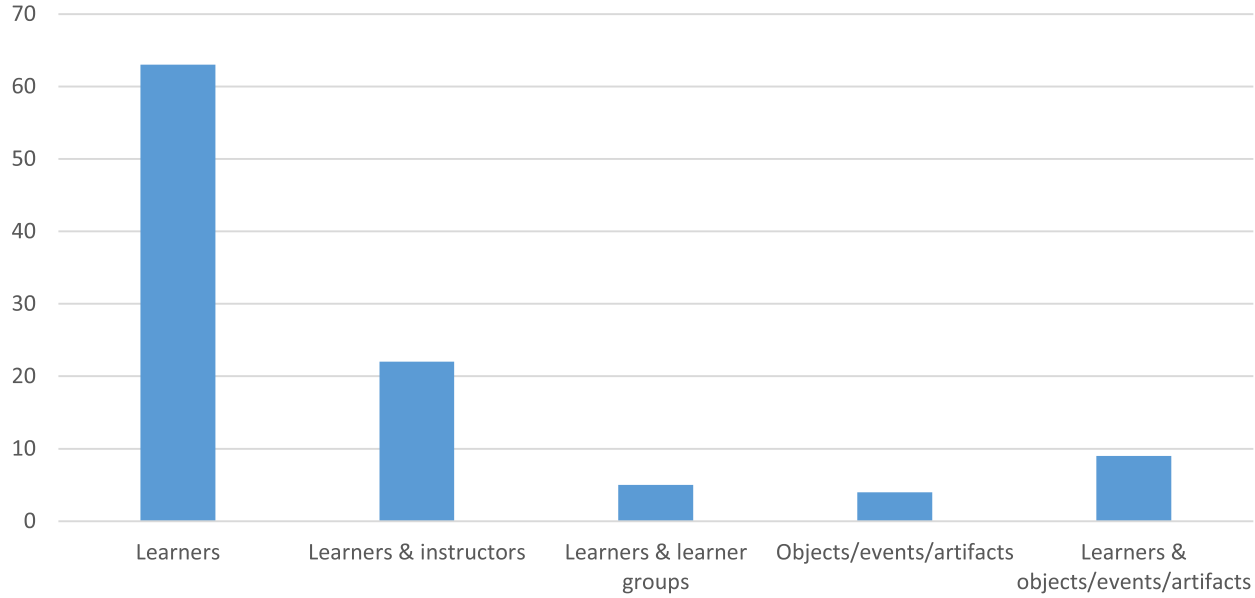


Fig. 2. Node types in the included papers.

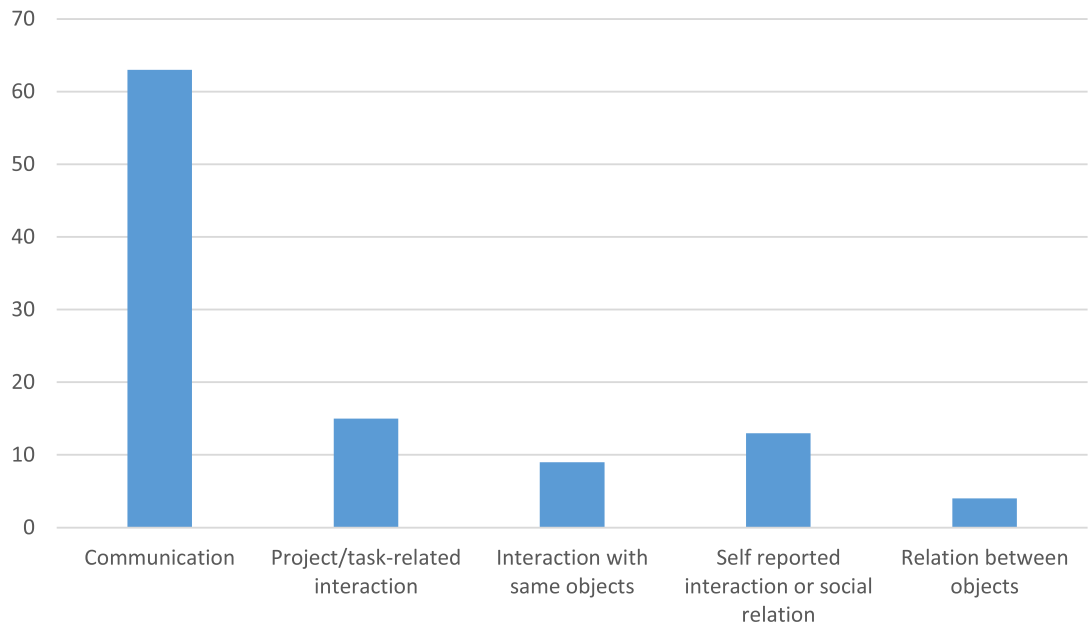


Fig. 3. Relational ties in the included papers.

3.2. RQ1: do current applications of SNA in CSCL research reflect the diversity of CSCL actors and interactions that influence learning?

To address the first research question, this subsection discusses the CSCL actors and relational ties found in the included papers. Fig. 2 and Fig. 3 demonstrate the distribution of the actor and relational tie types, respectively, in the included papers.

Overall, the analysis reveals that SNA is mostly applied to investigate direct interaction (communication) between learners during CSCL. This is evidenced by the fact that SNA was used most frequently to analyze one-mode actor networks of learner-learner relations (n = 63, 71%) and communication-based relational ties (n = 63, 71%). Such relations are established when learners posts on discussion forums (e.g., Rienties et al., 2014), reply to each other's chat messages (e.g., Cadima, Ojeda, & Monguet, 2012), or post on each other's blogs (e.g., Nguyen-Ngoc & Law, 2009). Only a small portion of SNA studies looked into mediated interactions between learners and artifacts as well as artifact-artifact relational structures. These studies are discussed in more detail in the following section.

Table 2
Included studies with non-actor and two-mode networks.

Authors and year	Learning activity	Nodes (two-mode or non-actor)	Artifact type	Ties (non-communication)	Findings
Agarwal & Ahmed (2017)	Project or Task based	Learners and written output (articles)	Knowledge	Number of times a learner edited an article.	*Content engagement*: "Each article is edited by at least 2 students, demonstrating collaboration … several articles are edited multiple times by the same student, [demonstrating] a rich student-content engagement …" (p. 20)
Casquero, Ovelar, Romo, Benito, & Alberdi. (2016)	Discussion-based	Learner and blog comments	Technological	Accessing and commenting on resources (e.g., blogs)	*Implications on social capital* (relationship with learners in other courses): learning performance improves with the increase in the size of the personal network (p. 10)
Hecking, Ziebarth, & Hoppe (2014)	Project or Task based	Learners and learning materials	Knowledge/ instructional	Accessing resources	*Learning material engagement/access*: "[Students] access the lecture slides assigned to the topic of that week and the wiki articles written by other students … During the exam preparation phase … [students] start preparation late and are much more focused on lecture videos and wiki articles …" (p. 181)
Kim, Lee, Yoo, Sung, Jo, & Park (2015)	Discussion-based	Learners and discussion threads	Technological	Participation in the same topic thread	*Learner participation:* "This two-mode network presents three distinct groups of students. The first group is those who are in center of network. This means that these students participated in most of all discussions. On the other hand, the second group who are positioned at the peripheral area participated in several discussions only. The last group is three isolated students located outside of network." (p. 8–9)
Lotsari, Verykios, Panagiotakopoulos, & Kalles (2014)	Discussion-based	Learners and discussion threads	Technological	Participation in the same topic thread	*Learning and participation*: "We can select the discussions that contain a specific group of terms we are interested in … thus, we can distinguish the topics in which the majority of students are involved, and as result, we can identify either any weaknesses a group of students possibly has with respect to the understanding of the study materials …" (p. 307)
		Terms and posts	Technological/ Knowledge	Occurrence of the same terms in the discussion posts	
Martínez, Dimitriadis, Gómez-Sánchez, Rubia-Avi, Jorrín-Abellán, & Marcos (2006)	Project or Task based	Learners and folders	Technological	Link between the learner that creates a document and the folder in which that document is placed	*Learner participation*: "… tutors set up a folder for each phase of the course, and thus, the activity in each folder is also the activity in each phase. We can see that the activity in C1 was more intense on the folder for the creation of groups, corresponding to the first phase. It is also very easy to identify the students that only participated actively in the general workspace during this phase or even did not create a document at all." (p. 398)
Nurmela, Lehtinen, & Palonen (1999)	Project or Task based	Written output	Knowledge	Reference links connecting documents	*Connections between students' output:* "Of the more than 200 documents, only 34 were linked to at least one other document. These 34 documents form altogether 11 components (subgroups of linked documents) … we considered the most important component as the one with 8 documents, [which] was linked together by four student pairs. Only one of these references was "against" while the rest were supportive "for" references." (p. 8–9)
Rodríguez, Sicilia, Sánchez-Alonso, Lezcano, & García-Barriocanal (2011)	Project or Task based	Learners and discussion threads	Technological	Writing in the same thread	*Student interests:* "Thread T*i* corresponds to the *i* theme of course. Partitions T5, T6 and T7 deal with practical topics … This clearly differentiates the group of Student 1 from the group commencing with Student 2 … this group shows less interest in threads T4H2 and T4H4, linked to topics dealing with theoretical issues on IMS Learning Design …" (p. 325)
Sha, Teplovs, & van Aalst (2010)	Discussion-based	Written output (notes)	Knowledge	Structural network: Reference links to other notes	*Connections between students' output*: "Visually, the number of lines in the structural network is obviously much less than that in the semantic network, [meaning] notes that are not linked to one another by a physical collaborative learning action are not necessarily disconnected with each other semantically." (p. 933)
		Written output (notes)	Knowledge	Semantic network: Semantic connections between notes	

Table 2 (*continued*)

Authors and year	Learning activity	Nodes (two-mode or non-actor)	Artifact type	Ties (non-communication)	Findings
Tervakari, Marttila, Kailanto, Huhtamäki, Koro, & Silius (2013)	Project or Task based	Learners and written output	Knowledge	Amount of contributions/ amount of reading	*Content engagement:* "… students read content produced by other students, especially from other disciplines. However, they seemed to divide into their own groups. For example, hypermedia students in particular read more content produced by journalists." (p. 4)
Toikkanen, & Lipponen (2011)	Peer feedback	Learners and discussion threads	Technological	Writing in the same thread	*Learner participation and group formation*: "… all pupils were interconnected by reading each other's posts, but when writing new posts, many courses formed several isolated groups. This indicates that pupils in several courses … formed smaller groups, which monitored others groups' work, but did not comment on them." (p. 8)
		Threads		Common discussion participants between threads	

Note. The table only displays information regarding non-actor and two-mode networks in the selected papers, which may also conduct analyses on actor-actor, communication-based networks.

3.2.1. *Indirect/mediated interaction via artifacts*

Table 2 displays the 11 papers that have investigated two-mode networks and non-actor networks. Two-mode network studies typically incorporated technological or knowledge artifacts to reveal an indirect/mediated relationship or interaction between learners, which have several implications on learners' interests and engagement, as well as the content of the communication that transpired between them. Artifacts or non-actor networks of knowledge artifacts have been used to investigate meaningful connections or similarities between learner output, which may be used to infer information about the cohesiveness of the results of the collaborative activity.

3.2.1.1. Technological artifacts. Six of the 11 papers included technological artifacts in their analysis of two-mode networks, of which 5 studied mediated interactions between learners and discussion forum threads that they responded to. Such networks also have implications on the content that was communicated between learners. Rodríguez and colleagues (Rodríguez, Sicilia, Sánchez-Alonso, Lezcano, & García-Barriocanal, 2011) used the information from learner-discussion topics networks to make inferences about learners' interests by looking at which learners were more involved in either practical or theoretical topics. Lotsari and colleagues (Lotsari, Verykios, Panagiotakopoulos, & Kalles, 2014) were able to find in which discussion topics students are most involved and identify which topics they might still have difficulties in. They also looked at specific terms from learners' discussion forum posts (which could be taken as a knowledge artifact) and created a network that connected these terms by the number of posts in which they co-occur, which allowed the researchers to focus their qualitative analysis on a subset of discussion posts that centered on the most important topics of the course.

Other studies investigated learner-technological artifact networks to understand how individuals participate in the collaborative environment. Kim and colleagues (Kim, Lee, Yoo, Sung, Jo, & Park., 2015) were able to identify groups of learners based on how actively they engaged in the discussion; the most active learners were shown in the network to have participated in most of the discussion threads, whereas the least active learners only participated in a fraction of discussion threads in the network. The technological artifact used in the analysis by Martínez and colleagues (Martínez et al., 2006) were folders that correspond to specific phases of the collaborative activity and into which learners were required to submit their output. Through this method, the researchers were able to determine which phase of the collaborative activity experienced the most engagement, and which learners were most active at which phase of the activity.

3.2.1.2. Knowledge/instructional artifacts. Knowledge artifacts, or the product of the joint CSCL activity, were investigated in 8 of the 11 studies. Non-actor networks of only knowledge artifacts were used to demonstrate cohesiveness or commonalities between the products of students in the network. Nurmela et al. (1999) found that of the more than 200 documents written by student pairs, only 34 were linked to (i.e., referencing) at least one other document. When comparing two non-actor networks of written notes, namely a "structural network" representing physical reference links and a "semantic network" representing semantic connections, Sha, Teplovs, and van Aalst (2010) found more ties in the semantic network, which shows that the notes were related on a conceptual level, in spite of a lack of physical references to each other.

The results of analysis of two-mode networks of learners and knowledge artifacts revealed more information about the collaborative learning process. Hecking, Ziebarth, and Hoppe (2014) looked into resource access of university students in a course and found that students access both lecture slides and wiki articles written by their peers throughout the course and when preparing for the final examinations. Similarly, Tervakari and colleagues (Tervakari et al., 2013) found that learners, who were tasked to collaboratively design and implement a journalistic publication, read the contributions of other learners from disciplines other than their own. These results suggest that individual learning is at least partially informed by peer contributions.

3.3. RQ2: how are SNA measures related to CSCL outcomes?

To address this question, this subsection first summarizes the SNA measures that were utilized in the included papers to analyze CSCL interactions, then outlines the supplementary analysis methods that were used to relate SNA findings with CSCL outcomes.

Majority of included papers (n = 77, 86%) analyzed social networks from a local/individual level of analysis, followed by global level analysis (n = 53, 60%). Centrality is the most common local/individual measure (n = 70, 79%). In CSCL networks, the most central learners have been defined as those who actively participate in or contribute to the learning activity, for example by communicating to other learners (e,g., Shin & Lowes, 2008), while the least central learners could be those who participate very little or not at all. The distinction between in-degree (incoming connections) and out-degree (outgoing connections) centralities is important. For example, a proportional distribution between in- and out-degree centralities (e.g., calculated from posts and received messages on the forum) could indicate equal effort and contribution by the learners in the course (e.g., Claros, Cobos, & Collazos, 2015); a learning environment where the teacher has the highest out-degree centrality may indicate that learners tend to rely on their teacher more than they collaborate with their peers (e.g., Zafar, Safdar, & Malik, 2014).

Density is the most commonly applied global measure (n = 41, 46%). In a CSCL context, a highly dense network may indicate high engagement, in that most of the learners are discussing, and thus collaborating, with each other on the learning platform (e.g., Li, Wang, & Yu, 2010), while low density may signal the absence of interaction or relations between learners.

Table 3
Studies that include correlation analysis on common SNA measures and learner characteristics.

Author & Year	n	SNA Measure	Variable	Correlation coefficient	Result	Interpretation
Cadima, Ojeda, & Monguet (2012)	76	Degree Closeness	Learning outcomes (grades, teachers' evaluation)	Pearson	0.62** (Group 1); 0.57* (Group 2) −0.67** (Group 1); −0.57* (Group 2)	"The greater the number of contacts of a student the better is his or her performance … the shorter the distance of one individual to all others in community, the better is his or her performance." (p. 302)
Cho, Gay, Davidson, & Ingraffea (2007)	31	Closeness Degree	Final grades	Pearson	0.442*	"The results indicate that the position of individual learners in a social network significantly influenced learning performance in a CSCL community. In other words, those who occupied central positions in a given learning network were more likely to get high performance rates in a distributed learning community" (p. 322)
Chung & Paredes (2015)	36	Density	Content richness Contribution index Efficiency	Pearson	−0.406**(one-tailed) −0.318*(one-tailed) −0.90**(one-tailed)	"It is better to have a few meaningful dialogues, rather than many meaningless conversations." (p. 249)
Claros, Cobos, & Collazos (2015)	18	Indegree, outdegree	Contributions of an individual and their peers (in- and out-degree centrality)	Pearson	[0.71; 0.87] **	"Social interaction processes among learners tend to be symmetric, i.e., students correspond with the interest showed by others in their resources through replies and comments to resources of mates." (p. 5)
Gaggioli, Mazzoni, Milani, & Riva (2015)	30	Density	Challenge-skill balance Action awareness merging Clear goals Concentration	Pearson	0.88* (Time 1), 0.95* (Time 2) 0.87* (Time 1) 0.90* (Time 1) 0.92* (Time 1)	"The positive relationship between density and Flow Subscales … is in line with the model's assumption that neighbour interactions can facilitate the emergence of group flow." (p. 164)
Hurme, Palonen, & Järvelä (2006)	16	Betweenness	Metacognitive monitoring	Pearson	0.752**	Central actors "participated in many ongoing discussions in which they clarified their own thinking" (p. 196)
Lee & Bonk (2016)	23	Indegree Outdegree	Indegree perceived emotional closeness Outdegree perceived emotional closeness Indegree perceived emotional closeness Outdegree perceived emotional closeness	Pearson	0.59** 0.48* 0.48* 0.51*	"The more frequently that the students participated in online interaction, the more popular they became in the network. In sum, it appears that the position that the students take in the peer relationship network is considerably dependent upon the degree of their online interactions." (p 43)

Table 3 (*continued*)

Author & Year	n	SNA Measure	Variable	Correlation coefficient	Result	Interpretation
Putnik, Costa, Alves, Castro, Varela, & Shah (2015)	49	Degree	Quality of work Volume of work Final grades	Spearman	0.32* 0.70** 0.50**	Central actors are more likely to have better grades for quality/volume of work and final grades (except for closeness centrality and quality of work, which was not significant)
		Betweenness	Quality of work Volume of work Final grades		0.34* 0.67** 0.53**	
		Closeness	Quality of work Volume of work Final grades		Not reported 0.63** 0.39**	
Rienties, Giesbers, Tempelaar, Lygo-Baker, Segers, & Gijselaers (2012)	143	Outdegree	Academic motivation (comparing two different learning systems)	Pearson	0.228* for intrinsic motivation to know (Learning System 1, e-PBL) 0.438** for identified regulation (Learning System 2)	"Intrinsically motivated learners in the e-PBL design were more likely to be central contributors to discourse, whereby they interacted with more learners … In the Optima design, learners who scored highly on identified regulation were more likely to be central contributors to discourse." (pp. 900-1)
Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers (2009)	82	Degree	Intrinsic motivation to know	Pearson	0.24*	"[H]ighly intrinsically motivated students distinguish themselves (much stronger) from extrinsically and amotivated students also with respect to their position in the network. Especially students with high levels of intrinsic motivation to know are central contributors to overall discourse" (p. 1202)
Siqin, van Aalst, & Chu (2015)	26	Betweenness in two phases: 1) fixed group collaboration; and 2) opportunistic collaboration	Participation (note creation, note reading and note responding contributions) Domain understanding	Pearson	0.61** (Phase 1) 0.70** (Phase 2) 0.42* (Phase 2)	Moderate correlation between betweenness centrality and (1) participation in both phases; (2) domain understanding during opportunistic collaboration
Toikkanen & Lipponen (2011)	362	Indegree, outdegree	Meaningfulness of the learning process Teacher guidance	Spearman	All coefficients below 0.2**	"SNA accounts for only a small portion of the variance … even though that portion is statistically significant." (p. 11)
		Density (reading behavior matrix, thread matrix)	Meaningfulness of the learning process Pupils' understanding of the learning process		0.50* (threads) −0.48*/−0.46*± (reading)	"If the reading density was high (meaning most pupils read messages from most other pupils), their grasp of the Progressive Inquiry learning method was lower. Part of the Progressive Inquiry is for the pupils to form small groups for intensive work, but also to monitor the other groups." (p. 11–12)
Xie, Yu, & Bradshaw (2014)	57	Indegree (as interaction attractiveness of learners as moderators or general participants)	Number of posts per peer Average length of post Times of non-posting log-ins Participation diversity (outdegree centrality)	Pearson	0.56** (general) -0.40** (general) 0.38** (general) 0.74** (general); 0.32* (moderator)	"When not assigned as the moderator, students' interaction attractiveness was positively correlated with their participation diversity, number of posts to peers, and times of non-posting logins, yet negatively correlated with average length of posts." (p. 16)
		Density (as group participation)	Average length of non-posting logins by moderators Number of posts Times of non-posting logins by all members Times of non-posting logins by whole group Average length of non-posting logins by whole group		0.41** 0.91** −0.36** −0.15** −0.36**	"Even though these non-posting participations [by the moderator] were not directly visible by student peers, they can be latent and have the influential power to change group participation." (p. 14–15)
Zafar, Safdar, & Malik (2014)	19	Outdegree	Tutor support	Pearson	−0.479*	"Although the tutor support is essential but too much of tutor support can have a negative impact on the student's online learning experience. If the students get all required information from their teacher sit will discourage peer discussion." (p. 393)

Notes. * - $p < 0.05$; ** - $p < 0.01$; ± - dichotomous matrix.

3.3.1. Statistical analysis on common SNA measures and CSCL outcomes

Majority of the included papers (n = 49, 55%) had limited analysis of the SNA data: only reporting the value of SNA measures and describing network characteristics based on the sociograms. Less than half of the included papers applied statistical or quantitative methods to extend the conclusions from the SNA data to learning outcomes. Correlation analysis was the most commonly applied method (n = 19, 21%), whereby researchers investigated the correlation between certain SNA measures and learner characteristics and outcomes. The results of these analyses will be examined in detail in a later section. Around 12 papers (13%) also investigated mean group differences using parametric and non-parametric statistical methods. For example, Shin and Lowes (2008) used ANOVA to compare "core" and "periphery" learners (grouped depending on whether their centrality values fall below or above the mean centrality value) on their active usage of the learning environment and their social presence.

Table 3 displays 12 studies which look into the correlations of centrality and density and CSCL outcomes, mostly on a cognitive and social level, although some studies also explored metacognitive, metasocial and motivational outcomes. Given the small number of studies and the heterogeneity of their analyses, effect sizes to aggregate the significance of these research results could not be calculated.

3.3.1.1. Cognitive- and metacognitive -level outcomes. Studies found that learners occupying a central position in the network tend to have better cognitive- and metacognitive-level outcomes. Cadima et al. (2012) and Cho, Gay, Davidson, and Ingraffea (2007) found that the amount of contacts a learner establishes (degree centrality) and the shorter the "distance" of a learner to other learners (closeness) are moderately correlated to their grades and teachers' evaluation. Putnik et al. (2015) also found that the degree, closeness and betweenness centralities of a learner (i.e., based on how many tasks they accomplished) were in general moderately correlated to the quality and volume of their work as well as their final grades. Domain understanding was also found to be moderately correlated to betweenness centrality (Siqin, van Aalst, & Chu, 2015).

Density was negatively correlated to a number of learning outcomes. Chung and Paredes (2015) found that density had a weak to moderate negative correlation to contribution and content richness, respectively, in the discussion forum discourse, stating that "it is better to have a few meaningful dialogues, rather than many meaningless conversations" (p. 249). Similarly, Toikkanen and Lipponen (2011) found that the density of a network based on learners' reading behavior is negatively correlated to learners' understanding of the learning process.

As for metacognitive-level outcomes, Hurme, Palonen, and Järvelä (2006) found a strong, positive correlation between betweenness centrality and metacognitive monitoring, meaning that central learners communicated with other learners in a way that profited their metacognitive processes.

3.3.1.2. Social- and meta-social level learning outcomes. Social activity in the collaborative platform is usually correlated to centrality. In some of these cases, centrality is used as an indicator of certain aspects of learner social activity; thus, these correlations were between two different centrality measures. Claros et al. (2015) found a high positive correlation between learners' forum contributions (indegree centrality) and peers' contributions (outdegree centrality), concluding that learners tend to respond to peers who have established contact with them. Xie and colleagues (Xie, Yu, & Bradshaw, 2014) correlated the "interaction attractiveness" (indegree centrality) of learners acting as student moderators in a forum and found a high positive correlation with "participation diversity" (outdegree centrality) and moderate correlations with their forum activity (number and average length of posts; and non-posting log-in times as an indicator of reading time). These factors were also correlated with density, which was characterized as group participation. Xie and colleagues found a high positive correlation between density and number of posts, a weak to moderate negative correlation with non-posting logins of the entire learner group, and a moderate positive correlation with student moderators' non-posting log-in times. The researchers concluded that the student moderators reading the forum posts (as part of their role) may have a latent influence in facilitating group participation.

Centrality has also been correlated to social activity between learners and teachers, which could have implications on learner-learner interactions. Zafar et al. (2014) found a moderate negative correlation between outdegree centrality and teacher support, stating that too much teacher support may impede learners from collaborating with each other. Similarly, Toikkanen and Lipponen (2011) found a small correlation between teacher guidance and centrality.

When it comes to metasocial learning outcomes, Gaggioli and colleagues (Gaggioli, Mazzoni, Milani, & Riva, 2015) found very highly positive correlations between density and group flow, indicating that frequent learner communication may help facilitate a collective state of mind. The researchers also found that meaningfulness of the learning process has a small correlation with centrality of learners but moderately correlated to density of the thread network, where the nodes are threads and the ties between them represent learners that they have in common. This means that the more actively learners are posting in several threads, the more meaningful the learning process is likely to be.

3.3.1.3. Motivational-level outcomes. Rienties, Tempelaar, Van den Bossche, Gijselaers, and Segers (2009, 2012) have found significant correlations between degree centrality measures and academic motivation. In two different studies, they found that intrinsic motivation has a low correlation with outdegree centrality, which means that intrinsically motivated learners are also likely to be the most active discussants in the forum. In one of these studies, Rienties et al. (2012) evaluated the effects of a CSCL problem-based learning environment with explicit scaffolding mechanisms. In terms of forum participation

(outdegree centrality), they found that extrinsic motivation (external regulation) was slightly more correlated than intrinsic motivation. The researchers conclude that the scaffolded CSCL environment resulted in greater participation from learners motivated by extrinsic factors, whereas intrinsically motivated learners may have found the scaffolding to be restrictive.

4. Discussion

SNA is a promising analysis method for CSCL research, as both share the same underlying assumption that learning and behavior are influenced by one's relations (Jones, 2015). SNA can be applied to analyze any relation that connects any number of actors—both active/human and passive/non-human—that are present in a social system (Carolan, 2014). This makes it an appropriate method for revealing various relational structures of CSCL settings, where learning outcomes at the cognitive, social, and motivational levels emerge when learners interact not just with each other, but with various artifacts in their environment. Moreover, SNA can be used to reveal information on verbal and nonverbal interactions from trace data from digital environments, which has not been adequately harnessed in CSCL research (Jeong et al., 2014).

The results of this methodological review depict a detailed picture of the extent to which current SNA applications and CSCL theories and existing methodological practices align in terms of (1) the diversity of actors and relational ties that are important in CSCL environments (RQ1); and (2) the implications of these relational ties as measured by SNA indices on CSCL learning outcomes (RQ2). CSCL acknowledges the importance of both direct interaction via communication and indirect/mediated interaction via non-human agents/artifacts. However, the results of the review suggest that (1) SNA applications do not reflect this diversity of CSCL actors and relational ties, with most papers investigating only one-mode networks of learners connected by communication-based relational ties; and (2) when it comes to analyzing SNA data and reporting the results, most papers either described the appearance of the network graphs generated from the data, or only reported the numerical value of the SNA measures, even though mathematical representation of SNA lends itself well to statistical analysis.

Overall, the results indicate SNA has been applied rather homogeneously throughout the CSCL literature. Considering previous studies about SNA applications in online learning (Cela et al., 2015), this suggests that SNA applications are appropriate for addressing the main goal of e-learning—information transfer. This is not an “incorrect” application per se, but it simply means there are many crucial aspects of CSCL that are not incorporated in the analysis of CSCL networked data. Nevertheless, the small subset of studies has explored nonverbal interactions, non-human artifacts and statistical inferences that help to align SNA applications beyond communication-based relational ties and descriptive analysis of SNA data.

4.1. Exploring indirect/mediated interaction using non-actor and two-mode networks

CSCL environments are rich with various technological, instructional and knowledge artifacts that learners can interact with and gain knowledge from (Stahl et al., 2014). Communication may be an integral aspect of CSCL, but it is by no means the only important type of interaction that transpires between learners in collaborative settings. Both SNA and CSCL are concerned not only with human actors and communication ties, but in any relation, connection, association between relevant human and non-human actors in order to understand processes and outcomes in the social context under analysis.

Although there is growing interest in the CSCL community in drawing conclusions from digital data sources from learning analytics (Jeong et al., 2014), the large focus on communication patterns could also be the result of the ubiquity of communication-related log files in CSCL systems (Cela et al., 2015). From these data sources, it is clear which behavior the trace data pertains to: information about direct communication established between users of a system. Researchers are undoubtedly interested in the implications of direct interactions on CSCL outcomes, and log files provide a convenient and more reliable way of gathering this information without relying on self-reported name generators, as was once the common practice for SNA data collection (Carolan, 2014). However, data pertaining to non-verbal interaction can also be derived from log files that records information based on actions that users enacts within the system, for example, when a user clicks on a hyperlink to a new resource. Unlike communication logs, however, it is less clear what the relevance of these interactions are to collaborative learning.

The challenge for CSCL researchers is to determine which artifacts to target for analysis and to establish hypotheses about the learning gains resulting from the observed non-verbal and indirect/mediated interaction between learners through these artifacts (Howison, Wiggins, & Crowston, 2011). For example, Hecking et al. (2014) and Tervakari et al. (2013) used trace data of learner access of the knowledge artifacts created by fellow learners in the CSCL system. This act of accessing these artifacts is taken to mean that the learners read and understood the contributions of their peers. Thus, learners reading other learners' knowledge artifacts may indicate metasocial thinking, that is taking into the consideration the learning output of their peers to inform their own learning. Similarly, for non-actor networks of knowledge artifacts—for example written texts (e.g., wiki articles) linked together by a common feature such as the same references or keywords—researchers have had to infer that the common links that run between these artifacts have a significance to learning. In some of the included papers, such a network represented cohesiveness of knowledge shared between the participants in the collaborative activity (e.g., Nurmela et al., 1999; Sha et al., 2010). Researchers must be careful about taking contextual information when defining relational ties and their implications on learning.

Not only can two-mode and non-actor networks be used to explore diverse relational ties beyond communication, but it also enriches the analysis of communication networks by including specific content-related aspects. Researchers would typically have to employ content analysis on discourse data to find out what has been communicated between learners.

However, a two-mode network in which learners and technological artifacts such as discussion forum threads are connected (based on whether a learner posted on a particular discussion thread) displays both the quantity of communication (e.g., how many times learners contributed to the same thread) and what was communicated (e.g., the topic of the threads that learners contributed to). By contrast, a one-mode communication network can only depict which learners replied to a fellow learner's forum post, not specifying which posts are meant and what those posts are about. Because two-mode networks demonstrate an explicit link between learners and artifacts in the learning environment, a subset of the included papers were able to make inferences about which factors in the learning activity or environment were most engaging or interesting to learners. Thus, including technological, instructional and knowledge artifacts in the analysis allows for more nuanced information about the kinds of topics or materials that reach learners during CSCL, which could have implications on what was actually learned during the interaction.

4.2. Expanding analysis of SNA data using statistical inference to explore CSCL learning outcomes

As a result of various directed and mediated interactions that occur within CSCL settings, learning in CSCL encompasses outcomes at the cognitive, social and motivational levels (Kirschner & Erkens, 2013). To gain a fuller picture of what and how something has been learned in CSCL settings, it is standard practice in CSCL research to apply different quantitative and qualitative methods and triangulate data from various sources (Jeong et al., 2014). SNA is one such method which could be used to analyze relational structures in CSCL. However, despite some of the included papers adopting a multimethod approach, only a small portion investigated the implications of SNA results on CSCL outcomes. That is, few papers conducted statistical analysis on local and global measures with cognitive, social and motivational outcomes of CSCL collected from questionnaires, rating scales and learners' performance measures. Some studies implemented content analysis of verbal data to gain more insight into the communication-based relational ties. However, this approach does not provide any information on how relational ties influence specific, measureable cognitive, social, and motivational outcomes.

Although statistical analysis of learning outcomes is not new in CSCL research, relating SNA data to non-network variables through statistical analysis is a relatively new practice (Carolan, 2014). The small subset of paper that did implement this practice demonstrates how network data could help explain certain learning-related aspects, such as performance and learners' experience of the collaborative activity. For example, several papers (e.g., Cadima et al., 2012; Claros et al., 2015) found that a high centrality value is positively correlated to optimal cognitive and social outcomes. This implies that learners that have more established interactional ties to their peers tend to perform better on learning outcomes. However, a high centrality value may not always be an ideal outcome when associated with certain actors, such as when a teacher rather than a learner occupies a more central role in the network (Zafar et al., 2014). Similarly, high density of communication ties may not always be associated with optimal learning: Chung and Paredes (2015) found a negative correlation between density and content richness of learner contributions, whereas Gaggioli et al. (2015) found a high positive correlation between density and metasocial measures of group flow. Based on these examples, it is clear that the interpretation of SNA results (i.e., whether a value is "good" or "bad" for learning) depends on the research questions, learning context, actors and relational ties of interest. Therefore, it would benefit researchers to consider what certain SNA values imply within the context of their empirical investigation.

These studies demonstrate statistical analysis may enrich SNA results by associating network patterns with certain learner variables that could influence CSCL processes and outcomes. Nevertheless, since statistical analysis on SNA data is relatively recent, researchers are still assessing the appropriateness with regard to conventional statistical models. Unlike questionnaire data, one of the most commonly used data sources in CSCL (Jeong et al., 2014), network observations are almost always non-independently sampled (Hanneman & Riddle, 2005). For example, centrality is based on the number of ties that connect to an actor, which means that the centrality value of Actor A includes its tie with Actor B, and vice versa. Thus, inferential statistical models do not apply for network data, since standard formulas for inferential tests generally assume independent observations. A number of non-standard statistical models have been proposed to accommodate network data and are robust against violations (see van Duijn & Vermunt, 2006).

4.3. Limitations and future directions

The results presented in this literature review may serve as a guide for researchers interested in applying SNA to analyze relational structures that arise from CSCL interactions. However, there are a number of limitations to bear in mind. The scope of this review is limited to formal learning (i.e., classroom) environments, which is the dominant research setting in CSCL research (Jeong et al., 2014). Other learning settings such as professional development may be characterized as networked learning (Jones, 2015) and thus may be suited for SNA so long as the environment promotes connections between learners, the community, and its learning resources. Future research could examine, for instance, how actors, relations and measures of interest differ between learning settings.

Given the pool of studies that include the same statistical methods on SNA data (many of which have sample sizes fewer than 50), their aggregated data would not be adequate for a meta-analysis and to generalize these effects to a larger population. Thus, this literature review is meant to introduce rather than prescribe SNA procedures; researchers carefully consider the implications of SNA results in relation to the context of their study. Future studies could also investigate which SNA measures are appropriate for studying certain pedagogical approaches. For instance, it would be interesting to compare

the implications of centrality measures on learning processes and outcomes when an inquiry-based learning or a problem-based learning strategy is employed.

Because the main emphasis of this literature review is on SNA as a research method, it is unclear how its advantages to researchers apply to educational practitioners and the learners themselves. CSCL research is also interested in the impact of visualizations as evaluation tools for researchers and as feedback mechanisms for teachers and learners, the latter being one core focus of learning analytics (Martin & Sherin, 2013). The small number of design studies may hint at the lack of SNA as an integrated tool in CSCL environments, although a separate literature review may be necessary to explore this hypothesis.

Since SNA has been used for learning analytics, future research could explore how the SNA applications in this review may be used as a basis for feedback for learners and teachers regarding CSCL interactions. Network visualizations can be used as a group awareness tool (Bodemer & Dehler, 2011) that would allow learners to reflect on their interactions based on the relational ties that are present or not (Howison et al., 2011). For example, using learner-instructional artifact network visualizations learners can reflect on the questions: What kinds of resources were accessed most/least often? Do the learners who are frequently accessing the same resources have something in common (e.g., academic performance)? Are there any important resources that are being ignored? Such feedback could help inform future behavior in productive ways. If a low density network of knowledge artifacts is presented to learners as feedback on an activity that requires learner outputs to be cohesive (e.g., writing a joint article), then learners could make an effort to increase the connections between their contributions.

From this literature review, it is evident that SNA is poised to become a relevant research method for understanding interactions in CSCL because of its adaptability to various contexts and units of analysis, and its ability to generate insights from large digital data sources. Future research can take the potential of SNA further by focusing on mediated interaction, integrating technical, instructional and knowledge artifacts as SNA actors, relating SNA findings with cognitive, social and motivational CSCL outcomes using statistical analysis, and integrating SNA results in CSCL environments to test its utility as a feedback mechanism. The unique contributions of SNA to CSCL from the applications discussed in this review should make this a worthwhile endeavor.

Acknowledgements

This work was supported by the Deutsche Forschungsgemeinschaft (DFG) under Grant No. GRK 2167, Research Training Group “User-Centred Social Media”.

Appendix A

Table A.1
Complete list of included studies (n = 89).

Authors	Actors	Ties	SNA measures	Additional analysis on SNA data
Agarwal & Ahmed (2017)	A, C, E	B, C	A	I
An, Shin, & Lim (2009)	A, B	A	A, B	B
Aviv, Erlich, & Ravid (2003)	A, C	A	A, D	I
Aviv, Erlich, & Ravid (2004)	A	A	B, C	I
Cadima, Ojeda, & Monguet (2012)	A	D	A, B	A
Casquero, Ovelar, Romo, Benito, & Alberdi (2016)	E	C	A, B, C	B,E
Chang, Chang, Hsu, & Chen (2007)	A	A	A, B	I
Chen & Watanabe (2007)	A	D	A	G
Cho, Gay, Davidson, & Ingraffea (2007)	C	D	A	A, E
Chung & Paredes (2015)	A	A	A, B, C	A
Claros, Cobos, & Collazos (2015)	A	B	A, B	A
Corallo, Maggio, Grippa, & Passiante (2010)	B	A	A, B	I
Daradoumis, Martínez-Monés, & Xhafa (2004)	B	B	A, B	I
De Laat, Lally, Lipponen, & Simons (2007a)	A	A	A, B	I
De Laat, Lally, Lipponen, & Simons (2007b)	A, B	A	A, B	I
Eryilmaz, Van der Pol, Kasemvilas, Mary, & Olfman (2010)	A	A	A	H
Gaggioli, Mazzoni, Milani, & Riva (2015)	A	A	B, D	A
Gloor, Paasivaara, Schoder, & Willems (2006)	A	A	A	A
Grippa, Secundo, & Passiante (2009)	A	D	B	I
Gutierrez, Zurita, Ochoa, & Baloian (2013)	A	A	A, C, D	I
Haythornthwaite (1999a)	A	A	A, C	I
Haythornthwaite (1999b)	A	D	A	A
Hecking, Ziebarth, & Hoppe (2014)	E	C	A, D	I
Heo, Lim, & Kim (2010)	C	A, B	A, B	I
Hong, Chen, Chang, Liao, & Chan (2009)	A	A	A	A
Hurme, Palonen, & Järvelä (2006)	A	A	A, B, C	A, C
Hurme, Veermans, Palonen, & Järvelä (2008)	B	A	A, B, C	C
Kim, Lee, Yoo, Sung, Jo, & Park (2015)	A, B, E	A, C	A, B	B,E

(continued on next page)

Table A.1 (*continued*)

Authors	Actors	Ties	SNA measures	Additional analysis on SNA data
Knutas, Ikonen, & Porras (2013)	A	D	A	I
Knutas, Ikonen, Nikula, & Porras (2014)	A	A	A	A
Lahti, Seitamaa-Hakkarainen, & Hakkarainen (2003)	A	A	A, B	I
Lakkala, Ilomäki, & Palonen (2007)	B	A	A, B	C
Lambropoulos, Bakharia, & Gourdin (2011)	A	A	B	H
Law & Nguyen-Ngoc (2008)	B	A	A, B	I
Law, Nguyen-Ngoc, & Kuru (2007)	B	A	A	I
Lee & Bonk (2016)	A	D	A, B	A, B
Li, Wang, & Yu (2010)	A	A	A, B, D	I
Li, Liao, Wang, & Huang (2007)	A	A	A	I
Lin, Mai, & Lai (2015)	A	A	B, D	H
Lipponen, Rahikainen, Lallimo, & Hakkarainen (2003)	A	A	A	C
Lotsari, Verykios, Panagiotakopoulos, & Kalles (2014)	A, D, E	A, C, E	A, D	I
Lu & Churchill (2010)	B	A	B	I
Lu & Churchill (2014)	A	A	A, B	I
MacKellar (2012)	A	D	A	I
Manca, Delfino, & Mazzoni (2009)	A	A	B	I
Mansur, Yusof, & Othman (2011)	B	B	A	I
Marcos-García, Martínez-Monés, & Dimitriadis (2015)	A	B	A, B	I
Marcos-García, Martínez-Monés, Dimitriadis, Anguita-Martínez, Ruiz-Requies, & Rubia-Avi (2009)	A	B	A, B	I
Martínez, Dimitriadis, Gómez-Sánchez, Rubia-Avi, Jorrín-Abellán, & Marcos (2006)	B, E	A, B, C	A, B	C
Nanclares, Rienties, & Van den Bossche (2012)	A	D	A, B, C	I
Nguyen-Ngoc & Law (2009)	B	A	A	I
Nguyen-Ngoc & Law (2010)	B	A	A	I
Nguyen-Ngoc & Law (2007)	B	A	A	I
Nuankhieo, Tsai, Goggins, & Laffey (2007)	B	A, B	B	I
Nurmela, Lehtinen, & Palonen (1999)	B, D	A,E	A	C
Palonen & Hakkarainen (2013)	A	A	A, B	C
Philip (2012)	A	B	A	I
Philip (2010)	A	A, D	A, B	I
Putnik, Costa, Alves, Castro, Varela, & Shah (2015)	C	B	A, B	A
Resendes, Scardamalia, Bereiter, Chen, & Halewood (2015)	A	B	A	B
Rienties, Giesbers, Tempelaar, Lygo-Baker, Segers, & Gijselaers (2012)	B	A	A	A, B
Rienties, Tempelaar, Giesbers, Segers, & Gijselaers (2014)	A	A	A	B
Rienties, Tempelaar, Van den Bossche, Gijselaers, & Segers (2009)	A	A	A	A, B
Rodríguez, Sicilia, Sánchez-Alonso, Lezcano, & García-Barriocanal (2011)	E	C	C	I
Rodríguez-Hidalgo, Torres-Alfonso, Zhu, & Questier (2011)	A	D	A, B, C, D	I
Secundo & Grippa (2010)	B	D	A, B	I
Sha, Teplovs, & van Aalst (2010)	D	E	A, B	I
Shin & Lowes (2008)	A	A	A, B	B
Siqin, van Aalst, & Chu (2015)	A	A, B	A, B, D	A, B
Stefanone, Hancock, Gay, & Ingraffea (2004)	A	D	B, C	H
Stepanyan, Borau, & Ullrich (2010)	A	A	A, B	D
Stepanyan, Mather, & Dalrymple (2014)	A	A	B	A, D
Suh, Kang, Moon, & Jang (2005)	B	A	A	F
Sundararajan (2009)	A	A	A	F
Sundararajan & Moore (2006)	A	A	A, C	I
Tapola, Hakkarainen, Syri, Lipponen, Palonen, & Niemivirta (2001)	A	A	A, B	B
Temdee, Thipakorn, Sirinaovakul, & Schelhowe (2006)	A	A	A	G
Tervakari, Marttila, Kailanto, Huhtamäki, Koro, & Silius (2013)	A, E	B,C	A	I
Thoms & Eryilmaz (2014)	A	A	A	I
Thormann, Gable, Fidalgo, & Blakeslee (2013)	A	A	A, B	I
Tirado, Hernando, & Aguaded (2015)	A	A	A, B	F
Toikkanen & Lipponen (2011)	A, D, E	A, B, C, E	A, B	A, H
Tsai (2011)	A	A	A, B	I
Uddin & Jacobson (2013)	A	A	B, D	D
Vercellone-Smith, Jablokow, & Friedel (2012)	A	A	A, B, D	I
Xie, Yu, & Bradshaw (2014)	A	A	A, B	A, B, E
Yao (2010)	B	A	A, B	I
Zafar, Safdar, & Malik (2014)	B	A	A	A
Zuo, Mu, & Han (2012)	A	A	A, B, D	I

Legend. Actors – A. Learner, B. Learners and instructors, C. Learners and learner groups, D. Objects/events/artifacts, E. Learners and objects/events/artifacts; Ties – A. Communication, B. Project/task-related interaction, C. Interaction with same objects, D. Self-reported interaction or social relation, E. Relation between objects; SNA measures – A. Local/individual measures, B. Global network measures, C. Positions, D. Subgroups and cliques; Additional analysis on SNA data – A. Correlation analysis, B. Comparison of means, C. Multidimensional analysis, D. Network simulation, E. Regression analysis/mediation, F. Structural equation modelling, G. Own metric, H. Other, I. None (descriptive analysis only).

References

* References marked with an (*) indicate studies included in the literature review.

* Agarwal, N., & Ahmed, F. (2017). Developing collective learning extension for rapidly evolving information system courses. *Education and Information Technologies, 22*(1), 7–37. http://dx.doi.org/10.1007/s10639-015-9394-4.

* An, H., Shin, S., & Lim, K. (2009). The effects of different instructor facilitation approaches on students' interactions during asynchronous online discussions. *Computers & Education, 53*(3), 749–760. http://dx.doi.org/10.1016/j.compedu.2009.04.015.

* Aviv, R., Erlich, Z., & Ravid, G. (2003). Cohesion and roles: Network analysis of CSCL communities. In V. Devedzic, J. M. Spector, D. G. Sampson, & Kishnuk (Eds.), *Proceedings of the 3rd IEEE international conference on advanced learning technologies* (pp. 145–149). http://dx.doi.org/10.1109/ICALT.2003.1215045.

* Aviv, R., Erlich, Z., & Ravid, G. (2004). Mechanisms and architectures of online learning communities. In L. C. Kinshuk, E. Sutinen, D. Sampson, L. Aedo, L. Uden, & E. Kahekonen (Eds.), *Proceedings of IEEE international conference on advanced learning technologies, 2004* (pp. 400–404). http://dx.doi.org/10.1109/ICALT.2004.1357445.

Bodemer, D., & Dehler, J. (2011). Group awareness in CSCL environments. *Computers in Human Behavior, 27*(3), 1043–1045. http://dx.doi.org/10.1016/j.chb.2010.07.014.

* Cadima, R., Ojeda, J., & Monguet, J. M. (2012). Social networks and performance in distributed learning communities. *Educational Technology & Society, 15*(4), 296–304. Retrieved from http://www.jstor.org/stable/jeductechsoci.15.4.296.

Carolan, B. V. (2014). *Social network analysis and education: Theory, methods and applications*. Thousand Oaks, CA: SAGE Publications.

* Casquero, O., Ovelar, R., Romo, J., Benito, M., & Alberdi, M. (2016). Students' personal networks in virtual and personal learning environments: A case study in higher education using learning analytics approach. *Interactive Learning Environments, 24*(1), 49–67. http://dx.doi.org/10.1080/10494820.2013.817441.

Cela, K. L., Sicilia, M. A., & Sanchez, S. (2015). Social network analysis in e-learning environments: A preliminary systematic review. *Educational Psychology Review, 27*(1), 219–246. http://dx.doi.org/10.1007/s10648-014-9276-0.

* Chang, Y.-J., Chang, Y.-S., Hsu, S.-Y., & Chen, C.-H. (2007). Social network analysis to blog-based online community. In *Proceedings of the 2007 international conference on convergence information technology, South Korea* (pp. 2193–2198). http://dx.doi.org/10.1109/ICCIT.2007.130.

* Chen, Z., & Watanabe, S. (2007). A case study of applying SNA to analyze CSCL social network. In *Proceedings of the seventh IEEE international conference on advanced learning technologies, Japan* (pp. 18–20). http://dx.doi.org/10.1109/ICALT.2007.3.

* Cho, H., Gay, G., Davidson, B., & Ingraffea, A. (2007). Social networks, communication styles, and learning performance in a CSCL community. *Computers & Education, 49*(2), 309–329. http://dx.doi.org/10.1016/j.compedu.2005.07.003.

* Chung, K. S. K., & Paredes, W. C. (2015). Towards a social networks model for online learning & performance. *Educational Technology & Society, 18*(3), 240–253. Retrieved from http://www.jstor.org/stable/jeductechsoci.18.3.240.

Cicchetti, D. V. (1994). Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. *Psychological Assessment, 6*(4), 284–290. http://dx.doi.org/10.1037/1040-3590.6.4.284.

* Claros, I., Cobos, R., & Collazos, C. (2015). An approach based on social network analysis applied to a collaborative learning experience. *IEEE Transactions on Learning Technologies, 9*(1), 190–195. http://dx.doi.org/10.1109/TLT.2015.2453979, 1–1.

* Corallo, A., Maggio, M. D., Grippa, F., & Passiante, G. (2010). A methodological framework to monitor the performance of virtual learning communities. *Human Factors and Ergonomics in Manufacturing & Service Industries, 20*(2), 135–148. http://dx.doi.org/10.1002/hfm.20205.

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. http://dx.doi.org/10.1007/s11412-007-9032-2.

* Daradoumis, T., Martínez-Monés, A., & Xhafa, F. (2004). An integrated approach for analysing and assessing the performance of virtual learning groups. In G. J. de Vreede, L. A. Guerrero, & G. Marín Raventós (Eds.), *Lecture notes in computer Science: Vol. 3198. Groupware: Design, implementation, and use. CRIWG 2004* (pp. 289–304). http://dx.doi.org/10.1007/978-3-540-30112-7_25.

* De Laat, M., Lally, V., Lipponen, L., & Simons, R. J. (2007a). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for social network analysis. *International Journal of Computer-supported Collaborative Learning, 2*(1), 87–103. http://dx.doi.org/10.1007/s11412-007-9006-4.

* De Laat, M., Lally, V., Lipponen, L., & Simons, R. J. (2007b). Online teaching in networked learning communities: A multi-method approach to studying the role of the teacher. *Instructional Science, 35*(3), 257–286. http://dx.doi.org/10.1007/s11251-006-9007-0.

Dillenbourg, P., Järvelä, S., & Fischer, F. (2009). The evolution of research on computer-supported collaborative learning. In D. N. Balacheff, D. S. Ludvigsen, D. T. de Jong, D. A. Lazonder, & D. S. Barnes (Eds.), *Technology-enhanced learning* (pp. 3–19). Dordrecht, Netherlands: Springer.

* Enriquez, J. G. (2008). Translating networked learning: Un-tying relational ties. *Journal of Computer Assisted Learning, 24*(2), 116–127. http://dx.doi.org/10.1111/j.1365-2729.2007.00273.x.

* Eryilmaz, E., Van der Pol, J., Kasemvilas, S., Mary, J., & Olfman, L. (2010). The role of anchoring discussion in mediating effective online interaction for collaborative knowledge construction. In *Proceedings of the 43rd Hawaii international conference on system sciences, USA* (pp. 1–10). http://dx.doi.org/10.1109/HICSS.2010.392.

* Gaggioli, A., Mazzoni, E., Milani, L., & Riva, G. (2015). The creative link: Investigating the relationship between social network indices, creative performance and flow in blended teams. *Computers in Human Behavior, 42*, 157–166. http://dx.doi.org/10.1016/j.chb.2013.12.003.

* Gloor, P., Paasivaara, M., Schoder, D., & Willems, P. (2006). Correlating performance with social network structure through teaching social network analysis. In *Network-centric collaboration and supporting frameworks* (Vol. 224, pp. 265–272). Springer US. Retrieved from http://dx.doi.org/10.1007/978-0-387-38269-2_28.

* Grippa, F., Secundo, G., & Passiante, G. (2009, September). An integrated model to monitor and evaluate Web 2.0 project-based learning. In *World summit on knowledge society* (pp. 50–59). http://dx.doi.org/10.1007/978-3-642-04754-1_6.

* Gutierrez, F., Zurita, G., Ochoa, S., & Baloian, N. (2013). Analyzing two participation strategies in an undergraduate course community. In P. Antunes, M. Gerosa, A. Sylvester, J. Vassileva, & G.-J. de Vreede (Eds.). *Lecture notes in computer Science: Vol. 8224. Collaboration and technology. CRIWG* (Vol. 2013, pp. 143–158). http://dx.doi.org/10.1007/978-3-642-41347-6_11.

Hanneman, R. A., & Riddle, M. (2005). Some statistical methods. In *Introduction to social network methods*. Riverside, CA: University of California, Riverside. Retrieved from http://faculty.ucr.edu/~hanneman/.

* Haythornthwaite, C. (1999a). Collaborative work networks among distributed learners. In *Proceedings of the 32nd annual Hawaii international conference on systems sciences, USA*. http://dx.doi.org/10.1109/HICSS.1999.772707.

* Haythornthwaite, C. (1999b). Networks of information sharing among computer-supported distance learners. In *Proceedings of the 1999 Conference on Computer support for collaborative learning, USA*.

* Hecking, T., Ziebarth, S., & Hoppe, H. U. (2014). Analysis of dynamic resource access patterns in a blended learning course. *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge, USA*, 173–182. http://dx.doi.org/10.1145/2567574.2567584.

* Heo, H., Lim, K. Y., & Kim, Y. (2010). Exploratory study on the patterns of online interaction and knowledge co-construction in project-based learning. *Computers & Education, 55*(3), 1383–1392. http://dx.doi.org/10.1016/j.compedu.2010.06.012.

* Hong, H. Y., Chen, F. C., Chang, H. M., Liao, C. C., & Chan, W. C. (2009). Exploring the effectiveness of an idea-centered design to foster a computer-supported knowledge building environment. In *Proceedings of the 9th international conference on computer supported collaborative learning, Greece* (Vol. 1, pp. 142–150).

Howison, J., Wiggins, A., & Crowston, K. (2011). Validity issues in the use of social network analysis with digital trace data. *Journal of the Association for Information Systems, 12*(12), 767–797.

* Hurme, T. R., Palonen, T., & Järvelä, S. (2006). Metacognition in joint discussions: An analysis of the patterns of interaction and the metacognitive content of the networked discussions in mathematics. *Metacognition and Learning, 1*(2), 181–200. http://dx.doi.org/10.1007/s11409-006-9792-5.
* Hurme, T. R., Veermans, K., Palonen, T., & Järvelä, S. (2008). Exploring changes in network structures during online discussions. In *Proceedings of the 8th international conference on International conference for the learning sciences, Netherlands* (Vol. 1, pp. 382–389).
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. http://dx.doi.org/10.1080/00461520.2016.115865.
Jeong, H., Hmelo-Silver, C. E., & Yu, Y. (2014). An examination of CSCL methodological practices and the influence of theoretical frameworks 2005–2009. *International Journal of Computer-supported Collaborative Learning, 9*(3), 305–334. http://dx.doi.org/10.1007/s11412-014-9198-3.
Jones, C. (2015). Theories of learning in a digital age. In C. Jones (Ed.), *Networked Learning: An educational paradigm for the age of digital networks* (pp. 47–78). Cham: Springer International Publishing.
* Kim, J., Lee, H., Yoo, Y., Sung, H., Jo, I. H., & Park, Y. (2015). Towards smart asynchronous discussion activity: Using social network analysis to investigate students' discussion patterns. In *Emerging issues in smart learning* (pp. 361–370). http://dx.doi.org/10.1007/978-3-662-44188-6.
Kirschner, P. A., & Erkens, G. (2013). Toward a framework for CSCL research. *Educational Psychologist, 48*(1), 1–8. http://dx.doi.org/10.1080/00461520.2012.750227.
Knoke, D., & Yang, S. (2008). *Social network analysis* (Vol. 154). Thousand Oaks, CA: SAGE Publications.
* Knutas, A., Ikonen, J., Nikula, U., & Porras, J. (2014). Increasing collaborative communications in a programming course with gamification: A case study. In *Proceedings of the 15th international conference on computer systems and technologies, Bulgaria* (pp. 370–377). http://dx.doi.org/10.1145/2659532.2659620.
* Knutas, A., Ikonen, J., & Porras, J. (2013). Communication patterns in collaborative software engineering courses: A case for computer-supported collaboration. In *Proceedings of the 13th koli calling international conference on computing education research, Finland* (pp. 169–177). http://dx.doi.org/10.1145/2526968.2526987.
Krippendorff, K. (2012). *Content analysis: An introduction to its methodology* (3rd ed.). Thousand Oaks, CA: SAGE Publications.
Lahti, M., Hätönen, H., & Välimäki, M. (2014). Impact of e-learning on nurses' and student nurses knowledge, skills, and satisfaction: A systematic review and meta-analysis. *International Journal of Nursing Studies, 51*(1), 136–149. http://dx.doi.org/10.1016/j.ijnurstu.2012.12.017.
* Lahti, H., Seitamaa-Hakkarainen, P., & Hakkarainen, K. (2003). Piloting participatory designing within a collaborative learning environment. *Journal of Interactive Learning Research, 14*(2), 185. Retrieved from https://search.proquest.com/docview/1468383632?accountid=10597.
* Lakkala, M., Ilomäki, L., & Palonen, T. (2007). Implementing virtual collaborative inquiry practises in a middle-school context. *Behaviour & Information Technology, 26*(1), 37–53. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/01449290600811529.
* Lambropoulos, N., Bakharia, A., & Gourdin, A. (2011). Distributed leadership collaboration factors to support idea generation in computer-supported collaborative e-learning. *Human Technology, 7*(1), 72–102. Retrieved from http://www.humantechnology.jyu.fi.
* Law, E. L. C., & Nguyen-Ngoc, A. V. (2008). Fostering self-directed learning with social software: Social network analysis and content analysis. In P. Dillenbourg, & M. Specht (Eds.), *Lecture notes in computer Science: Vol. 5192. Times of convergence. Technologies across learning contexts. Ec-TEL 2008* (pp. 203–215). http://dx.doi.org/10.1007/978-3-540-87605-2_23.
* Law, E. L. C., Nguyen-Ngoc, A. V., & Kuru, S. (2007). Mixed-method validation of pedagogical concepts for an intercultural online learning environment: A case study. In *Proceedings of the 2007 international ACM conference on supporting group work, USA* (pp. 321–330). http://dx.doi.org/10.1145/1316624.1316673.
Law, N., Yuen, J., Wong, W. O. W., & Leng, J. (2011). Understanding learners' knowledge building trajectory through visualizations of multiple automated analyses. In S. Puntambekar, G. Erkens, & C. Hmelo-Silver (Eds.), *Analyzing interactions in CSCL: Methods, approaches and issues* (pp. 47–82). Boston, MA: Springer US.
* Lee, J., & Bonk, C. J. (2016). Social network analysis of peer relationships and online interactions in a blended class using blogs. *The Internet and Higher Education, 28*, 35–44. http://dx.doi.org/10.1016/j.iheduc.2015.09.001.
* Lin, J.-W., Mai, L.-J., & Lai, Y.-C. (2015). Peer interaction and social network analysis of online communities with the support of awareness of different contexts. *International Journal of Computer-supported Collaborative Learning, 10*(2), 139–159. http://dx.doi.org/10.1007/s11412-015-9212-4.
Lipponen, L. (2002). Exploring foundations for computer-supported collaborative learning. In *Proceedings of the conference on computer-support for collaborative Learning: Foundations for a CSCL community* (pp. 72–81). International Society of the Learning Sciences.
Lipponen, L., Hakkarainen, K., & Paavola, S. (2004). Practices and orientations of CSCL. In J.-W. Strijbos, P. A. Kirschner, & R. L. Martens (Eds.), *What we know about CSCL: And implementing it in higher education* (pp. 31–50). Dordrecht: Springer Netherlands. http://dx.doi.org/10.1007/1-4020-7921-4_2. Retrieved from.
* Lipponen, L., Rahikainen, M., Lallimo, J., & Hakkarainen, K. (2003). Patterns of participation and discourse in elementary students' computer-supported collaborative learning. *Learning and Instruction, 13*(5), 487–509. http://dx.doi.org/10.1016/S0959-4752(02)00042-7.
* Li, Y., Wang, J., Liao, J., Zhao, D., & Huang, R. (2007, July). Assessing collaborative process in CSCL with an intelligent content analysis toolkit. In *Seventh IEEE international conference on advanced learning technologies, Japan* (pp. 257–261). http://dx.doi.org/10.1109/ICALT.2007.73.
* Li, W., Wang, X., & Yu, M. (2010). A research on collaboration knowledge construction in the virtual learning community by social network analysis. In *2010 international conference on educational and information technology (ICEIT)*. http://dx.doi.org/10.1109/ICEIT.2010.5607582C.
* Lotsari, E., Verykios, V., Panagiotakopoulos, C., & Kalles, D. (2014). A learning analytics methodology for student profiling. In A. Likas, K. Blekas, & D. Kalles (Eds.), *Lecture notes in computer Science: Vol. 8445. Artificial Intelligence: Methods and applications. SETN 2014* (pp. 300–312). http://dx.doi.org/10.1007/978-3-319-07064-3_24.
* Lu, J., & Churchill, D. (2010). Exploring interaction patterns of students on a social networking platform in a university class. In J. Herrington, & C. Montgomerie (Eds.), *Proceedings of EdMedia: World conference on educational Media and technology 2010* (pp. 330–336). Toronto, Canada: AACE.
* Lu, J., & Churchill, D. (2014). The effect of social interaction on learning engagement in a social networking environment. *Interactive Learning Environments, 22*(4), 401–417. http://dx.doi.org/10.1080/10494820.2012.680966.
* MacKellar, B. (2012). A case study of group communication patterns in a large project software engineering course. In *proceeding of the 25th IEEE conference on software engineering education and training (CSEE&T), China* (pp. 134–138). http://dx.doi.org/10.1109/CSEET.2012.21.
* Manca, S., Delfino, M., & Mazzoni, E. (2009). Coding procedures to analyse interaction patterns in educational web forums. *Journal of Computer Assisted Learning, 25*(2), 189–200. http://dx.doi.org/10.1111/j.1365-2729.2008.00296.x.
* Mansur, A. B. F., Yusof, N., & Othman, M. S. (2011). Analysis of social learning network for wiki in Moodle e-learning. In *Proceedings of the 4th international conference on interaction sciences (ICIS 2011), South Korea* (pp. 1–4).
* Marcos-García, J. A., Martínez-Monés, A., & Dimitriadis, Y. (2015). DESPRO: A method based on roles to provide collaboration analysis support adapted to the participants in CSCL situations. *Computers & Education, 82*, 335–353. http://dx.doi.org/10.1016/j.compedu.2014.10.027.
* Marcos-García, J., Martínez-Monés, A., Dimitriadis, Y., Anguita-Martínez, R., Ruiz-Requies, I., & Rubia-Avi, B. (2009). Detecting and solving negative situations in real CSCL experiences with a role-based interaction analysis approach. In T. Daradoumis, S. Caballé, J. Marquès, & F. Xhafa (Eds.). *Intelligent Collaborative e-Learning Systems and Applications* (Vol. 246, pp. 129–146). http://dx.doi.org/10.1007/978-3-642-04001-6_9.
* Martínez, A., Dimitriadis, Y., Gómez-Sánchez, E., Rubia-Avi, B., Jorrín-Abellán, I., & Marcos, J. (2006). Studying participation networks in collaboration using mixed methods. *International Journal of Computer-supported Collaborative Learning, 1*(3), 383–408. http://dx.doi.org/10.1007/s11412 006-8705-6.
Martin, T., & Sherin, B. (2013). Learning analytics and computational techniques for detecting and evaluating patterns in learning: An introduction to the special issue. *Journal of the Learning Sciences, 22*(4), 511–520. http://dx.doi.org/10.1080/10508406.2013.840466.
Mezzich, J. E., Kraemer, H. C., Worthington, D. R., & Coffman, G. A. (1981). Assessment of agreement among several raters formulating multiple diagnoses. *Journal of Psychiatric Research, 16*(1), 29–39.

* Nanclares, N. H., Rienties, B., & Van den Bossche, P. (2012). A longitudinal analysis of knowledge spillovers in the classroom. In P. Van Den Bossche, W. H. Gijselaers, & R. G. Milter (Eds.), *Learning at the crossroads of theory and practice* (pp. 157–175). Springer Netherlands. http://dx.doi.org/10.1007/978-94-007-2846-2_11.
* Nguyen-Ngoc, A. V., & Law, E. L. C. (2007). Evaluation of cross-cultural computer-supported collaborative learning: Preliminary findings for iCamp challenges. In C. Montgomerie, & J. Seale (Eds.), *Proceedings of the world conference on educational multimedia, hypermedia and telecommunications (ED-MEDIA 2007)*. Vancouver, Canada: AACE.
* Nguyen-Ngoc, A., & Law, E.-C. (2009). Challenges for blog analysis and possible solutions. In M. Spaniol, Q. Li, R. Klamma, & R. H. Lau (Eds.), *Lecture notes in computer Science: Vol. 5686. Advances in web based learning – ICWL 2009* (pp. 297–306). http://dx.doi.org/10.1007/978-3-642-03426-8_36.
* Nguyen-Ngoc, A. V., & Law, E. L.-C. (2010). Towards a structural model for variables in online cross-cultural collaborative learning environments. In J. Herrington, & C. Montgomerie (Eds.), *Proceedings of EdMedia: World conference on educational Media and technology 2010* (pp. 1545–1554). Toronto, Canada: AACE.
* Nuankhieo, P., Tsai, I.-C., Goggins, S., & Laffey, J. (2007, December). Comparing the social interaction pattern of online one-on-one peer and small group collaboration activities. In M. L. Shyu, & Q. Li (Chair) (Eds.), *Ninth IEEE international symposium on multimedia workshops. Symposium conducted at the meeting of IEEE computer society. Taichung, taiwan*. Retrieved from http://ieeexplore.ieee.org/abstract/document/4476009/.
Nurmela, K., Lehtinen, E., & Palonen, T. (1999). Evaluating CSCL log files by social network analysis. In *Proceedings of the 1999 conference on computer support for collaborative learning, USA* (pp. 434–444). Retrieved from http://dl.acm.org/citation.cfm?id=1150294.
Oshima, J., Oshima, R., & Matsuzawa, Y. (2012). Knowledge building discourse explorer: A social network analysis application for knowledge building discourse. *Educational Technology Research and Development, 60*(5), 903–921. http://dx.doi.org/10.1007/s11423-012-9265-2.
* Palonen, T., Hakkarainen, K., & Fishman, B. (2013). Patterns of interaction in computer-supported learning: A social network analysis. In B. J. Fishman, & S. F. O'Conner-Divelbiss (Eds.), *Fourth international conference of the learning sciences* (pp. 334–339). London, England: Lawrence Erlbaum Associates.
* Philip, D. N. (2010). Social network analysis to examine interaction patterns in knowledge building communities. *Canadian Journal of Learning and Technology, 36*(1). Retrieved from http://cjlt.csj.ualberta.ca/index.php/cjlt/article/view/577.
* Philip, D. N. (2012). Pilgrims' progress: The journey towards a knowledge building community in a university undergraduate class. *Canadian Journal of Learning and Technology, 38*(1). Retrieved from https://eric.ed.gov/?id=EJ968185.
Puntambekar, S., Erkens, G., & Hmelo-Silver, C. (2011). *Analyzing interactions in CSCL: Methods, approaches and issues* (Vol. 12). Berlin, Germany: Springer Science & Business Media.
* Putnik, G., Costa, E., Alves, C., Castro, H., Varela, L., & Shah, V. (2015). Analysing the correlation between social network analysis measures and performance of students in social network-based engineering education. *International Journal of Technology and Design Education, 26*(3), 413–437. http://dx.doi.org/10.1007/s10798-015-9318-z.
* Resendes, M., Scardamalia, M., Bereiter, C., Chen, B., & Halewood, C. (2015). Group-level formative feedback and metadiscourse. *International Journal of Computer-supported Collaborative Learning, 10*(3), 309–336. http://dx.doi.org/10.1007/s11412-015-9219-x.
* Rienties, B., Giesbers, B., Tempelaar, D., Lygo-Baker, S., Segers, M., & Gijselaers, W. (2012). The role of scaffolding and motivation in CSCL. *Computers & Education, 59*(3), 893–906. http://dx.doi.org/10.1016/j.compedu.2012.04.010.
* Rienties, B., Tempelaar, D., Giesbers, B., Segers, M., & Gijselaers, W. (2014). A dynamic analysis of why learners develop a preference for autonomous learners in computer-mediated communication. *Interactive Learning Environments, 22*(5), 631–648. http://dx.doi.org/10.1080/10494820.2012.707127.
* Rienties, B., Tempelaar, D., Van den Bossche, P., Gijselaers, W., & Segers, M. (2009). The role of academic motivation in computer-supported collaborative learning. *Computers in Human Behavior, 25*(6), 1195–1206. http://dx.doi.org/10.1016/j.chb.2009.05.012.
* Rodriguez-Hidalgo, R. C., Torres-Alfonso, A. M., Zhu, C., & Questier, F. (2011). Wikis supporting research workshops in higher education. In *Proceedings of the 2011 6th iberian conference on information systems and technologies (CISTI), Portugal* (pp. 1–10). Retrieved from http://ieeexplore.ieee.org/abstract/document/5974297/.
* Rodríguez, D., Sicilia, M.Á., Sánchez-Alonso, S., Lezcano, L., & García-Barriocanal, E. (2011). Exploring affiliation network models as a collaborative filtering mechanism in e-learning. *Interactive Learning Environments, 19*(4), 317–331. http://dx.doi.org/10.1080/10494820903148610.
Rummel, N., Deiglmayr, A., Spada, H., Kahrimanis, G., & Avouris, N. (2011). Analyzing collaborative interactions across domains and settings: An adaptable rating scheme. In S. Puntambekar, G. Erkens, & C. Hmelo-Silver (Eds.), *Analyzing interactions in CSCL: Methods, approaches and issues* (pp. 367–390). Boston, MA: Springer US.
Sangrà, A., Vlachopoulos, D., & Cabrera, N. (2012). Building an inclusive definition of e-learning: An approach to the conceptual framework. *The International Review of Research in Open and Distributed Learning, 13*(2), 145–159.
* Secundo, G., & Grippa, F. (2010). Designing, managing and assessing a Web 2.0 learning community to enhance inquiry based learning. *International Journal of Web Based Communities, 6*(2), 164–182. http://dx.doi.org/10.1504/IJWBC.2010.032233.
* Sha, L., Teplovs, C., & van Aalst, J. (2010). A visualization of group cognition: Semantic network analysis of a CSCL community. In K. Gomez, L. Lyons, & J. Radinsky (Eds.). *Proceedings of the 9th international conference of the learning sciences* (Vol. 1, pp. 929–936). Chicago, IL: International Society of the Learning Sciences.
* Shin, W., & Lowes, S. (2008). Analyzing web 2.0 users in an online discussion forum. In J. Luca, & E. R. Weippl (Eds.), *Proceedings of EdMedia: World conference on educational Media and technology 2008* (pp. 1130–1137). Vienna, Austria: Association for the Advancement of Computing in Education (AACE).
Sie, R. L. L., Ullmann, T. D., Rajagopal, K., Cela, K., Bitter-Rijpkema, M., & Sloep, P. B. (2012). Social network analysis for technology-enhanced learning: Review and future directions. *International Journal of Technology Enhanced Learning, 4*(3–4), 172–190. http://dx.doi.org/10.1504/IJTEL.2012.051582.
* Siqin, T., van Aalst, J., & Chu, S. K. W. (2015). Fixed group and opportunistic collaboration in a CSCL environment. *International Journal of Computer-supported Collaborative Learning, 10*(2), 161–181. http://dx.doi.org/10.1007/s11412-014-9206-7.
Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge*. Cambridge, MA: MIT Press. Retrieved from https://mitpress.mit.edu/index.php?q=books/group-cognition/.
Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 409–426). Cambridge, United Kingdom: Cambridge University Press.
Stahl, G., Ludvigsen, S., Law, N., & Cress, U. (2014). CSCL artifacts. *International Journal of Computer-supported Collaborative Learning, 9*(3), 237–245. http://dx.doi.org/10.1007/s11412-014-9200-0.
Stefanone, M., Hancock, J., Gay, G., & Ingraffea, A. (2004). Emergent networks, locus of control, and the pursuit of social capital. In *Proceedings of the 2004 ACM conference on computer supported cooperative work, USA* (pp. 592–595). http://dx.doi.org/10.1145/1031607.1031708.
* Stepanyan, K., Borau, K., & Ullrich, C. (2010). A social network analysis perspective on student interaction within the Twitter microblogging environment. In *Proceedings of the 2010 IEEE 10th international conference on advanced learning technologies (ICALT), Tunisia* (pp. 70–72). http://dx.doi.org/10.1109/ICALT.2010.27.
* Stepanyan, K., Mather, R., & Dalrymple, R. (2014). Culture, role and group work: A social network analysis perspective on an online collaborative course. *British Journal of Educational Technology, 45*(4), 676–693. http://dx.doi.org/10.1111/bjet.12076.
* Suh, H., Kang, M., Moon, K., & Jang, H. (2005). Identifying peer interaction patterns and related variables in community-based learning. In *Proceedings of the 2005 conference on computer support for collaborative learning: Learning 2005: The next 10 years!, taiwan* (pp. 657–661). Retrieved from http://dl.acm.org/citation.cfm?id=1149379.
* Sundararajan, B. (2009). Impact of communication patterns, network positions and social dynamics factors on learning among students in a CSCL environment. *Electronic Journal of e-Learning, 7*(1), 71–84. Retrieved from http://www.editlib.org/p/55185.

* Sundararajan, B., & Moore, C. (2006). Communication patterns and network roles in distance education computer-supported collaborative learning environments. In C. Crawford, R. Carlsen, K. McFerrin, J. Price, R. Weber, & D. Willis (Eds.), *Society for information technology & teacher education international conference* (pp. 547–554). Chesapeake, VA: Association for the Advancement of Computing in Education (AACE).

Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education, 50*(4), 1183–1202. http://dx.doi.org/10.1016/j.compedu.2006.11.007.

Suthers, D. D. (2012). Computer-supported collaborative learning. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning*. New York, NY: Springer.

Suthers, D. D., Dwyer, N., Medina, R., & Vatrapu, R. (2010). A framework for conceptualizing, representing, and analyzing distributed interaction. *International Journal of Computer-supported Collaborative Learning, 5*(1), 5–42. http://dx.doi.org/10.1007/s11412-009-9081-9.

Suthers, D., & Medina, R. (2011). Tracing interaction in distributed collaborative learning. In S. Puntambekar, G. Erkens, & C. Hmelo-Silver (Eds.), *Analyzing interactions in CSCL: Methods, approaches and issues* (pp. 341–366). Boston, MA: Springer US. https://doi.org/10.1007/978-1-4419-7710-6_16.

* Tapola, A., Hakkarainen, K., Syri, J., Lipponen, L., Palonen, T., & Niemivirta, M. (2001). Participation and motivation in computer-supported collaborative learning. In C. Montgomery, & J. Viteli (Eds.), *Proceedings of EdMedia: World conference on educational Media and technology* (pp. 1873–1878). Vienna, Austria: Association for the Advancement of Computing in Education (AACE). Retrieved from https://www.learntechlib.org/noaccess/9061.

* Temdee, P., Thipakorn, B., Sirinaovakul, B., & Schelhowe, H. (2006). Of collaborative learning team: An approach for emergent leadership roles identification by using social network analysis. In Z. Pan, R. Aylett, H. Diener, X. Jin, S. Göbel, & L. Li (Eds.), *Lecture notes in computer science, vol. 3942. Technologies for e-learning and digital entertainment* (pp. 745–754). http://dx.doi.org/10.1007/11736639_92.

* Tervakari, A. M., Marttila, J., Kailanto, M., Huhtamäki, J., Koro, J., & Silius, K. (2013). Developing learning analytics for TUT Circle. In T. Ley, M. Ruohonen, M. Laanpere, & A. Tatnall (Eds.), *Advances in information and communication Technology: Vol. 395. Open and social technologies for networked learning. IFIP* (pp. 101–110). http://dx.doi.org/10.1007/978-3-642-37285-8_11.

* Thoms, B., & Eryilmaz, E. (2014). How media choice affects learner interactions in distance learning classes. *Computers & Education, 75*, 112–126. http://dx.doi.org/10.1016/j.compedu.2014.02.002.

* Thormann, J., Gable, S., Fidalgo, P. S., & Blakeslee, G. (2013). Interaction, critical thinking, and social network analysis (SNA) in online courses. *The International Review of Research in Open and Distributed Learning, 14*(3), 294–318. http://dx.doi.org/10.19173/irrodl.v14i3.1306.

* Tirado, R., Hernando, Á., & Aguaded, J. I. (2015). The effect of centralization and cohesion on the social construction of knowledge in discussion forums. *Interactive Learning Environments, 23*(3), 293–316. http://dx.doi.org/10.1080/10494820.2012.745437.

* Toikkanen, T., & Lipponen, L. (2011). The applicability of social network analysis to the study of networked learning. *Interactive Learning Environments, 19*(4), 365–379. http://dx.doi.org/10.1080/10494820903281999.

* Tsal, I. C. (2011). Levels and patterns of participation and social interaction in an online learning community for learning to teach. *Journal of Interactive Learning Research, 22*(2), 191–239. Retrieved from https://www.learntechlib.org/p/33056.

* Uddin, S., & Jacobson, M. J. (2013). Dynamics of email communications among university students throughout a semester. *Computers & Education, 64*, 95–103. http://dx.doi.org/10.1016/j.compedu.2013.01.014.

van Duijn, M. A., & Vermunt, J. K. (2006). What is special about social network analysis? *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 2*(1), 2. http://dx.doi.org/10.1027/1614-2241.2.1.2.

* Vercellone-Smith, P., Jablokow, K., & Friedel, C. (2012). Characterizing communication networks in a web-based classroom: Cognitive styles and linguistic behavior of self-organizing groups in online discussions. *Computers & Education, 59*(2), 222–235. http://dx.doi.org/10.1016/j.compedu.2012.01.006.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.

Wellman, B., Salaff, J., Dimitrova, D., Garton, L., Gulia, M., & Haythornthwaite, C. (1996). Computer networks as social networks: Collaborative work, telework, and virtual community. *Annual Review of Sociology, 22*(1), 213–238. Retrieved from http://annualreviews.org/doi/abs/10.1146/annurev.soc.22.1.213.

* Xie, K., Yu, C., & Bradshaw, A. C. (2014). Impacts of role assignment and participation in asynchronous discussions in college-level online classes. *The Internet and Higher Education, 20*, 10–19. http://dx.doi.org/10.1016/j.iheduc.2013.09.003.

* Yao, Y. (2010). Comparing two discussion designs in terms of student online interactions. In *Proceedings of the 2nd international conference on education technology and computer (ICETC), China* (Vol. 1, pp. V1–V219). http://dx.doi.org/10.1109/ICETC.2010.5529264.

* Zafar, S., Safdar, S., & Malik, B. (2014). Online behaviour of students in a new blended learning course: An experience report. In *Proceedings of the international conference on teaching, assessment and learning (TALE), New Zealand* (pp. 387–394). http://dx.doi.org/10.1109/TALE.2014.7062569.

* Zuo, P., Mu, S., & Han, X. (2012). A social network analysis of students' online interaction in hybrid learning – a case study of "media and teaching" course. In S. K. S. Cheung, J. Fong, L. F. Kwok, K. Li, & R. Kwan (Eds.), *Lecture notes in computer Science: Vol. 7411. Hybrid learning. ICHL 2012* (pp. 155–164). http://dx.doi.org/10.1007/978-3-642-32018-7_15.

3. STUDY 2: ON THE ADOPTION OF SOCIAL NETWORK ANALYSIS METHODS IN CSCL RESEARCH - A NETWORK ANALYSIS

On the Adoption of Social Network Analysis Methods in CSCL Research - A Network Analysis

Marielle Dado, Tobias Hecking, Daniel Bodemer, H. Ulrich Hoppe
University of Duisburg-Essen (Germany)
marielle.dado@uni-due.de, hecking@collide.info, bodemer@uni-due.de, hoppe@collide.info

Abstract: Originating from mathematical sociology, social network analysis (SNA) is a method for analyzing and representing relational structures in online communities. SNA applications in learning settings and CSCL scenarios are growing in popularity, which is in-line with new trends in learning analytics. For the CSCL research community, the adoption of SNA techniques as part of the methodological repertoire requires adequate understanding of the core concepts, their potential contributions, and limitations. We started from the hypotheses that (1) most applications of SNA in CSCL research make use of a small set of basic methods; and (2) the discourse related to SNA is partly inadequate or imprecise. To further analyze and corroborate these "issue hypotheses" we have used network analysis techniques in order to reveal relations between SNA measures and specific aspects of CSCL research (activities, contexts, research methods) based on a corpus of 90 published studies. Based on the results we pinpoint specific issues and outline new opportunities.

Introduction

The methodological foundation of CSCL creates a genuine interest in computational methods to analyze and formally represent relevant characteristics of learning groups and communities based on large amounts of digital data (e.g., log files) collected in technology-enhanced learning settings (Jeong, Hmelo-Silver, & Yu, 2014). Rooted in sociological studies of communities, social network analysis (SNA) provides a well-defined and elaborate mathematical apparatus that resonates with theoretical models based on actor-actor and actor-artefact relations (Wasserman & Faust, 1994). The adoption of SNA in CSCL started more than 15 years ago (Nurmela, Lehtinen & Palonen, 1999; Reffay & Chanier, 2003). Originally, networks derived from email and discussion boards were the most prominent type studied, such as the study of cohesion in learning groups using a shared forum (Reffay & Chanier, 2003). Martínez et al. (2003) present an evaluation method that combines SNA with traditional sources of data and analyses in blended collaborative learning scenarios. More recently, the interest in network analysis techniques related to the study of learning with CSCL and online learning as particular cases has been strengthened by the emergence of learning analytics as a new research paradigm (Haya et al., 2015).

Given the existing usage of SNA in CSCL research, it is not surprising that such methods have been subject to meta-level analyses. One example is a co-citation network analysis of CSCL studies from 2006 to 2013 by Tang, Tsai, & Lin (2014) which found that the most widely cited works in the field pertain to issues regarding CSCL communication and interaction patterns. Social interaction has been referred to as the "key" to collaborative learning: "If there is collaboration then social interaction can be found in it… if there is no social interaction then there is also no real collaboration" (Kreijns, Kirschner, & Jochems, 2003, p. 338). Interactions characterized as "collaborative" do not merely refer to how frequently peers in a joint activity interact, but also to how influential these interactions are in their cognitive processes (Dillenbourg, 1999). Suthers and colleagues consider the fundamental basis of CSCL interactions as the relationship present when one actor's learning activities builds upon that of another actor (Suthers et al., 2010).

Similarly, from the social network perspective, social relations are more important for understanding the behavior of groups and communities than individual attributes. In a group, actions and beliefs are strongly determined by social contexts and conditions (Wasserman & Faust, 1994). In this sense, the perspectives of CSCL and SNA coincide in focusing on social relations that go beyond individual characteristics. CSCL considers learning as a social endeavor, occurring as a result of relationships among learners and between learners and objects in the learning environment (Jones, 2015). By interacting, communicating, and sharing knowledge via computers, learners form "computer-supported social networks" from which learning emerges through constructive information exchange (Haythornthwaite, 1999). A social network approach to CSCL would thus help researchers and practitioners answer the questions: How is information distributed among learners? How much does the group share its information? What media supports this collaboration?

CSCL research has a vibrant, interdisciplinary research tradition that incorporate both qualitative and quantitative techniques (Jeong et al, 2014). SNA itself is also not exclusively one or the other, a trait that has been

an attractive incentive for educational researchers with regards to quantifying social phenomena (Carolan, 2014). Nevertheless, the adoption of SNA methods requires a certain degree of familiarity with mathematical concepts from graph theory and network algorithms, similar to foundations of quantitative-empirical research in statistics. Yet, even after overcoming this first barrier, the new concepts have to be appropriated and integrated with the "CSCL epistemology" so that "technical" SNA are smoothly inter-related with pedagogical interpretations. The bridges that we use in this context should be sound and precise, not just surface-level shortcuts. One example of a problematic bridge is the notion of "interaction pattern" that is frequently mentioned in conjunction with SNA studies. Also, without a deeper understanding of the formal-analytic background a large part of the potential of SNA may remain unexploited.

To empirically study and corroborate these "issue hypotheses", we have applied network analysis techniques to a corpus of publications at the intersection of CSCL and SNA to detect and visualize relations between SNA measures and procedures and specific aspects of CSCL research. These networks encode concept-concept relations based on co-occurrence extracted from the abstracts and the results of publications which were previously subjected to a qualitative literature review. The concepts have been categorized, which allows for introducing a cross-category perspective in the form of multi-mode networks. The themes and trends that emerged from this analysis are then evaluated based on technical definitions of the SNA techniques and may serve as a springboard for researchers to (1) understand how CSCL research is currently viewed through the lens of SNA and (2) identify opportunities to apply underexplored SNA techniques to expand the current knowledge base in CSCL.

Data Sample and Qualitative Findings

The application of SNA in education research has grown in the last decade. However, relative to other research methods, the use of SNA in CSCL settings is not as well-established. A recent review of SNA in a related field, e-learning research (Cela, Sicilia, & Sanchez, 2015), revealed that SNA is mostly applied to study direct interactions between learners collaborating in online discussion forums based on communication patterns; these are usually measured using density and centrality indices. SNA is also often combined with qualitative content analysis to provide a deeper understanding of the nature of learner interaction within the network. The review however is preliminary and limited in that the general search term "e-learning" may have excluded relevant studies that use more specific terminology (e.g., CSCL).

In order to uncover trends in the application of SNA in CSCL research, a qualitative literature review was conducted. Ninety full-text studies published as peer-reviewed journal articles, book chapters, and conference papers were collected from October to November 2015 using the following keywords: social network analysis" AND "computer-supported collaborative learning" online OR computer OR collaborat* (e.g., "collaborative" and "collaboration") OR learning. To be included in the analysis, studies must: (1) use primary data; (2) be set in an instructional course/program up to the postgraduate (Masters) level; (3) use SNA techniques, explicitly mentioned in the Methods section; (4) report SNA findings in the Results section; and (5) analyze collaborative learning activities between learners using computers. Information on the general methodology (research design, learning setting, collaborative activity, non-SNA methods) and SNA features (actor type, relational tie, SNA measures and analysis on SNA data) were identified in each paper and quantified using content analysis.

Similar to the findings of Cela et al (2015) in the e-learning literature, between 50% to 70% of the analyzed studies measured interaction as direct communication between learners during project or task-based activities in blended learning settings, primarily using centrality and density indices. About a quarter of papers conducted content analysis to supplement SNA findings, although analyses of SNA data in most studies were limited to a descriptive report of the SNA indices. More sophisticated SNA procedures, such as identifying network positions and detecting cliques and subgroups, appeared in less than 20% of studies. A handful of studies conducted correlational analysis or inferential statistics on SNA and learner characteristics to enhance the implications of network data on learning.

These results suggest that applications of SNA in CSCL research are rather homogenous, dominated by the basic local and global measures of centrality and density as indicators of social interaction in CSCL environments. Although SNA is a promising method for analyzing collaborative learning in computer-mediated settings, the qualitative literature review lends support to the hypothesis that the analysis of CSCL interactions using SNA may not be adequate due to the limited range of applied SNA measures. In the present paper, we extend the qualitative results by exploring which CSCL activities, contexts, and research methods are associated with which SNA measures and procedures, using network analysis as a technique for meta-level literature analysis (cf. Tang et al, 2014).

Methodology

In network text analysis (NTA) words or concepts are linked by relations based on proximity of occurrence in a text, manual coding, or grammar relations. By extracting terms in a set of texts and constructing a network based on how these terms relate to each other, NTA aims at preserving the conceptual structure of texts. More recently, NTA has also been applied to model and visualize the conceptual structure of learners within a knowledge domain based on questions and answers (Daems, Erkens, Malzahn, & Hoppe, 2014). When used in this manner, NTA could be considered automated technique for classical content analysis (Diesner & Carley, 2005). Our NTA approach is based on the network extraction pipeline used in state of the art NTA tools, such as Tools Automap (Diesner & Carley, 2005) and ConText (Diesner, 2014), and comprises three main steps: (1) concept identification, (2) concept normalization and classification, and (3) relation extraction.

First, the abstracts and the results section of the papers were prepared for analysis by removing non-relevant words (articles, auxiliary verbs, etc.) and stemming by removing suffixes. Then, parts-of-speech identification was done to identify nouns, adverbs and adjectives that represent concepts in the literature. The extraction process produced 3,057 unigrams (single nouns) and 38,934 bi-grams (two terms, combination of nouns, adjectives and adverbs), from which the top 150 unigrams and bigrams were included in the next step.

Table 1 Codebook example.

Term	Concept	Categories
knowledge construction	KNOWLEDGE_CONSTRUCTION	CSCL_ACTIVITY
construction of knowledge	KNOWLEDGE_CONSTRUCTION	CSCL_ACTIVITY
online course	ONLINE_COURSE	CSCL_CONTEXT
content analysis	CONTENT_ANALYSIS	CSCL_METHOD
betweenness centrality	BETWEENNESS_CENTRALITY	SNA

An excerpt of the codebook used to identify and classify concepts in the pool of studies is displayed on Table 1. The first column contains concrete terms occurring in the texts. To account for different spellings and synonyms, the second column maps the specific terms in the first column to a general concept. The third column assigns each concept to one of the four categories: (1) “CSCL activity” for terms associated with aspects of a collaborative learning activity (e.g., “knowledge building”, “score”); (2) “CSCL context” for terms pertaining to physical/virtual settings or platforms where CSCL activities take place (e.g., “class”, “forum”); (3) “CSCL method” for terms pertaining to other analysis methods applied alongside SNA (e.g., “correlation”); (4) “SNA”, for terms related to SNA procedures and techniques (e.g., “centrality”). After combining synonyms and spelling variations, the final analysis included 101 concepts: 22 SNA, 45 CSCL activity, 23 CSCL context, 11 CSCL method. Figure 1 shows how the codebook is used to automatically identify and classify the concepts in text.

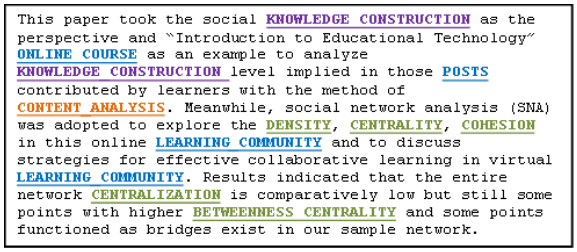


Figure 1 Concept identification, normalization and classification
(purple: CSCL_ACTIVITY, blue: CSCL_CONCEPT, orange: CSCL_method, blue: CSCL: CONTEXT, green: SNA)

Once the CSCL and SNA concepts have been identified, the next step is to extract a concept network that reflects the associations made between the different concepts in the selected CSCL literature. First, for each publication the identified concepts from the codebook are interlinked to a fully connected network (or concept clique). Second, the concept cliques corresponding to particular publications are merged by overlaying these networks such that the result is a single network which contains all concepts and all links from the original networks. It is important to mention that in order to account for the relationships between SNA and CSCL a bipartite version of the network was used, which restricts the original one to having edges solely between SNA and CSCL concepts. The weight of each edge between two concepts corresponds to the number of concept cliques containing this edge, i.e., the number of papers in which the concepts co-occur.

The resulting edge-weighted and bipartite network together with the category attributes of nodes is the basis for our further analyses. In particular, we analyze the network in terms of distance between concepts and cohesive clusters, which will be described in more detail in the following section.

Analysis and Results

For a first overview we provide a frequency count of the number of publications mentioning the 22 SNA concepts. The result shown in Figure 2 supports the findings of the qualitative literature review that the usage of SNA in CSCL research is mostly restricted to centrality analysis. The most basic measure "degree centrality" appears in the abstracts and result sections of 70 of the 90 papers. In contrast, more advanced techniques such as modularity of sub-communities, positional analysis using blockmodels, or network simulation are rarely mentioned.

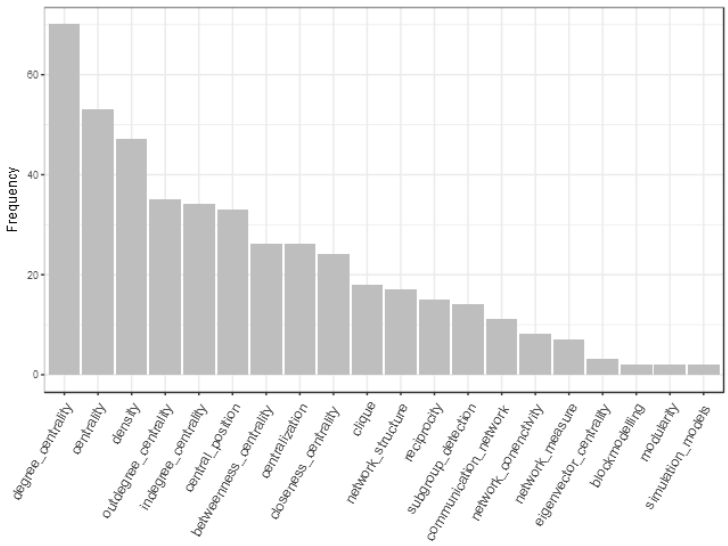


Figure 2 Number of occurrences of different SNA concepts in the 90 documents.

To further investigate the contexts in which particular SNA concepts are applied, the previous findings are extended by identifying for each SNA concept the closest CSCL concepts based on geodesic distance in the concept network. The edge weights (i.e., number of co-occurrences) of concepts were taken into account by setting the edge distance between connected concepts to the inverse of its weight.

Table 2: Profiles of SNA concepts based on proximities to different types of CSCL concepts.

SNA	CSCL Activity	CSCL Context	CSCL Method
Degree Centrality	groupwork, interaction, help	course, message, class	interaction_pattern, correlation, questionnaire
Centrality			correlation, content_analysis, interaction_pattern
Density	groupwork, interaction, communication		
Outdegree Centrality			
Indegree Centrality			interaction_pattern, correlation, questionnaire
Central Position	groupwork, interaction, role	message, course, post	content_analysis, correlation, interaction_pattern
Betweenness Centrality	groupwork, interaction, discussion		correlation, interaction_pattern, questionnaire
Centralization	groupwork, interaction, communication	course, message, class	content_analysis, interaction_pattern, correlation
Closeness Centrality	groupwork, help, interaction		correlation, interaction_pattern, questionnaire
Clique		course, message, post	
Network Structure	groupwork, interaction, communication	course, message, class	
Reciprocity			
Subgroup Detection	groupwork, interaction, help		
Communication Network	communication, groupwork, interaction		

Network Connectivity	groupwork, communication, help		
Network Measure	groupwork, discussion, interaction		
Eigenvector Centrality	groupwork, help, interaction		
Blockmodelling	communication, groupwork, discussion	course, discussion_forum, message	
Modularity		class, post, course	
Simulation Models	communication, groupwork, participation	course, message, class	time_period, interaction_pattern, correlation

Table 2 lists for all SNA concepts the three closest CSCL concepts of each category (Activity, Context, Method) yielding characteristic profiles of the SNA concepts in terms of their proximity to CSCL concepts. “Groupwork”, “interaction”, and “communication” as CSCL activities are the closest to most SNA terms, which suggests that interactions within CSCL group activities are often characterized by communication. The proximity of the concept “help” to the node- and group-centric SNA concepts (e.g., centrality, clique) suggests that help or support are mostly associated with positions of individuals in a social network. In the CSCL method category, “correlation analysis” and “questionnaire” alongside “interaction pattern” appeared in almost every profile. As was found in the qualitative literature review, this indicates that SNA is commonly used in combination with empirical data collected from questionnaires to relate structural network properties to quantitative measures of learning. Simulation models for social networks constitute the only SNA concept that is closely related to time (“time_period” in the category CSCL Method).

Next, we have specifically analyzed the relation between SNA concepts and CSCL concepts in terms of cohesive bipartite network clusters to reveal the inherent organization of the complex network. Cohesive clusters in such a network stand for subgroups or clouds of terms that are more densely connected among each other than the average of the network. This cohesiveness can be characterized by the “modularity” measure (cf. Barber, 2007), here particularly using *bipartite modularity maximization* (Hecking, Steinert, Göhnert, & Hoppe, 2014). The clustered network representation shown in Figure 3 results from the following workflow: (1) filtering out of “weak” edges with weight below 8; (2) further reduction of the network to its 2-core to ensure that the remaining nodes are connected to at least 2 others (no singular or satellite nodes); (3) identification of mixed clusters of SNA and CSCL concepts based on bipartite modularity; (4) visualization, as presented in Figure 3. The color of the nodes indicates cluster association and node size is scaled according to its degree in the weighted network. The shapes of the nodes represent the different categories.

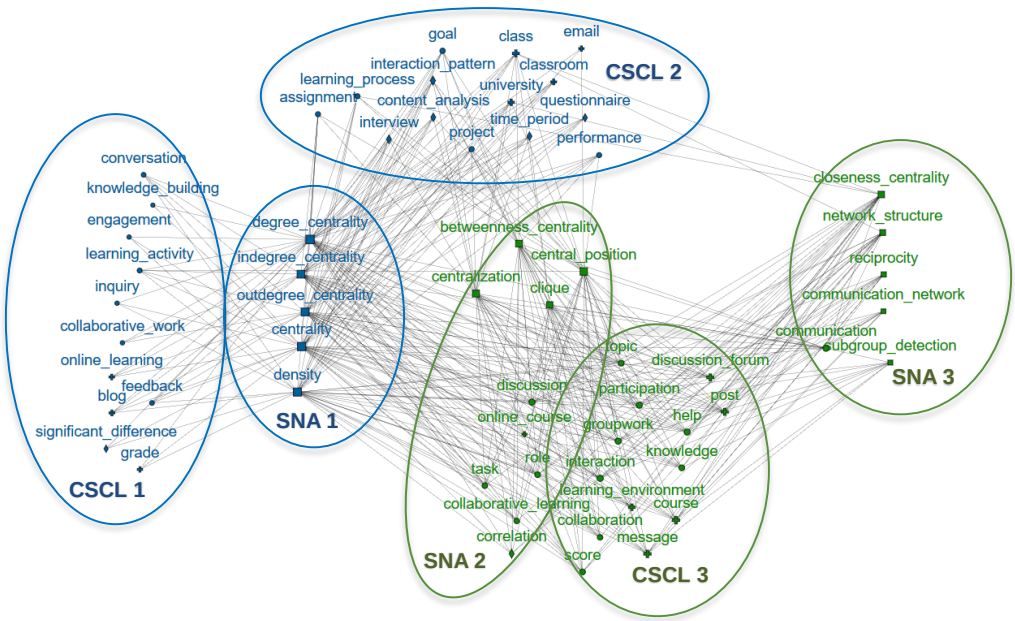


Figure 3 Result of the bipartite modularity optimization.
(• - CSCL activities, ♦ - CSCL research methods, ✚ - CSCL context, ■ - SNA concepts)

The applied clustering algorithm identifies two clusters. The network is very densely connected, however interesting relational patterns between different parts of the network are salient. The blue cluster can be further divided into three groups of concepts indicated by the ellipses in Figure 3. The group "CSCL 1" contains general CSCL activities that are almost solely linked to the most common SNA concepts (SNA 1) and not to third blue group (CSCL 2), which in turn is strongly connected to the SNA concepts in its cluster (SNA 1) as well as in the other cluster (SNA 2). A similar pattern can be discovered for the green cluster. Here there is a group of SNA concepts (SNA 3) that is almost completely separated from the blue cluster. The concepts in this group can be considered as less common compared to the other SNA concepts in the network. The green cluster further contains SNA concepts (SNA 2) and CSCL concepts (CSCL 3) that act as bridges between the two large concept clusters. The distinction between groups of concepts based on "strong" connections to groups within the same cluster and "weak" connections to groups of the other cluster can be used to reveal the overall relational structure of SNA and CSCL concepts in the investigated literature. This macro-structure is shown in Table 3, which is also called an image matrix (Wasserman & Faust, 1994). Image matrices depict the presence or absence of pre-defined relations (here weak, strong, or absent) between different parts of a network and can be considered as a characteristic to help interpret the inherent organization of a given network

Table 3: Relationships between different parts of the concept network as image matrix.

	CSCL 1 (blue cluster)	CSCL 2 (blue cluster)	CSCL 3 (green cluster)
SNA 1 (blue cluster)	strong	strong	weak
SNA 2 (green cluster)	absent	weak	strong
SNA 3 (green cluster)	absent	absent	strong

SNA concepts in SNA 1 (indegree/outdegree centrality, centrality, degree centrality) and CSCL 3 (e.g., course, post, collaborative_learning, groupwork), are interlinked to most parts of the network, and can be considered as the conceptual core of the usage of SNA in CSCL research. Note that the terms in CSCL 3 are the same as the CSCL terms that appear in the proximity analysis in Table 2. The least connected CSCL group (CSCL 2) pertain to specific environments (e.g., blogs), pedagogical approaches (e.g., knowledge building), or processes (e.g., engagement); these are studied using most common SNA indices of centrality and density (SNA 1). Similarly, the least connected SNA group (SNA 3) contains techniques that are less frequently applied; this cluster is only associated with the most prominent CSCL concepts (CSCL 3).

Discussion

Overall the analyses presented in this paper demonstrate a visible relational structure and conceptual core of SNA and CSCL activities, contexts, and methods that are present in the CSCL literature. The profiles generated using network analysis techniques corroborate the findings of the qualitative literature review, namely that SNA applications in CSCL research aim to understand CSCL "interaction patterns" based on communication. This was the case for all SNA indices included in the analysis and not only the most frequently used indices of centrality and density. The results also show that there have been efforts to associate these interaction patterns with learning-related variables using statistical methods (correlation), which could be seen as a way of bridging research perspectives between CSCL and education traditions (Carolan, 2014). In this section we critically discuss the core CSCL concept of "interaction patterns" in relation to the technical underpinnings of the core SNA indices.

Given the high connectivity of "interaction" and "communication" to the most prominent SNA concepts in our pool of studies, one might think that "interaction pattern" is a technical term derived from SNA. However, the basic SNA measures that were used frequently in our sample, especially centrality measures but also subgroup detection methods, only characterize relational attributes based on the connectivity of single nodes (actors), sub-networks, or the entire network. Centralization and reciprocity are global measures that indeed reveal certain general network characteristics and can characterize the topology of communication in networked learning environments. This can be conceived as a certain type of structural-relational pattern, but it is not about repeated concrete constellations, especially not in a temporal sense. The SNA technique of blockmodeling would be a means of detecting roles and role models based on consistent network structures and relational similarity. However, as our results show, it has been rarely used in CSCL studies.

Furthermore, single instances of social networks do not represent time-dependent relations, but rather capture and aggregate relations harvested during a given time window. Hoppe, Harrer, Göhnert, Hecking (2016) have made the point that the choice of different time windows as a step prior to the network generation can have systematic effects on the ensuing analysis results. While SNA research has developed several ways to handle dynamic networks that evolve over time (Aggarwal & Subbian, 2014), such techniques are not widely adopted in

CSCL: the only indication of considering time dependencies in combination with CSCL concepts was related to network simulation models, which is one of the least common SNA methods in our results. Since it has been argued that the explicit consideration of temporal processes is crucial to make sense of data produced in CSCL environments (Reimann, 2009), a future advancement of SNA in CSCL can be to consider dynamic network analysis methods based on time series of graphs.

All this indicates that the notion of "interaction patterns" as measured in SNA is indeed not very specific in a technical sense: what constitutes "interaction patterns" is not strictly operationalized in SNA. Thus, the actual technical definitions of SNA measures should be clarified when interpreting SNA findings. The SNA concept of "density", the third frequent in our list of SNA concepts is another example for potential issues: There is a general caveat concerning the usage of density as a comparative measure applied to networks of different sizes (including growing networks). *Density* as a general measure for graphs is equal to the *average degree divided by the number of nodes* in the graph. On the other hand, in most naturally evolving networks the *average degree* will grow (if at all) at a much lower rate than the number of nodes. For scale-free networks (Barabasi & Bonabeau, 2003) the average degree is inherently constant. This means that the smallest networks will have the highest density. Hoppe, Engler & Weinbrenner (2012) have discussed this effect when studying student-generated concept maps. This makes it difficult to definitively identify an "optimal" density level of communication in CSCL research, where units of analysis tend to vary in size (Stahl, 2015). Density can be reasonably used as a comparative measure only with networks that have an identical number of nodes, otherwise the ratio of *number of edges per number of nodes* (which is proportional to the *average degree*) should be used.

In sum, the results indicate mismatches between the intended aims of applying SNA in CSCL (i.e., to investigate interaction patterns) and the actual technical definitions of SNA concepts even at the most basic level. SNA *describes* characteristics of network structures based on several common indices, and those descriptions do not necessarily capture consistent patterns of interaction that persist over time and onto other contexts. A number of sophisticated SNA techniques that are able to accomplish this, such as blockmodeling, measures on time series of networks, and network simulations, are largely underexplored.

Conclusion

The adoption of SNA techniques in CSCL is very much focused on understanding and modeling "interaction patterns". However, we also argue that CSCL "interaction patterns" do not necessarily become apparent from the basic and most commonly used SNA indices. However, despite SNA originating from a different analytical tradition, its use in combination with statistical analysis shows how SNA is able to cut through disciplinary boundaries. We hope that interested CSCL researchers will use our analysis as a basis for expanding the current knowledge body to include advanced SNA techniques for exploring other network dimensions such as time. This challenge would not only contribute to a more nuanced analysis on CSCL interactions, but it would also enrich the interdisciplinarity of research methods and the skill sets of CSCL researchers. As long as the CSCL community is interested in the study of social interactions, there is a place for SNA in this research field.

Acknowledgements

This work was supported by the Deutsche Forschungsgemeinschaft (DFG) under Grant No. GRK 2167, Research Training Group "User-Centred Social Media".

References

Aggarwal, C., & Subbian, K. (2014). Evolutionary network analysis: A survey. *ACM Computing Surveys (CSUR), 47*(1), 10. doi:10.1145/2601412.

Barabási, A. L., & Bonabeau, E. (2003). Scale-free networks. *Scientific American, 288*(5), 50-59.

Barber, M. J. (2007). Modularity and community detection in bipartite networks. *Physical Review E, 76*(6), 066102. https://doi.org/10.1103/PhysRevE.76.066102

Carolan, B. V. (2014). *Social network analysis and education: Theory, methods & applications*. California: Sage Publications.

Cela, K. L., Sicilia, M. A., & Sanchez, S. (2015). Social network analysis in e-Learning environments: A preliminary systematic review. *Educational Psychology Review, 27*(1), 219–246. doi:10.1007/s10648-014-9276-0.

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.

Daems, O., Erkens, M., Malzahn, N., & Hoppe, H. U. (2014). Using content analysis and domain ontologies to check learners' understanding of science concepts. *Journal of Computers in Education, 1*(2), 113-131. doi.10.1007/s40692-014-0013-y

Diesner, J. (2014). *ConText: Software for the integrated analysis of text data and network data.* Paper presented at the Social and Semantic Networks in Communication Research. Preconference at Conference of International Communication Association (ICA), Seattle, WA.

Diesner, J., & Carley, K. M. (2005). Revealing social structure from texts: Meta-matrix text analysis as a novel method for network text analysis. In V.K. Narayanan and D. Armstrong (eds.), *Causal mapping for information systems and technology research* (p. 81-108). Hershey, PA: IGI Global.

Haythornthwaite, C. (1999). Collaborative work networks among distributed learners. In R. Sprague (ed.), *Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences, 1999. HICSS-32, Hawaii, US* (pp. 1023-39). Virginia, US: IEEE Computer Society Press. doi:10.1109/HICSS.1999.772707

Haya, P. A., Daems, O., Malzahn, N., Castellanos, J., & Hoppe, H. U. (2015). Analysing content and patterns of interaction for improving the learning design of networked learning environments. *British Journal of Educational Technology*, *46*(2), 300-316. doi:10.1111/bjet.12264

Hecking, T., Steinert, L., Göhnert, T., & Hoppe, H. U. (2014). Incremental clustering of dynamic bipartite networks. In *Proceedings of the 2nd European Network Intelligence Conference (ENIC 2014) Wroclaw, Poland* (pp. 9-16). Los Alamitos, CA : Conference Publishing Services. doi:10.1109/ ENIC.2014.15

Hoppe, H. U., Engler, J., & Weinbrenner, S. (2012). The impact of structural characteristics of concept maps on automatic quality measurement. In J. van Aalst, K. Thompson, M. Jacobson, and P. Reimann (eds.), *Proceedings of the 10th International Conference of the Learning Sciences (ICLS 2012), Sydney, Australia* (pp. 308-316). Sydney: International Society of the Learning Sciences. www.isls.org/icls2012

Hoppe, H. U., Harrer, A., Göhnert, T., & Hecking, T. (2016). Applying network models and network analysis techniques to the study of online communities. In U. Cress, J. Moskaliuk, and H. Jeong (eds.), *Mass Collaboration and Education* (pp. 347-366). Switzerland: Springer International Publishing.

Jeong, H., Hmelo-Silver, C. E., & Yu, Y. (2014). An examination of CSCL methodological practices and the influence of theoretical frameworks 2005–2009. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 305–334. doi:10.1007/s11412-014-9198-3.

Jones, C. (2015). *Networked learning: an educational paradigm for the age of digital networks*. Switzerland: Springer International Publishing.

Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: A review of the research. *Computers in Human Behavior*, *19*(3), 335–353. doi:10.1016/S0747-5632(02)00057-2.

Martínez, A., Dimitriadis, Y., Rubia, B., Gómez, E., & De La Fuente, P. (2003). Combining qualitative evaluation and social network analysis for the study of classroom social interactions. *Computers & Education*, *41*(4), 353-368. doi:10.1016/j.compedu.2003.06.001

Nurmela, K., Lehtinen, E., & Palonen, T. (1999). Evaluating CSCL log files by social network analysis. In C. Hoadley and J. Roschelle (eds.), *Proceedings of the 1999 Conference on Computer Support for Collaborative Learning*, article no. 42. International Society of the Learning Sciences. http://dl.acm.org/citation.cfm?id=1150294.

Suthers, D. D., Dwyer, N., Medina, R., & Vatrapu, R. (2010). A framework for conceptualizing, representing, and analyzing distributed interaction. *International Journal of Computer-Supported Collaborative Learning*, *5*(1), 5–42. doi:10.1007/s11412-009-9081-9.

Stahl, G. (2015). A decade of CSCL. *International Journal of Computer-Supported Collaborative Learning*, *10*(4), 337–344. doi:10.1007/s11412-015-9222-2.

Tang, K. Y., Tsai, C. C., & Lin, T. C. (2014). Contemporary intellectual structure of CSCL research (2006–2013): a co-citation network analysis with an education focus. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 335–363. doi:10.1007/s11412-014-9196-5.

Reffay, C., & Chanier, T. (2003). How social network analysis can help to measure cohesion in collaborative distance-learning. In B. Wasson, S. Ludvigsen, and H. U. Hoppe (eds.), *Designing for change in networked learning environments* (pp. 343-352). Springer Netherlands. doi:10.1007/978-94-017-0195-2

Reimann, P. (2009). Time is precious: Variable-and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning*, *4*(3), 239-257. doi:10.1007/s11412-009-9070-z.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 1). Cambridge University Press.

4. STUDY 3: SOCIAL AND COGNITIVE GROUP AWARENESS TO AID ARGUMENTATION ABOUT SOCIALLY ACUTE QUESTIONS ON SOCIAL MEDIA

Social and Cognitive Group Awareness to Aid Argumentation about Socially Acute Questions on Social Media

Marielle Dado, Daniel Bodemer, University of Duisburg-Essen
marielle.dado@uni-due.de, bodemer@uni-due.de

Abstract: Debates about socially acute questions (e.g., migration) may help develop argumentation skills. However, students may be hesitant to present different views to maintain interpersonal relationships, hindering communication and integration of multiple perspectives. Social networking sites (SNS) have been used to extend classroom discussions to such real-world topics. However, their flat-structured layout may not suit argumentation activities. This quasi-experiment in an applied classroom setting investigates the effects of a group awareness tool (GAT) that combines social (group members' names) and cognitive (discussion points/ stance in initial arguments) information in a network graph to aid communication behavior and integration of multiple perspectives during argumentation on a flat-structured SNS. Students supported by the GAT engaged in discussions with non-friends and students outside their class more than the control group, though the latter integrated multiple perspectives more. The GAT appears to have increased familiarity among non-friends. The potential influence of interpersonal relationships on integration of multiple perspectives is discussed.

Introduction

Interpersonal relationships have been found to influence learning outcomes, especially when it comes to discussions about *socially acute questions* (SAQs): social dilemmas that are often controversial and that have implications on several fields of knowledge (Simonneaux, 2007). Students tend to be exposed to media representations of SAQs that are socio-sociological (e.g., immigration, globalization) or socio-scientific (e.g., global warming, cloning) in nature, which means that students may already have personal opinions about these issues (Zeidler & Nichols, 2009). Thus, introducing SAQs in the classroom provides an opportunity for differing views to emerge, and therefore for argumentation skills to develop. However, given the controversy that often surrounds SAQs, students may be hesitant to express disagreement in the interest of maintaining harmonious interpersonal relationships (Kuhn, Wang, & Li, 2010). This is a challenge because demonstrating and acknowledging awareness of opinions and perspectives other than one's own is a marker of good argumentation quality (Sadler & Donnelly, 2006). In order to develop argumentation skills, students should be exposed to multiple perspectives through social interaction and discourse in order for them to evaluate claims, analyze evidence, and make informed judgements about these issues (Simonneaux, 2007; Leitão, 2000).

Recently there has been growing interest in the use of social networking sites (SNS) such as Facebook and Google Community to support discussion and mutual learning between students (Manca & Ranieri, 2013). One big motivation for teachers to adopt SNS in their classroom is to have a platform to discuss real-world issues related to the current lesson (Chen & Bryer, 2012). This suggests that social media may be an appropriate platform to discuss SAQs. However, since many SNS platforms were built for commercial rather than learning purposes, they may lack structural features that promote meaningful discussions between learners. Kirschner (2015) particularly criticized the "flat structure" arrangement of discussions on SNS: that is, unlike hierarchical and threaded discussions, posts on a typical SNS appear all in one page in reverse chronological order, with replies to each post appearing un-nested below each post. This makes it difficult to find one's own postings, let alone those of others (Kirschner, 2015). In an argumentation activity, this could make it difficult for learners to become aware of others' discussion points and to connect their claims to the arguments of their peers. To overcome this limitation, group awareness tools (GATs) could be designed to provide information through visualizations about members of a learning group to implicitly aid individual learners to behave, communicate, and reflect in ways that are productive for collaboration and learning (Janssen & Bodemer, 2013). This information can be broadly categorized as (1) social/behavioral awareness, such as who are the group members, who they are communicating with, or how they are contributing to the task; or (2) cognitive/knowledge awareness, such as the level of prior knowledge of group members, the information that they possess or opinions that they hold. When GATs are designed to allow for comparison of one's knowledge or behavior to that of their peers', learners may adapt their actions accordingly. For example, GATs that highlight knowledge differences led learners to communicate with their peers to fill their knowledge gaps (Erkens, Schlottbom, & Bodemer, 2016) or to discuss perceived conflicts with peers in a more interactive way (Bodemer, 2011).

Studies about GA support specifically for social and attitudinal characteristics of group members during argumentation in SNS have yielded some promising results. In a series of controlled lab experiments, Tsovaltzi and colleagues supported group awareness on a Facebook-like platform by informing participants, as they were preparing their individual arguments prior to collaborative discussion, that their arguments may be published after completion of the experiment for other students to comment and amend. In one study (Tsovaltzi, Puhl, Judele, & Weinberger, 2014), they found beneficial interaction effects on individual argument elaboration when combined with argumentation scripts, but a detrimental main effect on learning. In another study, they additionally found that group awareness did not lead to considering multiple perspectives (Tsovaltzi, Judele, Puhl, & Weinberger, 2015). The researchers hypothesize that group awareness in this case led to overcautiousness whilst constructing their initial arguments, which led to more individualistic behavior. Puhl, Tsovaltzi & Weinberger (2015) found that displaying in a 2-dimensional space the communication attitudes of the group members' relative to one's own attitudes led to gains in domain knowledge and a change of attitude towards multi-perspective communication.

Previous work suggests that the interpersonal relationships between students may have an influence on their awareness of multiple perspectives, which is essential for successful argumentation. Although previous GAT research in argumentation in SNS have demonstrated some promising effects, none so far have addressed overcoming the "flat-structuredness" of SNS by bringing awareness to the diversity of arguments in the community and enabling comparison of one's opinions to the opinions of others. The present study investigates the effects of a GAT that attempts to address these concerns: by combining social information (names of group members) and cognitive information (discussion points and stance of each group member) in a network graph to aid argumentation on a flat-structured SNS. Particularly, the influence of GA support on communication behaviour, learning outcomes, shifts in opinions, awareness and integration of multiple perspectives are evaluated in a SNS in applied classroom setting, which is different from most GA studies on argumentation in SNS which are usually conducted in laboratory settings (Tsovaltzi et al, 2015; Bodemer, 2011). In addition, the study also describes how users interact with a GAT arranged in a network graph and what these interactions imply about how the information contained in it is processed productively.

Method

Design and participants

A quasi-experiment was conducted with twenty-nine Year 12 students (*mean age*=17.2, *SD*=.45) in two Economics classes with the same teacher in an International Baccalaureate (IB) school in Germany. Because the experiment sessions were embedded as classroom activities, the research design was selected in the interest of ecological validity and in order not disrupt the remaining class time. One class (n=14) was randomly assigned as the control group and the other (n=15) was assigned as the GAT (i.e., experimental) group. Their final Economics grades in Year 11 (7 is the highest possible grade) shows that prior academic performance between the control (M=6.2, SD=1.17) and GAT (M=5.86, SD=1.1) groups is similar. In terms of English language ability, most of the students are placed in English A class (native/native-like speakers), except for 1 student in the control group and 3 students in the GAT group. However, the teacher believes that both classes are competent in academic English, and the English B students perform well in their economics classes. Six Year 12 students (all 17 years old) from an IB school in Australia also took part in the experiment as a classroom activity and interacted with participants; however, due to technical difficulties their data was excluded from the analysis.

Social media learning environment, learning activity and instructions

The social media platform used for the study is called Google+, an SNS created by Google, which allows users to create "Communities" in which users can engage in asynchronous discussions about specific topics. The format can be described as flat-structured (e.g., posts appear chronologically and replies to posts were not nested). This platform was selected by the IB Economics teacher as it could be easily integrated into the students' existing web tools, since all student email addresses were hosted by Google's email service Gmail, which is required to access Google+. The teacher created a private Google Community for his 2 Economics classes, as well as the economics class of a former colleague in Australia, to provide a platform for debates about real-world issues related to economics. Apart from a brief session in which each student had to post a short self-introduction, participants had no prior experience with Google+ before the experiment sessions.

Four experiment sessions were integrated as class activities in 4 separate 50-minute Economics class periods over the course of 4 weeks (1 session per week). Both groups completed Sessions 1, 3 and 4 on the same days. Due to some technical problems, Session 2 for the GAT group was postponed to the day after the control group completed Session 2. No class was allowed to proceed to the next session until all students have

participated in the current one. Students worked on the experiment sessions on their own computers and were not allowed to engage in off-task behavior or speak to their classmates. They were also not allowed to interact on Google Community outside experiment sessions.

The first 3 experiment sessions corresponded to the knowledge building cycle proposed by Leitão (2000) whereby students first (1) construct an initial argument (Session 1); (2) have the opportunity to construct a response/counterargument (Session 2); and (3) construct a reply to responses they received and revise initial argument (Session 3). “Migration” was selected as the topic for discussion for its relevance to the Development Economics unit of the IB Economics syllabus and informal observations that suggested a diversity of perspectives among the students. In Session 1, each student was asked to create a post on Google Community with a 4-6 sentence argument to the question: “To what extent do you agree with the statement: ‘Migration from developing to developed countries leads to economic development.’?” Each post had to (1) mention at least 1 economic stakeholder and whether it benefits from migration; and (2) had to be supported by at least 1 article from a credible online resource (students were provided with links to appropriate sources). In Session 2, both control and GAT groups were given the same instructions to follow when commenting, namely (1) comment on at least 1 post; (2) structure comments around their initial arguments in Session 1; (3) if they hold the same perspective, write down exactly what they agree on and why; (4) if they hold a different perspective, write down exactly what they disagree on and why; (5) ask questions if something is not clear or if they would like more information; (6) give feedback or suggestions and explain why they think this could be helpful. Students were also explicitly instructed to read as many posts as they can before commenting, as well as how to use the “Search” function to find posts by specific people, so that they do not simply comment on the first post they see. In Session 3, students were instructed to (1) add to or edit their Session 1 argument if their perspective has changed, or to write new 4-6 sentence response to the initial question; or (2) write about why their perspective has stayed the same. In Session 4, students answered a survey about their experience during the experiment.

Group awareness tool

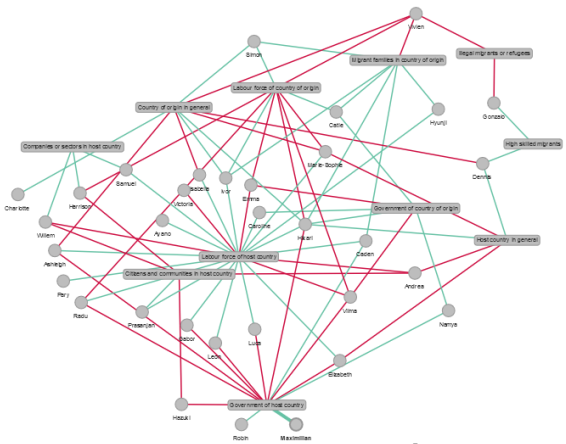


Figure 1: Group awareness tool

The GAT provided to the GAT group visualizes how each student’s initial argument (Session 1) is positioned with respect to the opinion/responses of their peers (see Figure 1). The tool is a network graph composed of *2 types of nodes*: (1) *students* (circles); and (2) migration *stakeholders* (rectangles). An *edge* is drawn between these 2 node types *if the student mentions that stakeholder* in their initial argument, with the *color (green or red) indicating the stance* of the student (whether it benefits or does not benefit from migration, respectively). Two coders jointly identified 11 stakeholders from the initial arguments and independently coded the stances (Cohens’ k=0.86). The network graph was then created using the R package visNet that produced an interactive graphic that allowed users to click and rearrange the graph elements. The following clickstream data was logged by the tool: *drag view* (i.e., zooming, panning and scaling the view of the graph), *click node, drag node, click edge, drag edge*. The tool itself is hosted on a separate URL and was not integrated on Google Community. Therefore, students had to keep two browser windows open during the experiment sessions (one for the tool, one for Google Community). The tool was intended for students in the GAT group to help them select which student (posts) to reply to in Session 2, based on their initial arguments on the discussion topic in Session 1. Somewhat similar to the GAT of Puhl et al (2015) on a 2D space, the networked arrangement of students and stakeholders (i.e., discussion points) allows not only a general overview of the initial arguments in the entire community, but also enables individuals to compare their arguments to those of others based on their connections (or lack thereof) to the same stakeholders. Based on previous GAT research that also enabled users to compare their information to others (e.g., Erkens et al, 2016), this arrangement along with the color-coded edges should help students to easily identify differences between stances on the same stakeholders and use it as a point of discussion. Thus, in order to overcome the flat-structured layout of Google Community, the GAT was designed to influence communication behavior on the basis of social (names of group members) and cognitive information (discussion points and stance of each group member), specifically with regards to differences in opinion.

Procedure

In *Session 1*, students were first given 5 minutes to answer a survey that asked for their opinion on specific migration stakeholders (see "Measures…" section). Then they were asked to create individual posts on Google Community with their initial arguments regarding the topic of migration, as stated in the "Social media learning environment…" section. Students were also encouraged, but not required, to use the sentence starter "I agree/do not agree with the statement…". Students were given 15 minutes to post their initial arguments. In *Session 2*, the *control group* proceeded to read and comment on their peers' posts on Google Community for 15 minutes, whereas the *GAT group* was first introduced to the GAT in two phases. First, students were trained on how to interpret the GAT using a small-scale version with dummy data and were prompted to identify student pairs that had the same/different opinion on the same stakeholder. Second, they viewed the GAT and were instructed to find their name and compare their Session 1 arguments with the arguments of their peers. They were explicitly told that the GAT is interactive, and that they could click and drag the graph elements. Students were then asked in a survey to identify at least 1 student that shared/did not share their opinion on the same stakeholder. They were given 5 minutes for the training phase and 10 minutes to explore the GAT, before being given a further 15 minutes to comment on at least 1 of their peers' posts on Google Community, just like the control group (the tool was made available to them during this time). In *Session 3*, students were instructed to read their Session 1 arguments and reflect on whether their perspective has changed since reading, commenting and receiving comments on their posts. Then, in the form of a comment on their Session 1 post, they were instructed to revise their initial opinions and respond to the comments they received. They were given 15 minutes to complete Session 3. *Session 4* was a post-study questionnaire that asked students about their experiences in the Google Community activity (see "Measures…" section).

Measures, research question, and hypotheses

Communication behavior is defined as how students chose to reply to certain posts over others on Google Community in Session 2. The initial opinions of each student as expressed in Session 1 (i.e., stakeholders mentioned and stance) were compared the initial opinion of the student that they replied to in Session 2, and categorized as having: (1) the same opinion on at least 1 stakeholder; (2) a different opinion on at least 1 stakeholder; or (3) having no shared opinion on a stakeholder. Students were also asked to indicate who among the students in the Google Community they would consider as their friends to check whether *friendships* had any influence on their communication behavior. *Integration of multiple perspectives* was based on Leitão's (2000) description of the impact of others' perspectives from the discussion on one's initial argument: multiple perspectives can be dismissed, localized (alternative perspectives are acknowledged but the initial argument is retained), integrated with initial opinions (e.g., allowing for some exceptions or conditions), or fully accepted. The final arguments were coded accordingly by two coders (kappa=.76).

To measure *learning outcomes*, the teacher administered two practice exams for IB Economics (as is standard practice in the school) before Session 1 and after Session 4. These covered topics from the Development Economics unit of the IB Economics syllabus. One question (worth 8 points) required students to apply their economics knowledge to evaluate a reference news article (pre-test: the impact of the involvement of China in Ethiopia's economy; post-test: strategies that the Haitian government can use to improve their economy). As stated in the grading rubric, to successfully answer the essay question "students must offer a considered and balanced review that includes a range of arguments, factors or hypotheses. Opinions or conclusions should be presented clearly and supported by appropriate evidence". Therefore, students were required to apply the same argumentation skills in both the exam question and the experiment sessions.

Another measure administered before and after the experiment was *opinions on migration stakeholders*. In Session 1 (before posting initial arguments) and Session 4, students rated 8 economic stakeholders of migration in both the host (developed) country and country of origin (developing) according to whether migration negatively or positively benefits them (1 – very negative impact to 5 – very positive impact). *Awareness of the multiple perspectives* was evaluated in Session 4 by asking students, for each of the 11 stakeholders appearing on the GAT, whether they perceived the overall opinion in the community of the impact of that stakeholder on migration as mostly positive, negative, or rather well-distributed between the two stances. One point was given for each correct answer for a total of 11 points. In addition to the dependent variables and the clickstream data logged by the GAT, *self-reports on the experiences of the GAT group with the GAT* were collected in Session 4. Students were asked to rate (1 – strongly disagree to 5 – strongly agree) 4 statements pertaining to the usefulness of the GAT in (1) representing their initial argument; (2) providing them with an overview of the Community's opinion on migration stakeholders (3) helping students identify which of their peers agreed/disagreed with their opinions; and helping students decide which posts to (3) read and (4) comment on in Session 2. Participants were also asked to *assess their own change in perspective*: whether their

perspectives (1) completely changed, (2) did not change at all, (3) changed by integrating new perspectives with original ones, or (4) did not change, but they were able to acknowledge alternative perspective (i.e., localized, Leitão, 2000). They were also asked to specify the most influential source of their change in perspective.

Finally, several control variables were also analyzed to investigate how they may impact the findings on the dependent variables. First, *argumentation quality of initial arguments* in Session 1 were assessed based on whether a credible source was cited, as well as on Sadler & Donnelly's (2007) rubric on "position and rationale" for argumentation, specifically whether or not the claims were grounded ("offers a coherent, logically consistent argument that includes an explanation and rationale for his/her position", p. 1474). Second, *argumentation moves* in Session 2 responses were categorized as either as an (1) agreement; (2) disagreement (including local agreement) or (3) non-argumentative move (e.g., questions, off-topic comments). Finally, for each student, their initial argument in Session 1 and their reply to in Session 2 were compared to check *whether students used their initial arguments as a basis for their peer discussions*: (1) complete consistency; (2) partial consistency; and (3) not consistent at all. These variables were coded by two coders; Cohen's kappa is .88 for argumentation quality, .87 for argumentation moves and .94 consistency of comments to initial arguments.

The overall research question for the present study is: Can a GAT depicting (1) students (social information) (2) discussion topics and (3) opinion stances (cognitive information) foster argumentation and learning on a social media platform? It is hypothesized that students supported by the GAT will post arguments on posts that reflect a different opinion than their initial arguments (*communication behavior*) (H1); be more likely to demonstrate *integration* (H2) of multiple perspectives; will receive higher scores on *learning outcomes* (H3); (2) and exhibit a greater *shift in opinions* on migration stakeholders (H4), and demonstrate better *awareness* (H5) of multiple perspectives.

Results

Table 1: Sample size per experiment session and final sample size associated with each variable

	Control	GAT	Total	Variables analyzed with this sample size
Class size	14	15	29	None
Session 1	13	14	27	Argument quality
Session 2	13	13	26	Communication behavior; argumentation moves; consistency of comments to initial argument
Session 3 and Session 4	12	13	25	Number of friends; learning outcomes, opinion shifts; (1) awareness and (2) integration of multiple perspectives; self-reported perspective change

Some students were unable to complete all experiment sessions due to absences. Thus, Table 1 summarizes the final sample sizes for each of the measured variables. The 6 Australian students participated in Sessions 1-4. However, in Session 2 they mostly interacted with their fellow classmates, except for 2 students who replied to 1 student in each group. Therefore, their influence on the data is expected to be minimal.

Descriptive information on Session 1 (initial arguments) and Session 2 (comments)

A total of 33 initial arguments were posted on Google Community in Session 1 (27 from the experimental groups and 6 students in Australia). The *quality of arguments* was quite high among most students: both groups were able to make well-grounded claims in their initial arguments (p=1.00, Fisher Exact Test). On average, students in the control group mentioned 2.7(SD=.99) out of 11 stakeholders, of which they took a "benefits from migration" stance for 1.7 (SD=1.49) stakeholders and a "does not benefit" stance for 1(SD=.88) stakeholder. The GAT group mentioned 2.23 (SD=1.59) stakeholders, of which they took a "benefits from migration" stance for 1.69 (SD=1.37) stakeholders and a "does not benefit" stance for .54 (SD=.78) stakeholder. The mean difference of the two groups on their "does not benefit from migration" stance on stakeholders was significant (Mann Whitney U=48.5, p=.029, r=-.419), indicating that the control group was more likely to express this stance in their initial arguments than the GAT group. In Session 2, control group received on average 1.08(SD=1.24) comments and the GAT group received 1.15(SD=.9) comments. However, not all students were able to receive comments on their posts: 5 from the control group and 3 from the GAT group. In terms of *argumentation moves*, the proportion of students that wrote counterarguments in their comments was 0.62 in the control group and 0.38 in the GAT group, although this difference was not significant (p=.546, Fisher Exact Test). Both groups were also *equally likely to use their initial arguments as the basis for the comments* ($\chi^2(1)$=.653, p=.419).

Dependent variables

In terms of the *learning outcomes*, mean pre and post-test scores for the control group are 4 (*SD*=1.1) and 3.83 (*SD*=1.6); for the GAT groups, mean pre and post-test scores are 3.31 (*SD*=1.3) and 4 (*SD*=1.6), respectively. However, a mixed ANOVA yielded no significant interaction effect between time and the presence/absence of the GAT ($F(1, 23)=1.626$, $p=.206$). Analysis of *communication behavior* in Session 2 also did not yield any significant group differences ($p=0.667$, Fischer's Exact Test). Both groups were equally likely to comment on peers' posts that expressed the same opinion as theirs (and had no differing opinions) on the same stakeholder (control=6, GAT=8). However, students in the control group were 12.6 times more likely to comment on friends' posts than students in the GAT group (95% C.I.: 1.19, 678.9, $p=0.03$, Fisher Exact Test). Furthermore, the odds that students would comment on posts written by their classmates were also 5.33 higher if they belonged to the control group ($\chi^2(1)=4.06$, $p=.044$). This finding is interesting considering that both groups tended to have friends from within and outside their classroom. The average *numbers of friends in the same class* were 3.5(*SD*=1.9) for the control group and 4.46(*SD*=2.9) for the GAT group, though this difference was not significant (Mann Whitney $U=69.5$, $p=.63$). In terms of *friends in the other Economics class*, the average numbers are 2.25 (*SD*=1.86) and 3.85(*SD*=2.82) for the control and GAT groups, respectively, although the difference is non-significant as well (Mann Whitney U=48.5, $p=.104$). A factorial ANOVA with aligned ranks transformation yielded no significant interaction effect between time (pre-test/post-test) and the presence/absence of the GAT in terms of *shifts of opinions* regarding the 16 rated stakeholders ($p>0.05$). In terms of *awareness of multiple perspectives*, the mean score for the GAT group was 5.8 (*SD*=1.1) and the control group mean score was 5.2 (*SD*=1.6), although the difference is non-significant (Mann Whitney $U=53.5$, $p=.171$). Finally, for *integration of multiple perspectives*, the final arguments of the students fell into only 2 out of the 4 categories in Leitão (2000): integration and dismissal. A chi-square test of independence revealed that the odds of students integrating multiple perspectives from the discussion in their final answers was 6.67 higher if they were not supported by the GAT than if they were ($\chi^2(1)=4.98$, $p=.026$). However, according to *self-reported change in perspective*, only 2 students in each group reported that their perspective "did not change at all". The self-reports also indicate that of the 21 students who reporting integrating new perspectives, 10 of them (control=4; GAT=6) that reading other students' posts was the most influential in their change of opinions in the final answer; followed by comments received on their posts (mentioned by 3 students in each group).

How the GAT group made use of and perceived the group awareness tool

In Session 2, the GAT group spent an average of 3.72 minutes (*SD*=1.9) exploring the GAT. There were 240 recorded interactions, most of which (84.6%) were of students zooming into, panning and scaling the view of the graph. This means that it is not possible to determine from the log data which elements of the graph students were paying attention to, or whether they noticed similarities and differences between student opinions. However, in the training phase in Session 2, all 14 students were able to correctly identify student pairs from the dummy data that had the same/different opinion on the same stakeholder. All 14 students were likewise able to correctly identify from the GAT at least 1 student each that shared/did not share their opinion on the same stakeholder, although only 5 students actually posted on the posts by the students they identified. In Session 4, the GAT group gave neutral to positive ratings on the usefulness of the tool. Students gave positive ratings to the statements "I was able to see which members agreed or disagreed with my perspective" (*M*=4.38, *SD*=.77) and "The graphic helped me gain a general overview of the perspectives of other members in Google Community" (*M*=4.3, *SD*=.85). However, they gave neutral ratings when asked how well they believe the tool represented their perspective (*M*=3.62, *SD*=.76) and whether the tool helped them decide which posts to read (*M*=3, *SD*=1.2) and comment on (*M*=3.30, *SD*=1.38) in Session 2. When prompted to explain their ratings, 7 students mentioned that seeing who shared or did not share their opinions on the same stakeholder helped them decide which posts to comment on. One student noted that the graph helped her find posts that talked about stakeholders that she did not mention in her initial argument. The remaining 5 students mention that they did not take the tool in consideration when deciding on posts to comment on, stating that it was confusing, provides little information and that it was difficult to remember which students agreed or disagreed with them.

Discussion

The present study investigated a GAT for argumentation about a socially acute question on a flat-structured SNS, which is often criticized as not being conducive for argumentation activities. Like previous GAT designs for argumentation in SNS, it attempted to provide both an overview of group information and encourage comparison of one's information to others. In this study, however, the GAT combines two kinds of GA information (social and cognitive) and was designed to guide a specific phase in the activity, whereby students must select peer group members to discuss their opinions on migration with. This was an important

consideration given that prior to the experiment, the participants already had relationships with each other, as well as opinions about migration, which could influence how they behave during argumentation activities.

In terms of communication behavior, no significant differences were found on the dependent variable measured (H1): both groups mainly conversed with students that expressed the same initial arguments as theirs on at least one stakeholder. It should be noted that both groups were equally likely to express approving and dissenting opinions during discussion. This could imply that discussions among students probably went beyond the topics (stakeholders) that they had in common. Based on the log files, interactivity with the details (e.g., nodes and edges) of the GAT was quite low, even though students were explicitly told that they could interact with the graph. Thus, it is likely that the GAT group did not deeply process the commonalities and differences between them and their peers. However, subjective ratings indicate that students supported by the GAT may have noticed the differences in perspectives in the group. Furthermore, students were able to correctly interpret network graphs with dummy and real data; thus, the networked visualization itself was not too complex to comprehend. However, from a technical perspective, clicking a name or stakeholder (nodes) as well as their stance (edges) did not automatically redirect users to the corresponding posts on Google Community, which could have discouraged the GAT group from interacting in Session 2 in accordance to the GAT. Nevertheless, despite having friends in both classes, students in the control group overwhelmingly decided to respond to their friends in the same class, whereas students in the GAT group were equally likely to comment on friends' and non-friends' posts. The control group's behaviour is consistent with studies showing that people tend to be more willing to express their opinions online to friends (Luarn & Hsieh, 2014). Studies have shown that unfamiliarity with community members demotivates active participation in online discussions (Preece, Nonnecke, & Andrews, 2004) and that familiarity increases the likelihood of participation in online discussion forums (Hew, Cheung, & Ng, 2010). Given that the most dominant action captured by the GAT is zooming, panning, and scaling implies that the GAT group paid more attention to the GAT as a whole, without dwelling too long on any finer node-edge relations. It is possible, then, that they were able to get an overview of who is in the community and which stakeholders they had an opinion about. Hence, the GAT may have created a sense of familiarity among the students and help them consider the posts of peers that they are not personally close to.

Another finding of the study is that the control group was more likely to integrate multiple perspectives from the discussion than the GAT group (H2). Since not all students in the control group received comments on Session 2, the integration of multiple perspectives could not have only been the result of receiving comments containing a different perspective; as suggested by the self-reports, reading posts with dissenting opinions may have also had an influence. However, the study was not able to track which posts were read by whom and whether the GAT influenced this behavior. Nevertheless, other studies have suggested that opinion change is influenced by the relationship of a person with their communication partners. People are more inclined to change their opinion when exposed to the opinions of people who are closely related to them; specifically, any dissimilarity in initial opinions is reduced by social influence (Friedkin & Johnsen, 1997). Even when friends tend to have the same initial opinions, friends are still more likely to express disagreement anyway, which could foster learning from opposing perspectives (Morey & Hutchens, 2012). This could explain why the control group, who mainly commented on each other's posts, were more open to changing their initial opinions after being exposed to the opinions of friends. When people are not closely related, as in the case of the GAT group students, then the social influence process does necessarily influence any changes in initial opinions (Friedkin & Johnsen, 1997). Another explanation could be that there were more diverse opinions on migration among the control group's initial arguments, as they were found to be more likely to take a "does not benefit" stance than the GAT group. Thus, the control group could simply have been more open-minded and receptive to different views after discussion (Barabas, 2004). Furthermore, self-reports show that only 4 students (2 in each group) indicated that their perspective did not change at all. It is perhaps possible that more students in both groups were able to integrate or localize new perspectives from the discussion, but did not express this when they revised their opinions in Session 3.

Overall, the study demonstrates that combining social and cognitive information in a GAT with a network visualization may influence communication behavior, but not necessarily in accordance to awareness of differences in initial arguments. Rather, the GAT helped students find posts in a flat-structured SNS that were written by students with whom they do not have a close personal relationship, potentially increasing familiarity among students in the community. Building familiarity could be an important consideration for argumentation in SNS to encourage students to freely discuss controversial SAQs in a supportive environment. The results further suggest that communicating with friends and exposure to the opinions with whom one has a close personal relationship may influence the likelihood of adopting new perspectives, although alternative explanations cannot be ruled out (i.e., that the control group could have been more open-minded). Thus, the seemingly contradictory results (i.e., familiarity may increase overall engagement among non-friends, but

communication among friends may lead to more multiple perspective taking) could be further investigated in relation to other variables (e.g., open-mindedness). As these issues will continue to be relevant inside and outside the classroom, it would be beneficial to understand how to best encourage students to discuss socially acute issues in a meaningful way.

References

Barabas, J. (2004). How deliberation affects policy opinions. *American Political Science Review*, *98*(4), 687–701. doi:10.1017/S0003055404041425

Bodemer, D. (2011). Tacit guidance for collaborative multimedia learning. *Computers in Human Behavior*, *27*(3), 1079–1086. doi:10.1016/j.chb.2010.05.016

Chen, B., & Bryer, T. (2012). Investigating instructional strategies for using social media in formal and informal learning. *The International Review of Research in Open and Distributed Learning*, *13*(1), 87–104. doi: 10.19173/irrodl.v13i1.1027

Erkens, M., Schlottbom, P., & Bodemer, D. (2016). Qualitative and quantitative information in cognitive group awareness tools: Impact on collaborative learning. In U. Cress (Ed.), *Transforming Learning, Empowering Learners: The International Conference of the Learning Sciences (ICLS) 2016*. Singapore: International Society of the Learning Sciences.

Friedkin, N. E., & Johnsen, E. C. (1997). Social positions in influence networks. *Social Networks*, *19*(3), 209–222. doi:10.1016/S0378-8733(96)00298-5

Hew, K. F., Cheung, W. S., & Ng, C. S. L. (2010). Student contribution in asynchronous online discussion: a review of the research and empirical exploration. *Instructional Science*, *38*(6), 571–606. doi:10.1007/s11251-008-9087-0

Janssen, J., & Bodemer, D. (2013). Coordinated computer-supported collaborative learning: Awareness and awareness tools. *Educational Psychologist*, *48*(1), 40–55. doi:10.1080/00461520.2012.749153

Kirschner, P. A. (2015). Facebook as learning platform: Argumentation superhighway or dead-end street? *Computers in Human Behavior*, *53*(Supplement C), 621–625. doi:10.1016/j.chb.2015.03.011

Kuhn, D., Wang, Y., & Li, H. (2010). Why argue? Developing understanding of the purposes and values of argumentative discourse. *Discourse Processes*, *48*(1), 26–49. doi:10.1080/01638531003653344

Leitão, S. (2000). The potential of argument in knowledge building. *Human Development*, *43*(6), 332–360. doi: 10.1159/000022695

Luarn, P., & Hsieh, A.-Y. (2014). Speech or silence: The effect of user anonymity and member familiarity on the willingness to express opinions in virtual communities. *Online Information Review*, *38*(7), 881–895. doi:10.1108/OIR-03-2014-0076

Manca, S., & Ranieri, M. (2013). Is it a tool suitable for learning? A critical review of the literature on Facebook as a technology-enhanced learning environment. *Journal of Computer Assisted Learning*, *29*(6), 487–504. doi:10.1111/jcal.12007

Morey, A. C., Jr, W. P. E., & Hutchens, M. J. (2012). The "who" matters: Types of interpersonal relationships and avoidance of political disagreement. *Political Communication*, *29*(1), 86–103. doi:10.1080/10584609.2011.641070

Preece, J., Nonnecke, B., & Andrews, D. (2004). The top five reasons for lurking: improving community experiences for everyone. *Computers in Human Behavior*, *20*(2), 201–223. doi:10.1016/j.chb.2003.10.015

Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015). Blending Facebook discussions into seminars for practicing argumentation. *Computers in Human Behavior*, *53*, 605–616. doi:10.1016/j.chb.2015.04.006

Sadler, T. D., & Donnelly, L. A. (2006). Socioscientific Argumentation: The effects of content knowledge and morality. *International Journal of Science Education*, *28*(12), 1463–1488. doi:10.1080/09500690600708717

Simonneaux, L. (2007). Argumentation in science education: An overview. In S. Erduran & M. P. Jiménez-Aleixandre (Eds.) *Argumentation in Science Education* (pp. 179-199). Springer, Dordrecht. doi: 10.1007/978-1-4020-6670-2_9

Tsovaltzi, D., Judele, R., Puhl, T., & Weinberger, A. (2015). Scripts, individual preparation and group awareness support in the service of learning in Facebook: How does CSCL compare to social networking sites? *Computers in Human Behavior*, *53*, 577–592. doi:10.1016/j.chb.2015.04.067

Tsovaltzi, D., Puhl, T., Judele, R., & Weinberger, A. (2014). Group awareness support and argumentation scripts for individual preparation of arguments in Facebook. Computers & Education, 76, 108-118.

Zeidler, D. L., & Nichols, B. H. (2009). Socioscientific issues: Theory and practice. *Journal of Elementary Science Education*, *21*(2), 49. doi:10.1007/BF03173684

5. STUDY 4: GROUP AWARENESS TO AID ARGUMENTATION ON SOCIAL MEDIA AMONG LINGUISTICALLY DIVERSE STUDENTS

Group Awareness to Aid Argumentation on Social Media among Linguistically Diverse Students

Marielle Dado and Daniel Bodemer

University of Duisburg-Essen
Institute for Research Methods in Psychology - Media-Based Knowledge Construction
Lotharstraße 65, D-47057 Duisburg, Germany

Manuscript submitted as “original research” to *Instructional Science: An International Journal of the Learning Sciences*

Abstract

This study investigates how a group awareness tool (GAT) can support collaborative argumentation on a social networking site (SNS) between linguistically diverse learners. SNSs are becoming popular platforms for argumentation. However, simply providing an online environment does not automatically lead to productive argumentation practices, such as multiple-perspective taking, particularly when students experience language-related difficulties. A GAT depicting (1) social information (learners) and (2a) discussion topics (e.g., economic stakeholders) and (2b) perspectives (cognitive information), upon which to anchor discussions, could therefore facilitate communication behaviors that lead to multiple-perspective taking (e.g., communicating with a peer with a different perspective). In a field experiment, an Economics class of 19 students belonging in different English classes (English A for proficient speakers, *n*=9; English B for English-as-a-Second-Language speakers, *n*=10) engaged in two argumentation sequences; the GAT was administered to all students in the second sequence. The results show that English B students used the GAT more and demonstrated better awareness of diversity of stakeholders and perspectives in the discussion. Nevertheless, students tended to respond to peers that mentioned the same cognitive information (i.e., same stakeholders and perspectives). Logged GAT interactions show that students focused on similarities in cognitive information. Thus, awareness of multiple stakeholders and perspectives did not automatically lead to multiple-perspective taking. English B students also exhibited more language anxiety, whereas English A showed superior argumentation skills. Future research could investigate combining GATs with collaboration scripts to emphasize different/unshared (less salient) group information, as well as differentiated support according to language or academic proficiency.

Keywords: group awareness, collaborative argumentation, social media, computer-supported collaborative learning

Group Awareness to Aid Argumentation on Social Media among Linguistically Diverse Students

Argumentation is essential for developing high-order thinking to understand how certain events and practices influence social phenomena (Nussbaum, 2011). One way of developing argumentation skills is by introducing socially acute questions—societal issues that are widely debated among experts in various disciplinary fields—as topics for classroom argumentation (Simmoneaux & Legardez 2010). Computer-mediated environments, especially social media platforms, are increasingly becoming the medium of choice for collaborative argumentation, as it enables learners to engage in discussions about real-world issues related to the current lesson (Chen & Bryer 2012). However, since social media platforms were not built for educational purposes, simply providing an online environment does not automatically lead to productive argumentation practices and learning (Kirschner 2015), particularly when students experience language-related difficulties or anxiety (Cheuk 2016). The present work investigates how group awareness tools can overcome these challenges during a collaborative argumentation activity on social media among students differing in English language proficiency.

Collaborative Argumentation

Collaborative argumentation is alternatively known as "argumentative knowledge construction" because it involves participation in a specific form of discourse, the frequency of which leads to the construction and acquisition of new knowledge (Weinberger & Fischer 2006). Learners are expected to communicate their viewpoints, consider the validity of others' perspectives, and rethink their original ideas based on the new information (Evagorou & Osborne 2013). Argumentative discourse is often made up of argumentative *moves*: an argument is composed of a *claim*, a statement of the position that a learner takes on a particular topic, and a *ground*, or a statement about evidence supports the validity of the claim (Weinberger & Fischer 2006).

Argumentative moves are then carried out in particular *sequences* (Leitão 2000). An argumentative sequence often begins when individual learners stating their initial claim regarding the topic, along with grounds to justify that claim. Generating these arguments is a form of self-explanation, whereby learners externalize their perspectives, allowing them to later integrate new knowledge to existing cognitive structure (Baker 2003). Next, the learners are given the opportunity to exchange perspectives, for instance by challenging each other's initial arguments by proposing counterarguments or alternative prespectives that "could potentially undermine [one's] argument" (Leitão 2003, p. 277). Exposure to different perspectives gives learners the opportunity to reflect on the validity of their initial arguments. Finally, learners construct and refine their initial arguments in light of the perspectives raised in the discussion in one of four ways. First, other perspectives can be *dismissed* or rejected, in which case the final argument is largely the same as initial argument. Second, learners can express agreement with a different perspective, but in the end choose to retain their initial argument—this is called *local agreement*. Such replies start with an acknowledgement of the validity of other perspectives, followed by shifting the focus to an idea that gives support to their original argument (e.g., "I acknowledge that... However, I still believe that…"). Third, alternative perspectives can be *integrated* to one's initial arguments. This is achieved by adding exceptions or conditions to their initial arguments to accommodate alternative perspectives (e.g., "I believe [initial argument]. In some cases, I also believe that [counterargument] may also be valid"). Finally, the initial argument can be *withdrawn* completely in favor of the other perspectives and discarding the initial argument altogether. Evidently, by participating in this sequence of argumentative discourse, learners may adapt multiple perspectives upon a particular topic (Weinberger & Fischer 2006). Being able to integrate or adopt multiple perspectives acquired during argumentative discourse facilitates learners' ability to apply new knowledge to solve novel problems (Sampson & Clark 2009).

Collaborative argumentation differs from debates and other forms of adversarial argumentation, because the goal is not necessarily to prove the superiority of one's arguments over others, but rather to "explore positions flexibly and to make concessions" (Nussbaum 2008, p. 349). In the course of presenting and discussing their perspectives, learners obtain a common frame of reference about the topic in a process of negotiation (Andriessen, Erkens, Van de Laak, Peters & Coirier 2003). The degree of knowledge acquisition depends on how this process of negotiating common ground is carried out (Weinberger & Fischer 2006). Studies have shown (Mason & Scirica 2006; Nussbaum, Sinatra, & Poliquin 2008) that being able to critically compare each other's beliefs to determine which one is more justified led to better argumentation skills and knowledge acquisition, compared to when learners simply agreed that each argument is equally valid or insisted on one right answer. This transactivity, or the ability of learners to refer and build upon the reasoning of their peers (Teasley 1997), is an indication that learners are profiting from the argumentative discourse.

However, before learners can begin to engage in argumentative discourse, they must first be given a task that maximizes the likelihood of learners communicating their ideas by reasoning, elaborating and arguing (Noroozi, Weinberger, Biemans, Mulder & Chizari 2012), as well as an appropriate platform for communication and discussion. The next subsections discuss how socially acute questions and social networking sites can be used to achieve meaningful argumentation and learning in this manner.

Socially acute questions. Socially acute questions (SAQs), despite the name, do not always appear in the form of questions, but are rather controversial topics or dilemmas that are frequently encountered (i.e., acute) in society and that are widely debated (i.e., questioned) by experts from various disciplinary fields (Simonneaux & Legardez 2010). They can be socio-sociological, such as immigration or unemployment, or socio-scientific, such as gene-cloning or climate change. This means SAQs are relevant to a number of academic and professional disciplines, resulting in competing points of view depending on the frame of reference that an expert draws upon.

As with any argumentation activity, argumentation with SAQs involves examining the issue from multiple perspectives, appreciating that SAQs are subjected to ongoing inquiry, and exhibiting skepticism in the presence of conflicting information (Sadler, Barab & Scott 2007). Multiple perspective taking is demonstrated when students consider the points of view of different stakeholders affected by the issue (Simmoneaux & Simmoneaux 2009), often because of diverging opinions, interests and concerns (Sadler 2004). In collaborative argumentation, multiple perspective taking is triggered when learners externalize their perspectives or knowledge, which may be unshared or divergent from those held by other group members (Clark, Sampson, Weinberger, & Erkens 2007). The extent to which learners refer to these contributions varies and have different implications on knowledge acquisition (Weinberger & Fischer 2006). Learners could respond by simply accepting these perspectives as valid in order to continue with the task or discourse (i.e., quick consensus building). Learners could also take over or modify each other's perspectives in an effort to enrich discourse and solve the problem at hand. Multiple perspective taking is most evident in the latter, which constitutes higher transactive social modes that results in a higher quality of knowledge exchange and construction (Teasley 1997). During collaborative argumentation about SAQs, learners are challenged not only to recognize that multiple perspectives exist through different stakeholders, but are also encouraged to weigh out the validity of each viewpoint to gain a well-rounded understanding of an issue, which ultimately leads to knowledge acquisition.

Collaborative argumentation and social media. In recent years, there has been growing interest in the adoption of social networking sites (SNS) as an educational tool, particularly for argumentation. SNSs, such as Facebook and Google+, were originally developed for users to establish online connections with each other, forming networks or communities of people (Lin & Lu 2011). These networks often reflect existing relationships in the offline world: for instance, students mainly use SNSs to stay in touch with fellow classmates on an informal basis (Madge, Meek, Wellens & Hooley 2009). Thus, SNSs asynchronous communication features are often used to complement synchronous, face-to-face interaction in the classroom in order to foster a sense of community and social connectedness (Hung & Yuen 2010).

By leveraging on the "real-world" social connections, educators hope to use SNSs widen the context of learning beyond the classroom (Manca & Ranieri 2013). In particular, they perceive SNSs as a platform to discuss real-world issues or applications related to the theories discussed in class (Chen & Bryer 2012). This means that SAQs, may be appropriate topics for discussion on SNSs, which are contemporary issues that affect formal knowledge disciplines and everyday life. Furthermore, consensus about SAQs continues to evolve as new information is discovered by experts, which are then widely discussed in society. Therefore, dynamic media sources, such as social media, are more likely to provide useful information for students to explore SAQs in a meaningful and timely manner (Sadler, Foulk & Friedrichsen 2017). Collaborative argumentation about SAQs on SNSs not only enable learners to extend their classroom knowledge to issues that have an impact on their lives and in society, but they also get to do so through a platform that suits the dynamic nature of these issues.

Challenges with Collaborative Argumentation

Although collaborative argumentation with SAQs provides learners with an enriching learning experience that is relevant to both inside and outside the classroom, optimal learning outcomes do not simply occur. In many cases, students engage in quick-consensus building which occurs, as mentioned briefly earlier, when learners reach an agreement without producing quality arguments because they are eager to simply complete the learning task as quickly as possible (Weinberger et al 2007). This section discusses the challenges that learners may face when it comes to developing quality arguments, particularly how social, linguistic and technical systems-related factors might hinder multiple-perspective taking and elaboration.

Socio-relational factors and language proficiency. One scenario that could lead to mere quick-consensus building is when learners focus excessively on socio-relational factors (Hijzen, Boekaerts & Vedder 2007). In a recent study, Asterhan (2018) found that students who were afraid of appearing incompetent relative to their peers are more inclined toward quick-consensus building. In another study, students who tend to believe that disagreeing is "not nice" have been found to benefit less from argumentation activities (Bathgate, Crowell, Schunn, Cannady & Dorph 2015). Such concerns may be exacerbated by problems arising when learners come from linguistically diverse backgrounds. Although English is widely recognized as the lingua franca of academic settings (Conrad & Mauranen 2003) and for many intercultural computer-mediated collaborative

learning initiatives, studies often do not consider how differing language proficiencies could influence collaborative learning (Vatrapu 2010). In an experiment in which pairs of students from dissimilar cultures collaborated on an online task in English (Popov et al 2014), most of the students cited differences in English language proficiency as one the biggest challenges. This result echoes other studies (Popov et al 2012; Spencer-Oatey & Dauber 2017) in which students report that insufficient English language skills are a major barrier to successful collaboration in multicultural learning groups. Furthermore, students who have English as a Second Language (ESL) or an Additional Language (EAL) may experience language-related anxiety when asked to collaborate with their peers and may subsequently hinder academic performance (Cheng, Horwitz & Schallert 1999). Anxiety towards speaking or writing in English could be a particular concern in argumentation activities, which less assertive students may view as adversarial and therefore anxiety-promoting (Nussbaum et al 2008). For instance, Gonzales-Howard and McNeill (2016) found in a case study of a science class with ESL speakers that statements such as "What is your claim?" or "What is your evidence" increased anxiety levels among students. Cheuk (2016) further notes that when classroom argumentation is not accompanied with clear norms about how to engage in a productive exchange of perspectives, students from diverse cultural and linguistic backgrounds may feel risk-adverse because of the activity's resemblance to everyday, confrontational disagreements or disputes. Therefore, students who experience anxiety may lack the confidence to post meaningful replies and could therefore increase the tendency towards quick-consensus building.

Using commercial SNSs for collaborative argumentation. The technical aspects of the communication tool could also affect the quality of argumentation. In particular, in spite of the growing interest in using commercial SNSs as an educational tool, they were primarily designed for recreational and informal communication and therefore lack structural features that promote meaningful argumentation. For instance, discussion forums for learning purposes typically arrange discussion posts in threads, with replies to particular posts appearing below it (i.e., "nested; Guzdial & Turns 2000). This makes it easy to see discussion themes and points that are related to each other, as well as which user is building on the ideas of another user. However, most discussions on SNSs have a "flat-structured" arrangement: all individual posts are displayed in one page in chronological order, with replies appearing unnested order below the post they refer to (Tu, Blocher, & Gallagher 2010). As more posts are contributed, it becomes more difficult find one's own posts, let alone those of their peers (Kirschner 2015). In order to orient oneself to the arguments in the discussion and to retrieve the most relevant information, students would have to read all the posts and replies, which poses considerable cognitive load on the learner (Llorens Cerda & Capdeferro Planas 2011). Since argumentation activities require learners to build on each other's arguments and exchange multiple perspectives (Weinberger & Fischer 2006), having difficulties finding and connecting those ideas on the tool itself limits opportunities for deeper reflective engagement with specific concepts, thus impeding productive learning outcomes.

To summarize, unproductive collaborative argumentation about SAQs can happen when learners place importance on socio-relational factors at the expense of providing perspectives that could enrich the discussion, particularly among EFL/EAL speakers who feel anxious about presenting arguments about controversial topics; or when the "flat-structuredness" of communication tools, particularly SNSs, makes it difficult to read and build on each other's arguments. The next section discusses how increasing group awareness during argumentation may help to overcome these challenges.

Group Awareness Tools and Argumentation

Group awareness refers to the knowledge that learners have of useful information about their peers that could aid collaborative learning through computers (Bodemer & Dehler 2011). This could be *social information* or *cognitive information* which are visualized by group awareness tools (GAT) to compensate for the lack of contextual clues in computer-mediated communication (Janssen & Bodemer 2013). When GATs depict social information, they identify the group members and how they behave in the learning platform, for instance how many contributions (i.e., posts) each learner makes in the discussion forum. GATs that depict cognitive information show what the group members know, for example concept maps that visualize one's knowledge structures. GATs may also help individual learners to see their own social or cognitive information relative to their peers', and in doing so implicitly guide them into monitoring and adjusting their own behaviours. For example, a GAT by Janssen and colleagues (2011) represented each learner as a sphere in a 2-dimensional space, with students who contributed more to the forum discussion appearing closer to the center. Seeing this visualization helped learners discuss disproportionate effort, leading eventually to more equal participation. Similarly, when students viewed their peers' concept maps (Engelmann & Hesse 2011), they were able to discuss concepts that their peers know about that they do not, and vice versa, eventually leading to better group output. In this manner, the core function of GATs is to provide learners with information about their group members, particularly similarities and differences between their own behaviour or knowledge and that of their peers, which could serve as a common frame of reference when communicating to each other (Janssen & Bodemer 2013).

When applied to collaborative argumentation, GATs could potentially increase learners' awareness of group members (i.e., social information) and their perspectives and beliefs about an issue (i.e., cognitive information). This may help learners shift their focus from maintaining a good social standing in the group to conducting their argumentation activities meaningfully, for instance finding relevant posts on a flat-structred SNS according to peers' perpsectives and ideas, and referring back to this information during their discussions. This information could be particularly valuable to learners struggling with language-related anxiety, as the GAT could provide more structure to the argumentation activity (Cheuk, 2016). However, studies about group awareness in argumentation activities have mostly focused on social or attitudinal aspects. For instance, Puhl and colleagues created a GAT for Facebook that depicted communication attitudes of group members in a 2-dimensional space, such that members whose data points appear closer together share similar attitudes. They found that learners who viewed this tool acquired knowledge about the topic and experienced a change attitude towards multiple-perspective communication (Puhl, Tzovaltzi, & Weinberger 2015a, 2015b); this tool was also helpful in combination with collaboration scripts in promoting interaction (Tsovaltzi, Dutta, Puhl & Weinberger 2017).

Until recently, no studies have investigated how social and cognitive group awareness can support meaningful argumentation about SAQs on SNSs. To meet this research gap, Dado & Bodemer (2018) created a tool that depicted social and cognitive information in a social network graph, which was evaluated among 29 Year 12 students at an international school who engaged in argumentation on Google+ Community about the benefits of migration on economic stakeholders. The GAT contained 2 types of nodes: (1) group members (i.e., social information) and (2) stakeholders mentioned in the initial claims and perspectives expressed about them (i.e., cognitive information). An edge is drawn between the two node types if a student mentions a particular topic in their initial claims as per Leitão's argumentation sequence (2000). The color of the edges represents the stance that the student took regarding that topic, thereby depicting another type of cognitive information. The GAT was designed so that students could identify which of their peers shared or did not share their cognitive information (i.e., which students mentioned the same/different stakeholders affected by migration and whether they believe this effect is beneficial), find those posts in the SNS and use this as a point for discussion in their responses or counterarguments. The results show that the GAT did not result in greater awareness of diversity of cognitive information, more counterarguments, or multiple-perspective taking. However, students who did not view the GATs only added responses or counterarguments to friends' and classmates' posts, whereas students who saw the GAT were equally like to reply to posts by friends/non-friends and classmates/non-classmates (both classes had an equal number of friends in either class). Furthermore, the control group demonstrated multiple-perspective taking more than the GAT group, perhaps due to being exposed to their friends' opinions. One caveat is that although students were able to perceive an overview of group information and interpret the GAT correctly, they interacted very little with its details (e.g., clicking and rearranging nodes/edges to study the information in greater detail). This could mean that, unlike in previous GAT studies, students were unable to compare their own cognitive information with their peers'. Nevertheless, the study suggests that the GAT could have helped students find posts written by acquaintances, which they might have otherwise ignored given the flat-structuredness of the SNSs, thereby increasing familiarity within the community.

Aims and Research Questions of the Study

The present study investigates the utility of a GAT that depicts social and cognitive information (Dado & Bodemer 2018) for supporting collaborative argumentation about SAQs on SNSs between learners with different English language proficiencies. Given that certain language-related difficulties as well as technical features of SNSs may impede collaborative argumentation, a tool that could increase awareness of group information, upon which to anchor discussions, could facilitate productive learning activities. Therefore, this study attempts to address the following questions:

- RQ1: Can a GAT depicting (1) learners (social information) and (2a) discussion topics and (2b) perspectives (cognitive information) influence behavior and learning during SAQ argumentation on SNSs among learners with differing English proficiencies?

There have been no studies thus far on GATs among learners that differ in language proficiency. Therefore, RQ1 investigates whether GAT support influences such learners differently in terms of awareness of multiple stakeholders and perspectives (i.e., cognitive information), communication behavior, multiple-perspective taking, knowledge acquisition, and anxiety towards writing in English.

- RQ2: Are there differences in the way that learners with varying English language proficiency understand the GAT?

RQ2 is an exploratory question that investigates how learners interact with a GAT for collaborative argumentation, which information is perceived, and whether learners with varying English language proficiencies differ in this regard.

Methodology

Participants

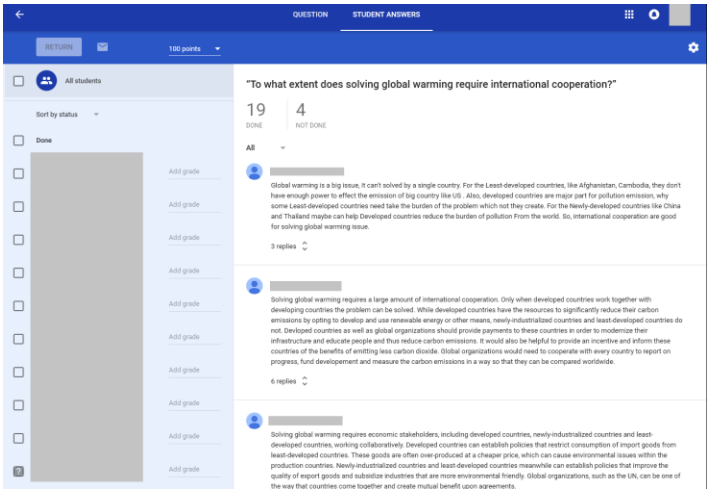
The participants of this study were 19 students (M_{age}=16.9, SD=0.44) in a Year 11 standard-level Economics class at an international school in Germany that follows the International Baccalaureate (IB) curriculum, with English as the language of instruction. The class was linguistically diverse: students spoke 9 languages in total, with 4 students identifying as bilingual. Only 3 students identified English as their first language. Nine students belong in the English A class for highly proficient English users. Ten students were in the English B class for EAL students; they either have Japanese (n=8) or Chinese (n=2) as their first language. The teacher notes that English B students tend to struggle not only with studying in English, but also comprehending Economics concepts, resulting in weaker academic performance.

Research Design

The study is a partial replication (as defined in Hendrick 1990) of a quasi-experiment conducted by Dado & Bodemer (2018) in order to evaluate whether the effects of the GAT can also be observed among ESL/EAL students. Both studies were conducted in the same school, subject, and teacher, but with students from different year levels; the activity, GAT, instructions and procedures were also similar. In the older study, the GAT was provided to only one group, resulting in a between-group (no tool/control vs GAT) design. In the present study, two argumentation sequences were conducted; all participants (N = 19) are supported by the GAT in the second sequence. English proficiency, as determined by their assigned English class (English A, n = 9 or English B, n =10), was used as the grouping variable. Therefore, this study includes both within-groups (presence/absence of GAT) and between-groups (English proficiency) comparisons. Other changes are: (1) the inclusion of "anxiety towards writing in English" as a dependent variable; (2) the use of Google Classroom instead of Google+ Community (see next subsection); (3) improved readability of GAT by blurring out unselected elements; and (4) scaffolding and worked examples for GAT in the training phase (see "Group Awareness Tool" section).

Learning Environment – Google Classroom

Fig. 1 Screenshot of Google Classroom "Question" page.



Google Classroom, a learning management system created by Google, was used as the argumentation platform in this study (see Fig. 1). The sessions for this study were conducted using the "Question" feature, on which the debate questions were posted to allow participants to submit their answers. Despite being marketed as a learning management platform, Google Classroom's discussion features share more similarities with the asynchronous discussion features of Google+ Community used in Dado & Bodemer (2018), including the "flat-structured" arrangement of posts and comments, than the threaded arrangement usually found in discussion forums for learning. Users, however, cannot view or comment on the responses of their classmates until they have submitted their own. The comment function could be disabled by the teacher, which was useful for the study as participants are only allowed to reply to each other in the second session. Thus, Google Classroom allowed more control over its functionalities during each session.

Learning Activity – Argumentation Sequence

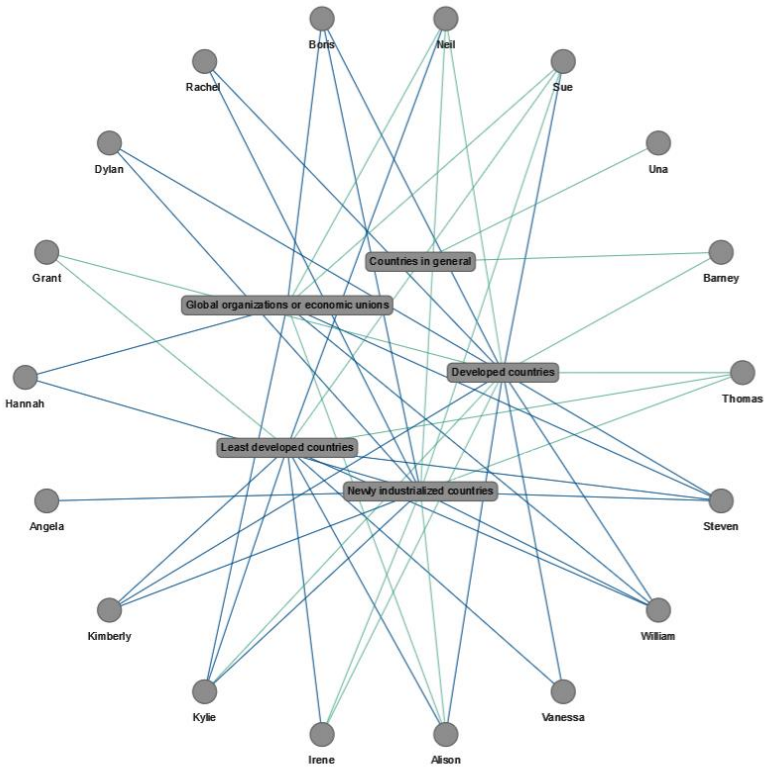
As in Dado & Bodemer (2018), the argumentation activities were structured into 3 sessions which corresponded to the argumentation sequence proposed by Leitão (2000) and embedded in separate 50-minute

Economics class periods. In Session 1, students constructed their initial arguments in response to the debate question. In Session 2, students constructed replies in response to the arguments proposed by their peers. Finally, in Session 3, students were given the opportunity to revise their initial arguments and respond to the replies and feedback from the previous session. Two argumentation sequences (i.e., Sessions 1-3) were conducted 8 weeks apart in order to study the effects of the presence or absence of the GAT on the dependent variables. The GAT was only introduced in the second argumentation sequence and required additional instructions. Also 2 different but related questions were used as debate topics to avoid practice effects. For the remaining sections, the first and second argumentation sequences will be referred to as the no-GAT and with-GAT sequences, respectively.

In the no-GAT sequence, students responded to the question **"**To what extent do you agree with this statement: 'Tradable permits are the best solution for reducing global carbon emissions'?**"** In the with-GAT sequence, students responded to the question "To what extent does solving global warming require international cooperation?" Climate change was selected as the overarching SAQ (socio-scientific issue) in these debate topics due to its relevance to the Microeconomics unit of the IB Economics syllabus, specifically about market failure. These topics had already been taught in class in the previous semester. The questions began with "to what extent" because this phrase is a "command term" used in IB examination questions to indicate the level of depth required from students' answers (Ziogas 2012). To successfully answer "to what extent" questions, students must "consider the merits or otherwise of an argument or concept. Opinions and conclusions should be presented clearly and supported with appropriate evidence and sound judgment". Thus, adding "to what extent" to the debate questions was done to trigger argumentation in a manner that is familiar to the students.

Group Awareness Tool

Fig. 2 Group awareness tool (GAT)



Note. Student names have been changed.

The GAT (Fig. 2) was introduced in Session 2 of the with-GAT sequence. The GAT was hosted on a separate URL from Google Classroom; students viewed the GAT on a separate browser tab/window. Similar to Dado & Bodemer (2018), the tool is a network graph that visually depicts how each student's initial argument in Session 1 is positioned with respect to the arguments of their classmates. It is composed of 2 nodes: (1) students (circles) and (2) economic stakeholders of the SAQ (rectangles). An edge is drawn between the 2 node types if the student mentions that stakeholder in their initial argument in Session 1. The colour of the edge depicts whether the student adopted an economic growth (blue) or environmental (green) perspective to make grounded

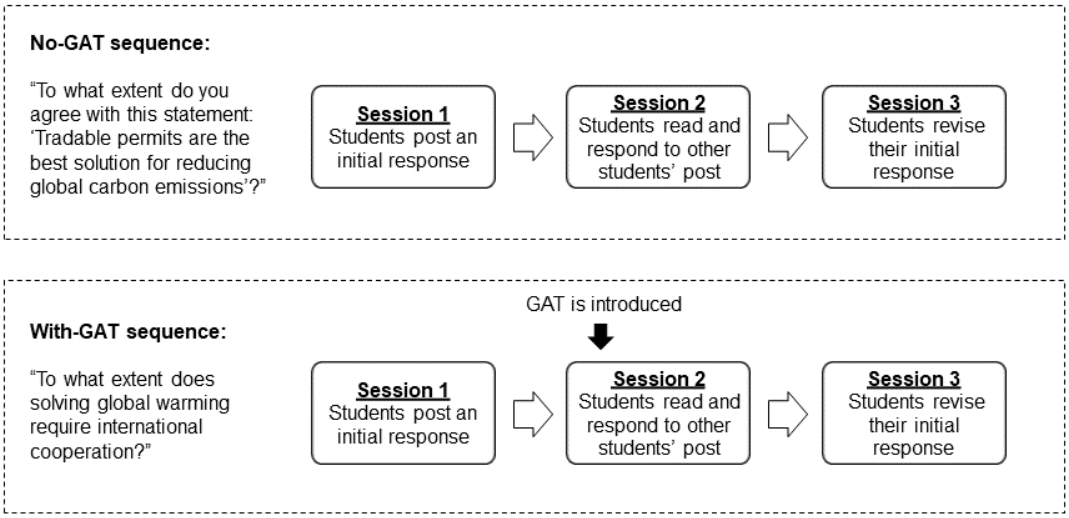
claims about a particular stakeholder (Wu & Tsai 2007). An example of an economic-oriented perspective would be "Developed countries should offer financial support to least-developed countries to help them transition to renewable energy sources". An example of an environmental-oriented perspective would be "China (a newly-industrialized country) produces about 30% of total global carbon emissions". Interrater reliability coefficients (Gwet's AC1) based on 2 independent coding results yielded very good interrater agreement (No-GAT phase: stakeholders=0.70 and grounded claims classification=0.79; With-GAT phase: stakeholders=0.90 and grounded claims classification=0.76), with all disagreements discussed until consensus was achieved.

The network graph used in the GAT was created using the R package "visNetwork", producing an interactive graph that allowed users to click and rearrange the nodes and edges. These actions were logged in order to determine which GAT elements students observed (see Process variables subsection).

Like the GAT in Dado & Bodemer (2018), the GAT was created to bring awareness of the diversity of cognitive information among group members. *Social information* was presented as nodes representing all the students in the class, whereas two types of *cognitive information* were shown: (1) stakeholders mentioned by the students represented as nodes; and (2) the perspectives (economic or environmental) of each student regarding that stakeholder represented in the color of the edges connected student and stakeholder nodes. Given the networked arrangement of these elements, students are provided with a general overview of the initial arguments of the class. Furthermore, the color-coded edges connecting student and stakeholder nodes enables users to compare their arguments to those of others based on their connections (or lack thereof) to the same stakeholders, as well as similarities or differences in perspective about the same stakeholders. Previous research on GATs suggests that when group information is arranged in a 2D space (e.g., Puhl et al 2015a), comparison between individual and group information is enabled. Learners can easily perceive and then discuss differences between one's information and the group's information. Hence, the GAT was designed to influence communication behaviour, which would otherwise be impinged by the flat-structuredness of Google Classroom, on the basis of awareness of social and cognitive information, especially with regards to differences in cognitive information that can be used as a common frame of reference.

Procedure

Fig. 3. Procedure of the two argumentation sequences



All sessions (see Figure 3) were conducted during class time which lasts approximately 50 minutes. An exception is Session 2 in the with-GAT sequence, which was conducted for 75 minutes, and for which additional instructions for the GAT were provided on a separate page. Instructions can be found in Appendix A.

In Session 1, students were asked to post an answer to the designated Question page. Their answers must be 4-6 sentences long and must include a description of the impact of the issues on at least 1 economic stakeholder. Once the students submitted their answers, they could view other answers, although commenting was disabled at this time.

In Session 2 of the no-GAT sequence, students were instructed to first read all the answers to the question. Then, they were instructed to comment on one of their classmates' answers. In addition, they were explicitly told to structure their comments based on their own initial arguments from Session 1. The students were also given some "Golden Rules" and sentence starters to follow (based on Prinsen, Volman, Terwel & van den Eeden 2009). The GAT was introduced at the start of Session 2 during the with-GAT sequence. Students were first trained on how to interpret the GAT by showing a network graph using dummy data similar to the GAT before viewing the actual GAT that reflects their own data. Scaffolds and worked examples were provided to ensure that students were able to correctly identify shared and unshared cognitive information. First, students were advised to select the node with their name in order to highlight the stakeholders and perspectives they mentioned in Session 1. Second, they were instructed to select on at least one of the stakeholders linked to their node to highlight other students who have mentioned the same stakeholders, paying attention to whether any of them shared the same perspectives. Finally, students were asked to explore the graph on their own, including the other (i.e., not shared) stakeholders and perspectives that were mentioned by their classmates. A manipulation check to evaluate the students' understanding of the dummy and actual GATs was also administered (see "Measures" section). After using the GAT, the session proceeded in the same manner as in the no-GAT sequence.

In Session 3, students were instructed to read their Session 1 answers again and reflect on whether their perspective has changed. Then, they were asked to answer the question once again on a separate Question page following the same instructions as in Session 1.

Participants also answered questionnaires before and after the sequences. In the no-GAT sequence, students answered the anxiety questionnaire before Session 1. Then, after Session 3, participants answered questions that evaluated their awareness of stakeholders and perspectives. In the with-GAT phase, participants answered a knowledge test before Session 1 and after Session 3. The questionnaire after Session 3 in the with-GAT sequence contained the following: (1) anxiety questionnaire, re-administered; (2) questions about students' awareness of stakeholders and perspectives (as in the no-GAT sequence); (3) self-reported behavior during the activity; (4) friendships in the class; these measures are discussed in the next session.

Measures

Dependent variables (RQ1).

To address RQ1, the following variables were measured (see Appendix B).

Awareness of multiple stakeholders and perspectives was measured after Session 3 in each argumentation sequence with two types of questions based on the Session 1 arguments. First, students were asked to rank each stakeholder mentioned in Session 1 from most to least mentioned by classmates. A full point (1) was granted for every correctly-ranked stakeholder; half points (0.5) were given if a student placed a stakeholder one rank above or below its correct ranking. Second, students were asked to evaluate whether majority of their classmates took a particular perspective with regards to each stakeholder, or if there were an equal number who took either perspective.

In the no-GAT sequence, students stated whether they believed tradable permits had a positive or negative impact on a stakeholder. As discussed later in the Results section, 6 stakeholders emerged in the no-GAT sequence; however, one of these was mentioned by only one student, thus there is no "split" in the distribution of perspectives for that stakeholder. Therefore, students could gain a maximum of 11 points (6 from the ranking task, 5 from the perspectives task) for the awareness measure in the No-GAT sequence. In the with-GAT sequence, students supported their claims about international cooperation against global warming from an environmental impact perspective or an economic growth perspective (as explained in the GAT section). Since 5 stakeholders emerged from Session 1 (see Results section), students could gain up to 10 points for the awareness measure in the with-GAT sequence.

Communication behavior was evaluated based on the classmate that students responded to in Session 2 (i.e., posting a comment on someone's post), namely: (1) whether they share cognitive information (i.e., discussed the same/different stakeholders and argument perspectives in their initial arguments, based on the appearance of the GAT); (2) whether (a) they are members of the same English class or (b) whether the respondent considers the peer a friend (based on the post-Session 3 questionnaire). Students also indicated in the post-Session 3 questions their reasons for selecting a post to reply to.

Multiple-perspective taking was analyzed using content analysis by comparing initial arguments in Session 1 and final arguments in Session 3. Categories based on Leitão's (2000) description of the impact of others' perspectives from a discussion on one's initial argument: (1) dismissal of counterarguments or new perspectives, (2) local agreement (original argument is mostly retained, but the validity of new perspectives is acknowledged), (3) integration (others' perspectives are included in the final argument) and (4) withdrawal of

initial arguments (i.e., full acceptance of counterarguments or others' perspectives). Interrater reliability coefficients for this variable were .82 and .76 in the no-GAT and with-GAT sequences, respectively. Students were also asked to report whether they believe their perspectives have changed.

Knowledge acquisition was measured with a 10-item multiple choice test about market failure. The questions were selected by the teacher from an Economics question bank (Glanville & Glanville 2013) and pertained to information that could be relevant for answering the question in the with-GAT sequence. This information was already familiar to the students from the previous semester, but was not actively discussed in class. The test was administered twice: prior to the first session and after the final session of the with-GAT sequence.

The Second Language Writing Anxiety Inventory (L2WAI) by Cheng (2004) and adopted into blended learning contexts by Bailey and colleagues (Bailey, Lee, Vorst & Crosthwaite 2017) was used to measure *the level of anxiety towards writing in English*. The inventory contained 22 questions in 3 subscales corresponding to somatic, cognitive and behavioral components of anxiety. Participants rate their agreement towards statements describing various anxiety states on a 5-point Likert scale (1 – strongly disagree to 5 – strongly agree). The ratings were then summed up for a score ranging between 22 and 110 points. Higher scores indicate higher English writing anxiety. In addition, the questionnaire included one open-ended question pertaining to their experiences with English during Economics class.

Process data: Clickstream data and Markov chains (RQ2).

Table 1.

Descriptions of the annotation labels of the logged interactions of the GAT

Annotation labels	Description	Logged action	Highlighted information
Own cognitive info	One's own information on the GAT	Click/drag node	Own cognitive information
Common stakeholders	Peer with whom student has stakeholders in common	Click/drag node	1. Social 2. Cognitive
No common stakeholders	Peer with whom student does not share common stakeholders	Click/drag node	
Unshared cognitive info	Stakeholders that student did not mention	Click/drag node or edge	1. Cognitive 2. Social
Same perspective	Peer has the same perspective on the same stakeholder	Click/drag edge	
Different perspective	Peer has the different perspective on the same stakeholder	Click/drag edge	
Reply: Student, shared cognitive info	Reply state of student if they responded to a peer that mentioned the same perspective on the same stakeholder	None—added manually	
Reply: Student, different perspective	Reply state of student if they responded to a peer that mentioned a different perspective on the same stakeholder	None—added manually	
Reply: Student, unshared cognitive info	Reply state of student if they responded to a peer with whom they do not share cognitive information	None—added manually	

In order to address RQ2, students' actions on the tool were logged. A total of 5 actions were collected: (1) *drag view* (i.e., zooming, panning and scaling the view of the graph), (2) *click node*, (3) *drag node*, (4) *click edge*, and (5) *drag edge*. When a node is clicked/dragged, that node, the edges attached to it, and the nodes connected to those edges are highlighted. When an edge is clicked/dragged, only the edge and the nodes that it connects are highlighted (see Fig. 4 in Appendix C). Therefore, each logged action highlights a primary and secondary group information. Actions were manually annotated according to the scheme in Table 1 (also see Appendix C for a sample log file). One of three "reply states" were manually added at the end of each students' log files depending on the characteristics of the peers that students replied to in Session 2 (i.e., communication behavior). The annotated log files were then aggregated and used to create Markov chains for each English class (Dornfeld, Zhao & Puntambekar 2017). Markov chains visualize and indicate the probability of transitioning from one state to the next depending on the previous states (i.e., selecting one element of the GAT to the next, given the other elements that were previously clicked). In this manner, Markov chains reveal sequences of how students navigated the GAT and reveal any patterns in the probability of replying to particular students given the GAT information that they noticed.

Explanatory variables. A number of variables that might influence the dependent variables beyond the intervention were also measured. Content analysis was used to analyze these variables, taking the whole responses in Sessions 1 and 2 as the units of analysis. As with the dependent variables, two independent raters coded these variables and category definitions were continually refined until consensus was reached. Disparities in coding were then discussed, and consensus was reached. Gwet's AC1 was used to calculate interrater reliability.

First, the *argumentation quality* of the initial arguments in Session 1 were evaluated based on Sadler & Donnelly's (2006) rubric for socio-scientific argumentation quality (p. 1470). Session 1 arguments were categorized as having (1) grounded claims; (2) grounds without claims; (3) no clear claim. Interrater reliability coefficients for argumentation quality were .88 and .87 in the no-GAT and with-GAT sequences, respectively. The claim in the context of the no-GAT sequence is whether students agreed or disagreed with the statement that tradable permits can reduce carbon emissions. In the with-GAT sequence, a claim is made when students state whether international cooperation is required to reduce global warming. Grounds are "data, warrants, or backings" that support the claim (Sadler & Donnelly 2006, p. 1469); in the context of the study, students who make sufficiently grounded claims if they mention specific stakeholders and how they were impacted by the issue from an economic or environmental perspective. In addition, the *word count* for the responses in all 3 sessions were also calculated, as the length of a response in a discussion forum is often positively correlated with quality content in CSCL discussion forums (Bratitsis & Dimitracopoulou 2007).

Argumentation moves, based on classifications found in Weinberger and Fischer (2006, p. 76), distinguishes between Session 2 replies that are (1) counterarguments ("an argument opposing a preceding argument"), (2) integrations ("statement that aims to balance and to advance a preceding argument"), (3) elicitations (questions to elicit further discussion), or (4) non-argumentative moves (clarification questions, simple agreement, or simply repeating peers' answers without adding new information). Interrater reliability coefficients for this variable were .82 and .78 in the no-GAT and with-GAT sequences, respectively.

Finally, the *consistency of the replies* (Session 2) to initial arguments (Session 1, which forms the basis of the information on the GAT) was assessed as according to (1) full consistency (e.g., claims in Session 2 are present in Session 1 arguments), (2) partial consistency (e.g., at least one of the claims in Session 2 replies are present in Session 1 arguments), and (3) completely inconsistent (e.g., all claims in Session 2 replies are absent from Session 1 arguments). Interrater reliability coefficients for consistency of arguments were .78 and .82 in the no-GAT and with-GAT sequences, respectively.

Manipulation check. As mentioned in the Procedure subsection, Session 2 in the with-GAT sequence included dummy data that was used to instruct students on interpreting network graphs before students viewed the GAT with their own data. Worked examples were included to scaffold the students into perceiving useful information from the GAT (i.e., the independent variable), as well as a manipulation check to evaluate whether they can correctly identify this information. In addition, the length (minutes) of students' interactions with the GAT were recorded, which would help determine whether students used the GAT.

There were 8 questions in total (see Appendix B). For the dummy GAT, students were asked to use specific sample students as a reference point to interpret perspectives based on edge color and common/not-shared stakeholders based on edge connectivity. Questions referring to the actual GAT were similar, except that students were explicitly asked to use their own nodes as a reference point to identify (1) the stakeholders and

corresponding perspectives that they mentioned in Session 1; (2) at least 1 classmate that gave the same perspective on the same stakeholders that they mentioned (3) at least 1 classmate that gave a different perspective on the same stakeholders that they mentioned and (4) at least 1 classmate who did not mention the same stakeholder. A full point was awarded for each correct answer for a total of 8 points. Partial points were also awarded: for example, if Steve correctly identifies only 3 of the 4 stakeholders he mentioned, then his score would be 0.75 (3/4).

Hypotheses for RQ1

Table 2.

A priori and exploratory hypotheses

Variables and statistical analysis	Hypotheses	
	A priori	Exploratory
H1 Awareness of multiple stakeholders and perspectives	**(H1a) Main effect for sequence:** Students will exhibit better awareness in the with-GAT sequence	**(H1b)** Effect of English class **(H1c)** Interaction effect between English class and argumentation sequence
H2 Communication behaviours	-	Effect of English class on responding to peers on the basis of **(H2a)** cognitive information (stakeholders/ perspectives); **(H2b)** friendships; **(H2c)** English class Compared to the No-GAT sequence, students will be more likely to respond to peers: **(H2d)** on the basis of cognitive information; **(H2e)** with whom they are not friends; **(H2f)** who belong to a different English class.
H3 Multiple-perspective taking	**(H3a)** English A and B students will differ in multiple-perspective taking	**(H3b)** Compared to the No-GAT sequence, students will be more likely to demonstrate multiple-perspective taking in the With-GAT sequence
H4 Knowledge acquisition	**(H4a)** Main effect of English class; **(H4b)** Main effect of argumentation sequence; **(H4c)** Interaction effect of English class and argumentation sequence English A will perform better than English B overall, but English B scores will improve after intervention.	-
H5 Anxiety towards writing in English	**(H5a)** Main effect of English class; **(H5b)** Main effect of argumentation sequence; **(H5c)** Interaction effect of English class and argumentation sequence English B will have higher anxiety scores than English A overall, but will decrease after intervention	-

Table 2 summarizes the hypotheses for the dependent variables in the study. Based on previous GATs, it is predicted that compared to the no-GAT sequence, in the with-GAT sequence, students will demonstrate awareness of diversity of cognitive information (stakeholders and perspectives) that is in accordance to the information in the GAT (H1). The GAT is also expected to have an effect on multiple-perspective taking (H3a), knowledge acquisition (H4) and anxiety towards writing in English (H5), particularly for English B students. Hypotheses were developed for variables in which differences due to English proficiency and academic performance could be expected (e.g., H1a, H3a, H4 and H5). Since there are no studies so far that compare the influence of GATs on groups with varying English proficiency, no *a priori* hypotheses for between-group comparisons were defined for variables that could be influenced by the presence or absence of the GAT, including communication behavior (H2) and interaction effect on multiple-perspective taking (H3b).

Results

Sample Size

Table 3.

Sample sizes per session in each argumentation sequence and the corresponding variables measured.

		English A	English B	Total	Variables measured
	Class size	9	10	19	Anxiety towards writing in English (pre-intervention)
No-GAT	Session 1	9	9	18	Number of stakeholders, grounded claims, Argument quality
	Session 2	8	10	18	Communication behavior (English class, friendships, perspectives), argumentation moves, consistency of comments
	Session 3	7	10	17	(1) awareness and (2) multiple-perspective taking; word count
With-GAT	All sessions	8	10	18	All variables

Table 3 summarizes the corresponding sample sizes per variable. In the No-GAT sequence, some students were unable to complete all experiment sessions due to absences. In the with-GAT sequence, 1 English A student dropped out of the class for the remainder of the school year, leaving 18 participants. There were no further drop-outs in this argumentation sequence.

Word Count, Stakeholders, and Grounded Claims

Table 4.

Average (standard deviation) word count, number of stakeholders mentioned, and type of grounded-claims mentioned

	No-GAT sequence		With-GAT sequence	
	English A	English B	English A	English B
Word count				
Session 1	100.67 (30.4)	79.30 (24.2)	132.1 (35.4)	111.7 (46.6)
Session 2	79.3 (24.23)	43.2(14.1)	84.5 (50.3)	48.8 (6.2)
Session 3	79.6 (55.1)	49.6 (23.87)	66.38 (24.5)	64.4 (23.8)
Number of stakeholders mentioned	1.37 (.74)	1.40(.69)	2.75(1.48)	2.7(.95)
Economic-oriented grounds	1.13(.99)	1.0(.82)	1.63(1.41)	1.1(1.37)
Environment-oriented grounds	.25(.46)	.4(.52)	.63(.92)	1.3 (1.25)

English A students wrote more words in all 3 sessions in both argumentation sequences (see Table 4). However, in the No-GAT sequence, Mann-Whitney U tests showed a statistically significant difference only in Session 2 (one-tailed Mann Whitney U=52.5, p=0.048, C.I.[4-694e-5,Inf], r=0.335). In the with GAT

argumentation sequence, differences in word count were statistically significant only in Session 1 (one-tailed Mann Whitney *U*=63, 95% C.I. [4.0, Inf], *p*=0.023, *z*= -2.0, *r*= 0.47) and Session 2 (one-tailed Mann Whitney *U*=70, 95% C.I. [14, Inf], *p*=0.004, *z*= -2.63, *r*= 0.62).

A total of 6 stakeholders and 4 stakeholders were mentioned in Session 1 of the no- and with-GAT sequences, respectively (see Appendix D). Students in either class mentioned about 1-3 stakeholders in their initial arguments and wrote more economic-oriented grounds than environment-oriented grounds to support their claims in the no-GAT sequence. In the with-GAT phase, English B students tended to write about an equal number of economic and environmental-oriented grounds. No significant differences on these variables were observed between the English classes.

Explanatory Variables and Manipulation Check

Table 5.

Cross-tabulation and corresponding Fisher Exact Test of English class and explanatory variables

	No-GAT sequence			With-GAT sequence		
	English A	English B	Fischer Exact Test	English A	English B	Fischer Exact Test
Argumentation quality			*p*=0.47			*p*=1.0
Grounded claims	9	7		8	9	
Claims without grounds	0	2		0	1	
Argumentation moves			*p*=0.1			*p*=0.045
Counterargument	2	1		4	0	
Integrative	2	4		2	5	
Elicitations	3	0		0	0	
Non-argumentative	1	5		2	5	
Consistency of arguments			*p*=1.0			*p*=0.352
Fully consistent	3	4		1	4	
Partially consistent	2	2		4	2	
Not at all consistent	3	4		3	4	

Table 5 summarizes the results for the explanatory variables. In terms of argumentation quality, nearly all students were able to provide grounded claims, except for 1-2 English B students (see sample responses in Tables E2-E4, Appendix E). However, half of English B students in either argumentation sequence wrote non-argumentative moves; only 1 wrote counterarguments (in the no-GAT sequence). A statistically significant difference in argumentation moves was observed in the with GAT argumentation sequence. Finally, students in either English class were equally likely to post replies that were fully, partially, or not at all consistent with their initial arguments.

English A students scored higher (*M*=7.62, *SD*=0.736) than English B students (*M*=6.5, *SD*=1.12) in the 8-point manipulation check for interpreting the GAT in Session 2. This difference is significant (Mann Whitney *U*=63, 95% C.I. [9.703e-5 2.375], *p*=0.039, *z*= -1.76, *r*= 0.415), implying that English A students were more likely to interpret group awareness information from the GAT accurately than English B students. Students that did not receive full points failed to answer the questions that require them to correctly identify peers with whom they had no stakeholders in common (English A=1, English B=4). Nearly all students (except for 1 English A student and 3 English B students) replied to the post of classmates whose name they identified in the manipulation check questionnaire. According to the logged clickstream data, English B students spent an average of 9.17 minutes (*SD*=4.45) interacting with the GAT, whereas English B students spent 4.42 minutes (*SD*=1.35) on average; this difference was found to be statistically significant (Mann Whitney *U*=2, *p*<0.001, z=-3.14, *r*=0.74).

Dependent Variables (RQ1)

Communication behavior.

Table 6

Cross-tabulation of English class and observed and self-reported communication behavior.

		No-GAT sequence (observed)		With-GAT sequence (observed)		With-GAT sequence (self-reported)	
		English A	English B	English A	English B	English A	English B
English class							
	Same class	7	6	6	7	-	-
	Different class	1	4	2	3	-	-
Friendship							
	Friends	8	7	7	8	0	0
	Non-friends	0	3	1	2	-	-
At least 1 stakeholder in common							
	Yes	4	6	7	10	5	8
	Perspective						
	Same	(2)	(2)	(4)	(7)	(3)	(7)
	Different	(2)	(4)	(3)	(3)	(2)	(1)
	No	4	4	1	0	0	2
Other reasons (e.g., replied to the first post they noticed)		-	-	-	-	3	0

Students in either argumentation sequence responded more to peers in the same English class and to those they consider their friends (see Table 6). Especially in the with-GAT sequence, students also responded to peers who mentioned at least 1 stakeholder that they also mentioned and also shared the same perspective; this was corroborated by the self-reports. No significant differences between English classes were observed in any of these variables. It should be noted that on average, English A and English B students tend to have the same number of friends in class, namely about half the total number of students ($M_{\text{English A}}$=7.38, *SD*=4.57; English B=8.6, SD=5.8, $t(16)=-0.487$, $p=.633$). They also had the same number of friends that belong to the same English class ($M_{\text{English A}}$=3.5, *SD*=1.85; $M_{\text{English B}}$=5.5, *SD*=3.21, $t(16)=-1.56$, $p=.138$) and different English class ($M_{\text{English A}}$=3.875, *SD*=3.4; $M_{\text{English B}}$=3.1, *SD*=2.96, $t(16)=0.517$, $p=.612$).

As for the self-reported communication behaviors, four students (English A=1, English B=3) reported communication behaviour that was inconsistent with their actual communication behaviour (e.g., mentioning that they responded to a post that had a different perspective, when they actually responded to a post with the same perspective).

Awareness of cognitive information. In the No-GAT phase, English A students scored an average of 5.4 (*SD*=1.5) out of 11 points on the awareness measures, whereas English B students scored 4.16 (*SD*=1.34) on average. However, in the with GAT phase, English A students (*M*=3.88, *SD*=1.36) scored lower than English B students (*M*=5.1, *SD*=2.27) out of 10 points. A 2x2 ANOVA (within: no/with GAT; between: English class) was performed on the standardized scores of students who completed the awareness measures in both argumentation sequences (English A=7; English B=9). No main effects were found; however, an interaction effect was found between the presence/absence of the GAT and English class ($F(1, 14) = 4.399$, $p=.006$, $\eta^2=.427$). This suggests that awareness of multiple stakeholders and perspectives among English B students improved after viewing the GAT, whereas English A demonstrated lower awareness when the GAT was introduced.

Appendix F shows the usefulness ratings of the GAT on a 5-point Likert scale. Students in both groups generally gave positive ratings on items referring to group awareness (questions 2-6). English A and English B students gave neutral to positive ratings on average regarding the usefulness of the GAT in helping them decide which posts to read (question 7) and comment on (question 8).

Multiple-perspective taking.

Table 7.

Cross-tabulation of English class and observed and self-reported multiple-perspective taking

	No-GAT sequence (observed)		With-GAT sequence (observed)		With-GAT sequence (self-reported)	
	English A	English B	English A	English B	English A	English B
Dismissal	2	5	3	4	1	2
Local agreement	1	3	2	1	4	5
Integration	4	2	3	4	3	3
Withdrawal of initial argument	0	0	0	1	0	0

Table 7 shows the extent to which final arguments in Session 3 differed from the initial arguments expressed in Session 1 (see sample responses in Table E1 of Appendix E). In the No-GAT sequence, half of the English B students dismissed the new arguments that they encountered during the activity. Four English A students were able to integrate multiple perspectives from the discussion into their final answers. The resulting p-value for a Fisher's Exact Test on this data was 0.46. Similarly, in the with-GAT sequence, there were no significant differences between the two groups (p=1, Fisher's Exact Test) in their final arguments in Session 3. Most students either dismissed or integrated multiple perspectives. One English B student stated that her perspective has changed entirely as a result of the activity. Comparing their self-reported change in perspectives, only 1 English A student and 2 English B students expressed that their perspectives did not change at all. However, only 5 students (English A= 1; English B= 4) gave self-reported change in perspective that were consistent with their observed integration of perspectives in Session 3 (e.g., reporting that they integrated multiple perspectives, which is visible in their Session 3 answers).

Knowledge acquisition and anxiety towards writing in English.

Table 8.

Average (standard deviation) scores on the knowledge test per English class in each argumentation sequence.

	Before with-GAT sequence	After with-GAT sequence
English A	7.5 (1.41)	6 (2)
English B	8.13(.64)	5.8(1.93)

Table 8 summarizes the results of the knowledge test before and after the intervention. A 2x2 ANOVA with time and English class as factors showed no interaction effect and no main effect for time. However, a significant main effect for English class ($F(1,16)= 7.8$, $p=.0135$, $\eta^2=.328$) indicates that English A performed significantly better than English B students in both pre- and post-tests.

Table 9.

Average (standard deviation) scores on the L2WAI questionnaire and frequency count of qualitative comments

	Before intervention		After intervention	
	English A	English B	English A	English B
L2WAI scores	40.33(11.3)	67.6 (5.19)	42.75 (12.2)	65.40 (8.2)
Qualitative comments				
Anxious about using English in Economics class	0	2	0	1
Confident using English in Economics class	6	2	6	6
Slight nervousness due to some language-related concerns	1	2	0	3
Anxiety is not due to English proficiency	2	3	2	0
No comment	0	1	0	0

Table 9 displays the results of the L2WAI questionnaire. A 2x2 ANOVA was performed on the scores of students who completed the anxiety questionnaire in both argumentation sequences (n=18). No interaction effect between English class and time were observed, as well as no main effect for time, which means that the levels of anxiety before and after the intervention were similar. A significant main effect for English class ($F(1,16)$= 55.14, $p<0.001$, η^2=.775) was observed, indicating that English B students experience greater anxiety towards English than their English A peers before and after the experiment.

Five different types of answers emerged when students were asked about their anxiety towards using English in Economics class over the past 4 weeks (sample responses can be found in Appendix E). Consistent with the low anxiety scores, English A reported that they feel confident with their level of English in Economics class, both before and after the experiment. On the other hand, only 2 English B students claim not to experience anxiety at all. After the experiment, only 1 student reported experiencing anxiety, whereas majority said that they experience slight to no anxiety during Economics class.

Process Data: Clickstream Data and Markov Chains (RQ2)

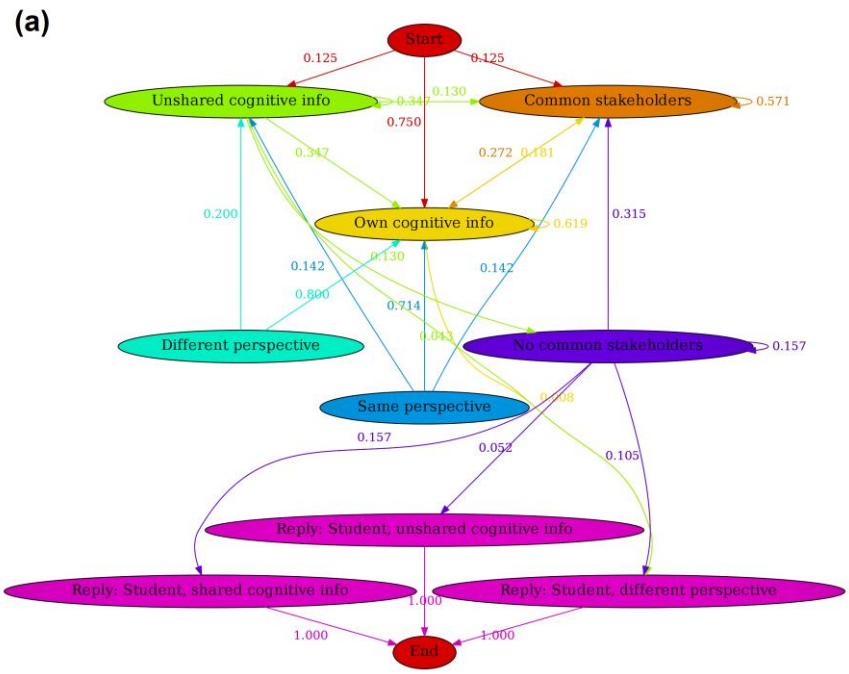
Table 10.

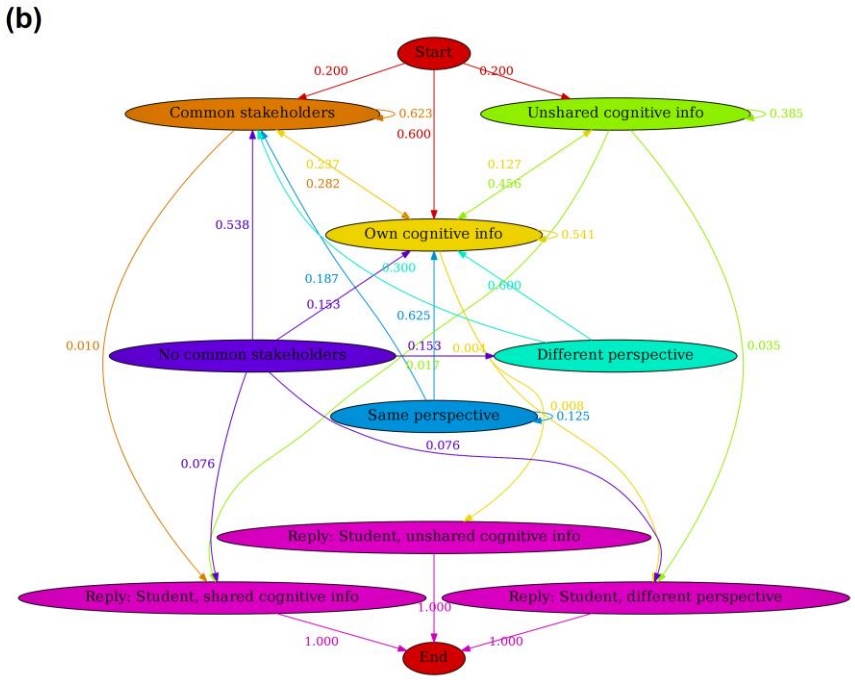
Distribution of logged interactions on the GAT per English class.

	% Interactions of Group	
Annotated label	English A	English B
Own cognitive info	48%	41.7%
Common stakeholders	31%	37.2%
Unshared cognitive info	9.1%	11.09%
No common stakeholders	7.5%	2.53%
Same perspective	2.8%	3.11%
Different perspective	1.98%	1.95%

Note. Values represent the percent of each interaction type in the total number of logged interactions.

Fig. 5 Markov chains showing GAT navigation patterns of English A (a) and English B (b) students.





Note. Values represent probabilities to transitioning (i.e., clicking) from one state (i.e., node) to the next. Colors correspond to nodes and their outgoing edges.

Table 10 summarizes the distribution of logged interactions of each class on the GAT. A one-tailed Mann Whitney test on the number of logged interactions indicates that English B students interacted more with the GAT (M=66.20, SD=43.90) than English A students (M=38.63, SD=15.4; U=19, 95% C.I. [Inf., -3.0], p=0.034, z= -2.0, r= 0.47). Fig. 5 shows the Markov chains for each English class. The nodes correspond to the annotated labels from the log files (see sample in Appendix C).

Coinciding with the scaffolding provided to students in Session 2 (Appendix A), both groups mostly clicked on their own information (i.e., own node and node of stakeholders mentioned by student). Students also paid attention to the nodes of their peers with whom they shared stakeholders in common in their initial arguments. Together, clicking on "own information" and "common stakeholder" elements make up around 79% of total logged interactions by the students. This result coincides with the Markov chains: most of the time, English A and English B students began by clicking on their own information ("own cognitive info"—75% and 60% respectively), then proceeded to investigate the stakeholder nodes attached to their nodes (looping edge in "own cognitive info"—62% and 54% respectively) or nodes of their peers with whom they have shared stakeholders ("common stakeholders"—English A=18.1%, English B=28.2%).

One notable difference is that English A clicked more often than English B students on nodes of peers with whom they did *not* have any shared cognitive information ("no common stakeholders"—7.5% and 2.53%, respectively). In the Markov chain of English A students (Fig. 5a), students clicked on these details 13% of the time after clicking on "unshared cognitive information". From this state, English A students may then decide to reply to peers with whom they share cognitive information (i.e., same perspective on the same stakeholder 15.7%); who have a different perspective on the same stakeholder (10.5%); or with whom they do not have shared cognitive information (5.2%). However, this could simply be the result of the manipulation check of the GAT: the final question required students to identify students with whom they do not share a stakeholder. In comparison, the English B Markov chain (Fig. 5b) does not have a defined previous state for "no common stakeholders" and the states prior to the reply states are varied and probabilities are rather small (<7%).

Discussion

Table 11.

Summary of results with reference to the hypotheses

Variables		Results	
		A priori	Exploratory
H1	Awareness of cognitive information	**(H1a)** No main effect of argumentation sequence on awareness	**(H1b)** No main effect of English class; **(H1c)** Significant interaction effect: English B exhibited significantly better awareness than English A in the with-GAT sequence
H2	Communication behaviour	-	No significant differences between English A and B students or argumentation sequences on the basis of **(H2a and H2d)** cognitive information; **(H2b and H2e)** friendships; **(H2c and H2f)** English class. Students responded to peers who mentioned the same stakeholders, with whom they are friends, and who belong to the same English class.
H3	Multiple-perspective taking	**(H3a)** No differences between English A and B students in multiple-perspective taking	**(H3b)** In both argumentation sequences, about half of students in either English class dismissed or integrated multiple perspectives
H4	Knowledge acquisition	**(H4a)** Confirmed: English A had significantly better scores in knowledge test; **(H4b)** No main effect of argumentation sequence; **(H4c)** No interaction effect: English B scores did not improve after intervention	-
H5	Anxiety towards writing in English	**(H5a)** Confirmed: English B have significantly higher anxiety scores; **(H5b)** No main effect of argumentation sequence; **(H5c)** No interaction effect: English B anxiety scores did not decrease after intervention	-

Table 11 displays the results of the study with regards to the hypotheses. In terms of awareness of cognitive information **(H1)** English B students were able to exhibit greater awareness of stakeholders and perspectives than English A students (H1c). When it comes to communication behavior **(H2)**, students regardless of English class or the argumentation sequence chose to communicate with peers with the same cognitive information, as well as with their friends and with peers in the same English class. In terms of multiple-perspective taking **(H3)**, students in each English class either dismissed or integrated new perspectives in both argumentation sequences. Finally, only two *a priori* hypotheses were confirmed for knowledge acquisition **(H4)** and anxiety towards writing in English **(H5)**. English A performed significantly better in pre- and post-knowledge test (H4a). Second, English B had significantly higher anxiety scores (H5a), which did not decrease after the intervention. As for the process data, the Markov chains demonstrate that English A and English B students used the GAT similarly. The clickstream data shows that English B students spent more time observing the GAT and studying it in detail; however, English A students noticed peers with whom they do not share cognitive information more.

English B students interacted with elements of the GAT and ultimately demonstrated better awareness of cognitive information. However, they did not exhibit different communication behaviours from English A students: most students responded to peers with whom they share cognitive information. There could be several explanations for this result. One could be due to similarities of initial arguments: for example, in the with-GAT sequence, most students mentioned around 1-3 stakeholders, meaning that the likelihood of peers having at least one stakeholder in common is rather high. Nevertheless, students also did not choose to engage with peers that expressed a different perspective on the same stakeholder. This could be due to the relative salience of elements in the GAT. It is easier to perceive social/cognitive information represented by nodes than the cognitive information represented by edge colour, as the latter involves more visual search operations and cognitive load to interpret the information vis-à-vis one's own (Suthers 2001). Furthermore, more visual search was required to identify peers with whom they did not share a stakeholder. Students needed to find a student node that did not have an edge connecting it to a common stakeholder; the high interconnectivity and edge crossings of the GAT makes this a challenging task. The process data confirm this: after students were prompted to select their own information, students were more likely to select the node of a peer that was also connected to the same stakeholder. The process data, along with the responses to the manipulation check, also show that some English B students had difficulties identifying peers with whom they do not share a stakeholder. Differences and unshared information were not as salient (Suthers 2001). Therefore, although English B students were more aware of the multiple perspectives in the discussion, it was more difficult to comprehend any diverging perspectives that could be discussed, which could have impeded communication that would have led to multiple-perspective taking.

Students may have also experienced "map shock" or feeling overwhelmed by the complexity and scale of a map (i.e., node-link diagrams), which leads to demotivation to process the information contained in it (Dansereau, Dees, & Simpson 1994). Students might still have felt disoriented with all the information about their group members that they received all at once and were unsure about how it could be used for productive argumentation, despite being supported with worked examples on interpreting node-link representations. Thus, despite developing awareness of multiple perspectives (in the case of English B students) and perceiving differences in cognitive information (which English A students were able to accomplish more than English B students), students might have failed to consider the merits of responding to someone with different or unshared cognitive information due to map shock.

Futhermore, unlike in Dado and Bodemer (2018), students in the present study also preferred to respond to their friends and to those in the same English class, particularly among English A students. This could be due to differences in the quality of initial arguments in Session 1. All English A students were able to make grounded claims; however at least 1 or 2 English B students would fail to do so. Combined with the fact that English B students also wrote significantly shorter arguments (based on word count), the grounds they provided were likely not as well-elaborated as those of their English A peers. English B students also did not produce any counterarguments in Session 2. Besides producing higher quality responses, English A students outperformed English B students in the knowledge test. Coupled with anecdotal evidence from their teacher, this implies that English A students exhibited better argumentation skills and perform better academically overall than English B students. This disparity, likely due to their varying levels of English proficiency, may have hindered collaboration between the two English classes, as observed in other studies (e.g., Popov et al 2014). Meanwhile, English B students, who consistently scored higher in anxiety towards English throughout the study, may have engaged in "peer seeking", a strategy for reducing foreign language anxiety by interacting with peers who they believe experience the same difficulties and struggles (Kondo & Ying-Ling 2004). This strategy is especially employed by students with lower levels of foreign language proficiency (Marwan 2007), as was the case for English B students. Thus, perceiving the diversity of opinions based on GAT information may not have provided EAL students with clear norms that could alleviate their anxiety and trigger exchange of multiple perspectives (Cheuk, 2016).

This difference in academic performance could also partially account for English A's lower viewing times and interaction (and ultimately lower awareness) with the GAT. In some circumstances, high-ability students tend to profit less from guidance during CSCL and may even consider it redundant (Janssen, Kirschner, Erkens, Kirschner & Paas 2010). For instance, one study found prompting high-ability students to consider their co-learners' self-explanations of a text when drawing inferences prior to collaborative discussion did not lead to deep text comprehension, whereas drawing inferences on their own knowledge did (Mende, Proske, Körndle & Narciss 2017). The researchers posit that high-ability students perform learning tasks more spontaneously, and that guidance impinges on this spontaneity. Similarly, English A students may have preferred to carry out the activity spontaneously, without considering co-learners' information.

Finally, not all students were able to demonstrate multiple-perspective taking in their final arguments in both argumentation sequences. Once again, this could be the result of quick consensus building: only a few

students (mostly in English A, especially in the with-GAT phase) were able to provide counterarguments in their replies, which could have influenced the quality of the discussion overall. However, in the self-reports, only 3 students stated that their perspective did not change at all. This implies that students may have in fact integrated or localized new perspectives from the discussion, but did not express this in their final arguments.

To summarize the findings in relation to the research questions, it appears that the GAT influences learner behavior during collaborative argumentation on SAQs on an SNS, in that it increases awareness of multiple stakeholders and perspectives (i.e., cognitive information) among students who interact with the GAT's elements, particularly those with lower English proficiency. However, students oriented their communication behaviors according to similarities rather than differences in cognitive information. The GAT also did not foster multiple perspective taking or communication between non-friends and English classes likely due to differences in English proficiency and anxiety towards writing in English (RQ1). Similarly, the process data from the GAT showed that students mainly observed the information they shared in common with peers; differences in or unshared cognitive information were less salient, particularly for those with lower English proficiency (RQ2). It appears that the networked arrangement of the GAT emphasized similarities in cognitive information. Therefore, unlike previous GAT studies, changes in behavior due to perceiving differences in information were not observed.

Limitations and Future Directions

In the interest of ecological validity, aspects of the classroom setting were considered in the design of the methodology, including between-groups comparisons based on a pre-existing variable (English proficiency) and selecting topics from the IB curriculum. However, due to the small sample size, a number of effects might have been overlooked. For instance, no significant differences between or within groups were found in terms of anxiety scores, although the qualitative comments suggest that some English B students became more confident with their English after the last argumentation sequence. Future studies could therefore adopt a more robust method that accommodate a larger sample size and take both ecological and internal validity into account, such as *in vivo* experimentation (Koedinger & Corbett 2006) in which Economics classes (same year-level with students with diverse English proficiencies) are randomly assigned to either the no- or with-GAT groups; the activity would still be embedded in normal class time.

The SAQ selected for the activity might have influenced engagement. SAQs make argumentation an intrinsically motivating activity especially when the topic is relevant in the learners' everyday lives (Lin & Mintzes 2010). In Dado & Bodemer (2018), the SAQ was about immigration, a topic that is highly personal given that most students come from outside of Germany. Inter-group communication and multiple-perspective taking were observed, whereas the same results were not found in the present study. This could be due to the lack of personal experiences with the economic impacts of climate change. Studies have shown that direct personal experiences of climate change-related events heavily shape one's perspectives and attitudes towards the topic (Lujala 2015). Therefore, it would be interesting to see whether the proximity of the SAQ to students' personal experiences influences engagement or argumentation quality. For instance, genetically-modified crops could be explored in an argumentation activity either by discussing its impact on the environment or one's health, with the latter presumably being of higher proximity.

Future research could also look into combining the GAT with argumentation scripts. In a study by Puhl and colleagues (2015b), they found that the GAT depicting communication attitudes combined with a script that prompted students to reflect on the information on the GAT led to attitude change, which was partly related to significantly better learning outcomes. Given the relative complexity of network graphs, the influence of the GAT in the present study on communication behavior and multiple-perspective taking could be strengthened if students are provided with scripts to prevent map shock or help them consider less visually salient information. Specifically, the script could guide learners not only to notice different or unshared cognitive information, but also to consider orienting their behaviors accordingly (i.e., to respond to peers with a different perspective). Scripts may also provide clearer norms for conducting argumentation activities than GAT information alone, which could be valuable for EAL students (Cheuk, 2016).

Differences in academic performance may have also influenced the results. Although there is some evidence that the proficient English speakers in the study perform better academically, the extent to which English proficiency, anxiety towards writing in English and proficiency in Economics are compounded is not known. Therefore, future studies could investigate whether the amount of guidance from GAT and/or scripts varies depending on English and academic ability. Scripts for students with lower English proficiency, weaker argumentation skills or higher levels of anxiety could additionally include explicit instructions on constructing arguments. For high ability students, argumentation scripts may simply include prompts that explain the merits of having group awareness and how to use this awareness productively.

Conclusion

The study adds to the understanding of how linguistically diverse groups of learners can be supported during collaborative argumentation on SNSs. It demonstates that awareness of multiple perspectives in a collaborative argumentation activity on SNSs does not automatically lead to behaviors that facilitate exchanging or taking up multiple perspectives. This could be due to the relative salience of similar versus different or unshared group information, learner differences in language and academic abilities, or anxiety that may arise due these differences. Thus, further research should investigate how collaboration scripts can help learners navigate a complex GAT to consider different/unshared (less salient) group information. Researchers may also look whether high ability versus low ability students require differentiated support to maximize learning opportunities for each group.

References

Asterhan, C. S. (2018). Exploring enablers and inhibitors of productive peer argumentation: The role of individual achievement goals and of gender. *Contemporary Educational Psychology*, *54*, 66-78, doi:10.1016/j.cedpsych.2018.05.002.

Andriessen J., Erkens G., Van De Laak C., Peters N., Coirier P. (2003) Argumentation as negotiation in electronic collaborative writing. In Andriessen J., Baker M., Suthers D. (Eds) *Arguing to Learn: Computer-Supported Collaborative Learning*, vol 1 (pp. 79-115). Springer, Dordrecht.

Bailey, D., Lee, A., Vorst, T., & Crosthwaite, P. R. (2017). An investigation of differences and changes in L2 writing anxiety between blended and conventional English language learning context. *Computer-Assisted Language Learning-Electronic Journal*, *18*(1), 22-39.

Baker, M. J. (2003). Computer-mediated argumentative interactions for the co-elaboration of scientific notions. In: J. Andriessen, M. Baker, D. Suthers (Eds.), *Confronting Cognitions*: *Arguing to Learn* (pp. 47-78). Netherlands: Kluwer Academic Publishers.

Bathgate, M., Crowell, A., Schunn, C., Cannady, M., & Dorph, R. (2015). The learning benefits of being willing and able to engage in scientific argumentation. *International Journal of Science Education*, *37*(10), 1590-1612, doi:10.1080/09500693.2015.1045958.

Bodemer, D., & Dehler, J. (2011). Group awareness in CSCL environments. *Computers in Human Behavior* *27*(3), 1043-1045, doi:10.1016/j.chb.2010.07.014.

Bratitsis, T., & Dimitracopoulou, A. (2007). Interaction analysis in asynchronous discussions: lessons learned on the learners' perspective, using the DIAS system. In C. Chinn, G. Erkens, & S. Puntambekar (Eds). *Proceedings of the 8th International Conference on Computer Supported Collaborative Learning* (pp. 90-92). New Brunswick, New Jersey: International Society of the Learning Sciences.

Chen, B., & Bryer, T. (2012). Investigating instructional strategies for using social media in formal and informal learning. *The International Review of Research in Open and Distributed Learning*, *13*(1), 87–104, doi: 10.19173/irrodl.v13i1.1027

Cheuk, T. (2016). Discourse practices in the new standards: The role of argumentation in common core-era next generation science standards classrooms for English language learners. *Electronic Journal of Science Education* *20*(3), 92-111, http://ejse.southwestern.edu/article/view/15860.

Cheng, Y. S., Horwitz, E. K., & Schallert, D. L. (1999). Language anxiety: Differentiating writing and speaking components. *Language Learning*, *49*(3), 417-446, doi:10.1111/0023-8333.00095.

Clark, D. B., Sampson, V., Weinberger, A., & Erkens, G. (2007). Analytic frameworks for assessing dialogic argumentation in online learning environments. *Educational Psychology Review*, *19*(3), 343-374, doi:10.1007/s10648-007-9050-7.

Conrad, S., & Mauranen, A. (2003). The corpus of English as lingua franca in academic settings. *TESOL Quarterly*, *37*(3), 513-527, doi:10.2307/3588402.

Dado, M., and Bodemer, D. (2018) Social and cognitive group awareness to aid argumentation about socially acute questions on social media. In J. Kay and R. Luckin (Eds.) *Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences (ICLS) 2018, Volume 1* (pp. 456-463). London, UK: International Society of the Learning Sciences.

Dansereau, D. F., Dees, S. M., & Simpson, D. D. (1994). Cognitive modularity: Implications for counseling and the representation of personal issues. *Journal of Counseling Psychology*, *41*(4), 513-523, doi:10.1037/0022-0167.41.4.513.

Dornfeld, C., Zhao, N., & Puntambekar, S. (2017). A mixed-methods approach for studying collaborative learning processes at individual and group levels. In B. K. Smith, M. Borge, E. Mercier, and K. Y. Lim (Eds.) *Making a Difference: Prioritizing Equity and Access in CSCL, 12th International Conference on*

Computer Supported Collaborative Learning (CSCL), Volume 1, (pp. 191-199). Philadelphia, PA: International Society of the Learning Sciences. Philadelphia, PA: International Society of the Learning Sciences.

Evagorou, M., & Osborne, J. (2013). Exploring young students' collaborative argumentation within a socioscientific issue. *Journal of Research in Science Teaching*, *50*(2) 209-237, doi:10.1002/tea.21076.

Glanville, A., & Glanville, J. (2013). *Multiple Choice Questions for Economics*. Exeter, UK: Glanville Books Ltd.

González-Howard, M. & McNeill, K. L. (2017). *Variation in how teachers support critique in argumentation discussions*. Paper presented at the annual meeting of the National Association for Research in Science Teaching, San Antonio, TX.

Guzdial, M., & Turns, J. (2000). Effective discussion through a computer-mediated anchored forum. *The Journal of the Learning Sciences*, *9*(4), 437-469, doi:10.1207/S15327809JLS0904_3.

Hendrick, C. (1990). Replications, strict replications, and conceptual replications: are they important? *Journal of Social Behavior and Personality*, *5*(4), 41-50.

Hijzen, D., Boekaerts, M., & Vedder, P. (2007). Exploring the links between students' engagement in cooperative learning, their goal preferences and appraisals of instructional conditions in the classroom. *Learning and Instruction*, *17*(6), 673-687, doi:10.1016/j.learninstruc.2007.09.020.

Hung, H. T., & Yuen, S. C. Y. (2010). Educational use of social networking technology in higher education. *Teaching in Higher Education*, *15*(6), 703-714, doi:10.1080/13562517.2010.507307.

Janssen, J., & Bodemer, D. (2013). Coordinated computer-supported collaborative learning: Awareness and awareness tools. *Educational Psychologist*, *48*(1), 40-55, doi:10.1080/00461520.2012.749153.

Janssen, J., Erkens, G., & Kirschner, P. A. (2011). Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior* *27*(3), 1046-1058, doi:10.1016/j.chb.2010.06.002.

Janssen, J., Kirschner, F., Erkens, G., Kirschner, P. A., & Paas, F. (2010). Making the black box of collaborative learning transparent: Combining process-oriented and cognitive load approaches. *Educational Psychology Review* *22*(2), 139-154, doi:10.1007/s10648-010-9131-x.

Kirschner, P. A. (2015). Facebook as learning platform: Argumentation superhighway or dead-end street? *Computers in Human Behavior*, *53*(Supplement C), 621–625, doi:10.1016/j.chb.2015.03.011.

Koedinger, K. R., & Corbett, A. (2006). Cognitive Tutors: Technology Bringing Learning Sciences to the Classroom. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 61-77). New York, NY, US: Cambridge University Press.

Kondo, D. S., & Ying-Ling, Y. (2004). Strategies for coping with language anxiety: The case of students of English in Japan. *ELT Journal*, *58*(3), 258-265, doi:10.1093/elt/58.3.258

Lin, K. Y., & Lu, H. P. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior* *27*(3), 1152-1161, doi:10.1016/j.chb.2010.12.009.

Lin, S. S., & Mintzes, J. J. (2010). Learning argumentation skills through instruction in socioscientific issues: The effect of ability level. *International Journal of Science and Mathematics Education*, *8*(6), 993-1017, doi:10.1007/s10763-010-9215-6.

Leitão, S. (2000). The potential of argument in knowledge building. *Human Development*, *43*(6), 332–360, doi: 10.1159/000022695.

Leitão, S. (2003). Evaluating and selecting counterarguments: Studies of children's rhetorical awareness. *Written Communication* 20(3) 269-306, doi:10.1177/0741088303257507

Llorens Cerdà, F., & Capdeferro Planas, N. (2011). Facebook's potential for collaborative e-learning. *International Journal of Educational Technology in Higher Education*, *8*(2), 197-210, doi:10.7238/rusc.v8i2.963.

Madge, C., Meek, J., Wellens, J., & Hooley, T. (2009). Facebook, social integration and informal learning at university: 'It is more for socialising and talking to friends about work than for actually doing work'. *Learning, Media and Technology*, *34*(2), 141-155, doi:10.1080/17439880902923606.

Manca, S., & Ranieri, M. (2013). Is it a tool suitable for learning? A critical review of the literature on F acebook as a technology-enhanced learning environment. *Journal of Computer Assisted Learning* 29(6), 487-504, doi:10.1111/jcal.12007.

Marwan, A. (2007). Investigating students' foreign language anxiety. *Malaysian Journal of ELT Research*, *3*(1), 19-52, http://journals.melta.org.my/index.php/majer/article/view/196.

Mason, L., & Scirica, F. (2006). Prediction of students' argumentation skills about controversial topics by epistemological understanding. *Learning and Instruction*, *16*(5), 492-509, doi:10.1016/j.learninstruc.2006.09.007

Mende, S., Proske, A., Körndle, H., & Narciss, S. (2017). Who benefits from a low versus high guidance CSCL script and why? *Instructional Science*, *45*(4), 439-468, doi:10.1007/s11251-017-9411-7.

Nussbaum, E. M. (2008). Collaborative discourse, argumentation, and learning: Preface and literature review. *Contemporary Educational Psychology*, *33*(3), 345-359, doi:10.1016/j.cedpsych.2008.06.001

Nussbaum, E. M. (2011) Argumentation, dialogue theory, and probability modeling: Alternative frameworks for argumentation research in education. *Educational Psychologist*, *46*(2), 84-106, doi:10.1080/00461520.2011.558816.

Nussbaum, E. M., Sinatra, G. M., & Poliquin, A. (2008). Role of epistemic beliefs and scientific argumentation in science learning. *International Journal of Science Education*, *30*(15), 1977-1999, doi:10.1080/09500690701545919

Noroozi, O., Weinberger, A., Biemans, H. J., Mulder, M., & Chizari, M. (2012). Argumentation-based computer supported collaborative learning (ABCSCL): A synthesis of 15 years of research. *Educational Research Review*, *7*(2), 79-106, doi:10.1016/j.edurev.2011.11.006.

Popov, V., Brinkman, D., Biemans, H. J., Mulder, M., Kuznetsov, A., & Noroozi, O. (2012). Multicultural student group work in higher education: An explorative case study on challenges as perceived by students. *International Journal of Intercultural Relations*, *36*(2), 302-317, doi:10.1016/j.ijintrel.2011.09.004.

Popov, V., Noroozi, O., Barrett, J. B., Biemans, H. J., Teasley, S. D., Slof, B., & Mulder, M. (2014). Perceptions and experiences of, and outcomes for, university students in culturally diversified dyads in a computer-supported collaborative learning environment. *Computers in Human Behavior*, *32*, 186-200, doi:10.1016/j.chb.2013.12.008.

Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015a). A long-term view on learning to argue in Facebook: The effects of group awareness tools and argumentation scripts In O. Lindwall, P. Häkkinen, T. Koschmann, P. Tchounikine & S. Ludvigsen (Eds.) *Exploring the Material Conditions of Learning: The Computer Supported Collaborative Learning (CSCL) Conference 2015*, Volume 1 (pp 110-117). Gothenburg, Sweden: The International Society of the Learning Sciences.

Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015b). Blending Facebook discussions into seminars for practicing argumentation. *Computers in Human Behavior*, *53*, 605-616, doi:10.1016/j.chb.2015.04.006.

Prinsen, F. R., Volman, M. L. L., Terwel, J., & Van den Eeden, P. (2009). Effects on participation of an experimental CSCL-programme to support elaboration: Do all students benefit? *Computers & Education*, *52*(1), 113-125, doi:10.1016/j.compedu.2008.07.001.

Sadler, T. D. (2004). Informal reasoning regarding socioscientific issues: A critical review of research. *Journal of Research in Science Teaching: The Official Journal of the National Association for Research in Science Teaching*, *41*(5), 513-536, doi:10.1002/tea.20009

Sadler, T. D., Barab, S. A., & Scott, B. (2007). What do students gain by engaging in socioscientific inquiry? *Research in Science Education*, *37*(4), 371-391, doi:10.1007/s11165-006-9030-9.

Sadler, T. D., & Donnelly, L. A. (2006). Socioscientific argumentation: The effects of content knowledge and morality. *International Journal of Science Education* *28*(12), 1463–1488. doi:10.1080/09500690600708717

Sadler, T. D., Foulk, J. A., & Friedrichsen, P. J. (2017). Evolution of a model for socio-scientific issue teaching and learning. *International Journal of Education in Mathematics, Science and Technology*, *5*(2), 75-87.

Sampson, V., & Clark, D. (2009). The impact of collaboration on the outcomes of scientific argumentation. *Science education*, *93*(3), 448-484, doi:10.1002/sce.20306

Simonneaux, J., & Legardez, A. (2010). The epistemological and didactical challenges involved in teaching socially acute questions: The example of globalization. *JSSE-Journal of Social Science Education*, *9*(4) 24–35, doi: 10.4119/UNIBI/jsse-v9-i4-1142.

Simonneaux, L., & Simonneaux, J. (2009). Students' socio-scientific reasoning on controversies from the viewpoint of education for sustainable development. *Cultural Studies of Science Education*, *4*(3), 657-687, doi:10.1007/s11422-008-9141-x.

Spencer-Oatey, H., & Dauber, D. (2017). The gains and pains of mixed national group work at university. *Journal of Multilingual and Multicultural Development*, *38*(3) 219-236, doi:10.1080/01434632.2015.1134549.

Suthers, D. (2001). Towards a systematic study of representational guidance for collaborative learing discourse. *Journal of Universal Computer Science*, *7*(3) 254-277, http://www.jucs.org/jucs_7_3/towards_a_systematic_stud.

Teasley S.D. (1997) Talking about reasoning: How important is the peer in peer collaboration?. In. L.B. Resnick, R. Säljö, C. Pontecorvo, & B. Burge (Eds) *Discourse, Tools and Reasoning. NATO ASI Series (Series F: Computer and Systems Sciences),* vol 160 (pp. 361-384). Springer, Berlin, Heidelberg

Tu, C. H., Blocher, M., & Gallagher, L. (2010). Asynchronous network discussions as organizational scaffold learning: threaded vs. flat-structured discussion boards. *Journal of Educational Technology Development and Exchange (JETDE)*, *3*(1), doi:10.18785/jetde.0301.04.

Tsovaltzi, D., Dutta, N., Puhl, T., & Weinberger, A. (2017). Group and individual level effects of supporting socio-cognitive conflict awareness and its resolution in large SNS discussion groups: A social network analysis. In Smith, B. K., Borge, M., Mercier, E., and Lim, K. Y. (Eds.) *Making a Difference: Prioritizing Equity and Access in CSCL, 12th International Conference on Computer Supported Collaborative Learning (CSCL) 2017*, Volume 1. Philadelphia, PA: International Society of the Learning Sciences, doi:10.22318/cscl2017.35.

Vatrapu, R. (2010). Comparative informatics: investigating cultural and linguistic influences in computer supported collaborative learning. In K. Gomez, L. Lyons, & J. Radinsky (Eds.) *Learning in the Disciplines: Proceedings of the 9th International Conference of the Learning Sciences (ICLS 2010) - Volume 2, Short Papers, Symposia, and Selected Abstracts* (pp. 105-106), International Society of the Learning Sciences: Chicago IL.

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., 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.

Wu, Y. T., & Tsai, C. C. (2007). High school students' informal reasoning on a socio-scientific issue: Qualitative and quantitative analyses. *International Journal of Science Education* 29(9), 1163-1187, doi:10.1080/09500690601083375.

Ziogas, C. (2012). *IB Economics: Study Guide.* Oxford, UK: Oxford University Press.

Appendix A

Instructions for Sessions 1-3

Session 1: Instructions posted on Google Classroom

Please post a response to the question:

> (no-GAT sequence): "To what extent do you agree with the statement: "Tradable permits are the best solution for reducing global carbon emissions"?
>
> (with-GAT sequence): "To what extent does solving global warming require international cooperation?"

Your answers must be 4-6 sentences long. -To support your stance, you should explain the impact of tradable permits on at least 1 stakeholder (no-GAT sequence) /how at least 1 economic stakeholder can solve global warming (with-GAT sequence).

Session 2:

No-GAT sequence – Posted on Google Classroom

Last week, you posted your response to the question: To what extent do you agree with the statement: "Tradable permits are the best solution for reducing global carbon emissions"? Today, you are going to read each other's posts and share your opinions about the topic.

Instructions:

1. Go back to last week's activity and read your classmates' posts
2. Share your opinion by commenting on 1 of your classmate's posts. Make sure to read your own answer again before commenting. You should structure your comments around your own answers to the question. As much as possible, your comments to your classmates should reflect the opinions and perspectives that you expressed in your own answer.
3. You are not allowed to talk to your classmates during the activity or reply to the comments on your own post—you will do this in the next session.

Use these "Golden Rules" and sentence starters for your comments (you may use your own sentence starters if you wish):

1. If you hold the same perspective, write down exactly what you agree on and why.
   - "I agree with your point about…because…"
   - "Like you, I think that…because…"

2. If you hold a different perspective, write down exactly what you disagree on and why.
   - "I have a different opinion than you about… Specifically, I think… because…"
   - "I disagree with your point that… because, in my opinion…"
   - "I agree with your point about…However, I disagree with your point about…because…"

3. Ask questions if something is not clear or if you would like more information.

- "A question I have about your post is..."
- "Could you please explain what you mean by..."
- "I am not sure what you mean by… could you please clarify…?"

4. Give feedback or suggestions and explain why you think this could be helpful.
   - "I think you should consider…because…"
   - "Building on your point, I suggest…because…"

With-GAT sequence - Instruction posted on a separate website; hyperlink posted on Google Classroom

Part 1: Recap

In the previous activity, you posted your opinion on the question: "To what extent does solving global warming require international cooperation?"

In your answers, you mentioned a number of important stakeholders:

- Developed countries (e.g., United States, UK, Japan, Germany, Singapore)
- Newly-industrialized countries (e.g., China, South Africa, Turkey, Thailand)
- Least-developed countries (e.g., Afghanistan, Cambodia)
- Global organizations or economic unions (e.g., United Nations, European Union)
- Countries in general
-

Furthermore, you supported your opinions by giving environmental and economic growth perspectives about these stakeholders. Here are some examples:

Environmental perspective: "China (a newly-industrialized country) produces about 30% of total global carbon emissions."

Economic perspective: "Developed countries should offer financial support to least-developed countries to help them transition to renewable energy sources."

Today, you are going to share your opinions with your classmates by commenting on each other's post from the last activity session. But before you start, we want to help you decide which posts to comment on.

Part 2: GAT training (scaffolding with worked example)

In the next page, you will be shown a graphic that displays your answers in the last Google Classroom activity. Specifically, it shows you which of your classmates hold similar or different opinions.

Below is a simplified example of the graphic you will see later (students see Fig. 3a in Appendix C)

- The circles represent you and your classmates.
- The rectangles represent the stakeholders that you and your classmates mentioned in the posts.
- A line connecting a circle to a rectangle means that you/your classmate wrote about that stakeholder.
    - A green line means that the student gave an environmental perspective about that stakeholder.

- A blue line means that the student gave an economic growth perspective about that stakeholder.

The graphic is interactive! Click and rearrange the shapes, zoom in/out (using your mouse or your computer's touchpad) or move left/right (click, hold and drag) to see the details of the graphic.

How to use the graphic: Let's take Julien as an example. This is his answer in the previous activity.

> Julien's answer: International cooperation is important because carbon emissions from newly-industrialized countries are on the rise. Therefore, developed countries must provide education or financial subsidies for renewable energy technologies in these countries.

STEP 1: Click on the circle with your name. Take note of the stakeholders connected to your circle, as well as the color of those lines.

Example:

- Julien sees a green line connecting his circle to "Newly-Developed Countries" because he gave an environmental perspective about this stakeholder (carbon emissions in newly developed countries).
- He also sees a blue line connecting his circle to "Developed Countries" because he gave an economic growth perspective about this stakeholder (financial support that developed countries should offer).

STEP 2: Select one of the stakeholders connected to your name. Take note of your classmates who are also connected to the same stakeholder, and observe whether you gave similar/different perspectives.

Example:

- Julien clicks on "Developed Countries". He sees that Liz and Marie are also connected to "Developed Countries". That means Julien, Liz and Marie wrote about developed countries in their answers.
- He notices that a blue line connects Liz to "Developed Countries". This means that both Julien and Liz gave the same perspective (economic growth) on developed countries.
- He notices that a green line connects Marie to "Developed Countries". This means that both Julien and Marie gave different perspectives on developed countries.

STEP 3: Play around with the graphic and have fun! Take note of the other stakeholders and perspectives that were mentioned by your classmates.

Example:

- Julien notices that Marcello is not connected to any of the stakeholders that Julien is connected to. This means that Julien and Marcello did not mention the same stakeholders in their answers.

Try it yourself! Analyze the graphic above and answer the questions (students do first part of manipulation check, see Appendix B).

> Part 3: Students view the GAT

(Students see the GAT as in Fig. 2)

Please spend at least 10 minutes exploring the graph.

(Students do second part of manipulation check, see Appendix B).

Part 4: Same instructions are shown as in the no-GAT sequence

Session 3: Instructions posted on Google Classroom

Today, you are going to revisit your answers to the question about tradable permits for reducing carbon emissions (no-GAT sequence)/ international cooperation against global warming (with-GAT sequence)

STEP 1: Read your original answer to the question.

STEP 2: After reading your answer, ask yourself, "has my perspective changed?" Feel free to respond to comments that you received on your post.

STEP 3: Add a comment below your own answer:

If your perspective has changed: Respond to the question again in 4-6 sentences. You may add to or edit your original answer, or you may craft an entirely new answer.

If your perspective has not changed: Write a short comment (4-6 sentences) explaining why your opinion has stayed the same.

Appendix B

Measures

Manipulation check (Session 2)

Part 1: Training phase (4 points)

1. What perspective did Marie give about developed countries? (Write "economic growth" or "environmental")
2. Name at least one student who mentioned a stakeholder that Marie did not mention in her answer. (Hint: which students are not connected to "Developed Countries"?)
3. Name the student that gave the same perspective as Ralph regarding newly-developed countries.
4. Name at least one student that gave a different perspective than Ralph regarding newly-developed countries.

Part 2: GAT (4 points)

1. According to what you see on the graphic, select all the stakeholders you mentioned in your answer on Google Classroom. Then, next to your answer(s), write whether you gave an (1) economic growth or (2) environmental perspective about that stakeholder.
2. Name at least 1 classmate who gave the same perspective on the stakeholders you mentioned.
3. Name at least 1 classmate who gave a different perspective on the stakeholders you mentioned.
4. Name at least 1 classmate who did not mention the same stakeholders as you.

Awareness of multiple stakeholders and perspectives

(Stakeholders in each argumentation sequence (see Appendix D) are listed after each item.)

1. Please rank the following stakeholders from most mentioned to least mentioned by your classmates.
    - No-GAT sequence (6 points)
    - With-GAT sequence (5 points)
2. Using your best judgement, how would you describe the overall perspective of your classmates on the following stakeholders?
    - Most of my classmates gave an economic growth perspective about this stakeholder.
    - Most of my classmates gave an environmental perspective about this stakeholder.
    - About an equal number of my classmates gave either an economic growth or environmental perspective about this stakeholder.
    - No-GAT sequence (5 points)
    - With-GAT sequence (5 points)

Friendship (after with-GAT sequence only)

In your economics class, who would you consider your friends? Your answers will be kept confidential, so please answer honestly.

(Participants then select their friends of a list of participant names, along with a “None” option)

Self-reported communication behavior (after with-GAT sequence only)

(Note: Only answer to #2 was reported in the Results section)

1. Read each statement carefully and select all that describe why you decided to comment on certain posts on Google Classroom.

“I chose to add a comment on certain posts...”

> … because they expressed a different perspective than mine about a stakeholder that I mentioned in my own post.
>
> …because they had already received several comments.
>
> … because they expressed the same perspective as mine about a stakeholder that I mentioned in my own post.
>
> ... because it was the first post I noticed.
>
> … because they were written by my friends.

… because they mention stakeholders that I did not mention in my own post.

…because they had not yet received comments.

… because they were at the top of the Google Classroom page.

2. Out of all the reasons you select, which one influenced your decision the most?

Self-reported multiple-perspective taking (after with-GAT sequence only)

(Note: Options in this question were based on the argumentation argumentation sequences of Leitão (2000))

Which statement best describes your change in perspective on international cooperation against global warming?

Choose one of the following answers:

- My perspective did not change at all.
- My perspective changed to some degree. I have integrated others' perspectives into my own.
- My perspective completely changed.
- My perspective did not change, but I was able to acknowledge alternative perspectives.

Open-ended question about anxiety towards writing in English

Think about your experiences at Economics class in the last month.

In the last month, did you feel nervous or anxious when you had to speak or write in English in your Economics class? If so, what was that experience like?

Appendix C

Interpreting the GAT and sample annotated log file

Fig. 4 Screenshots of the GAT with dummy data

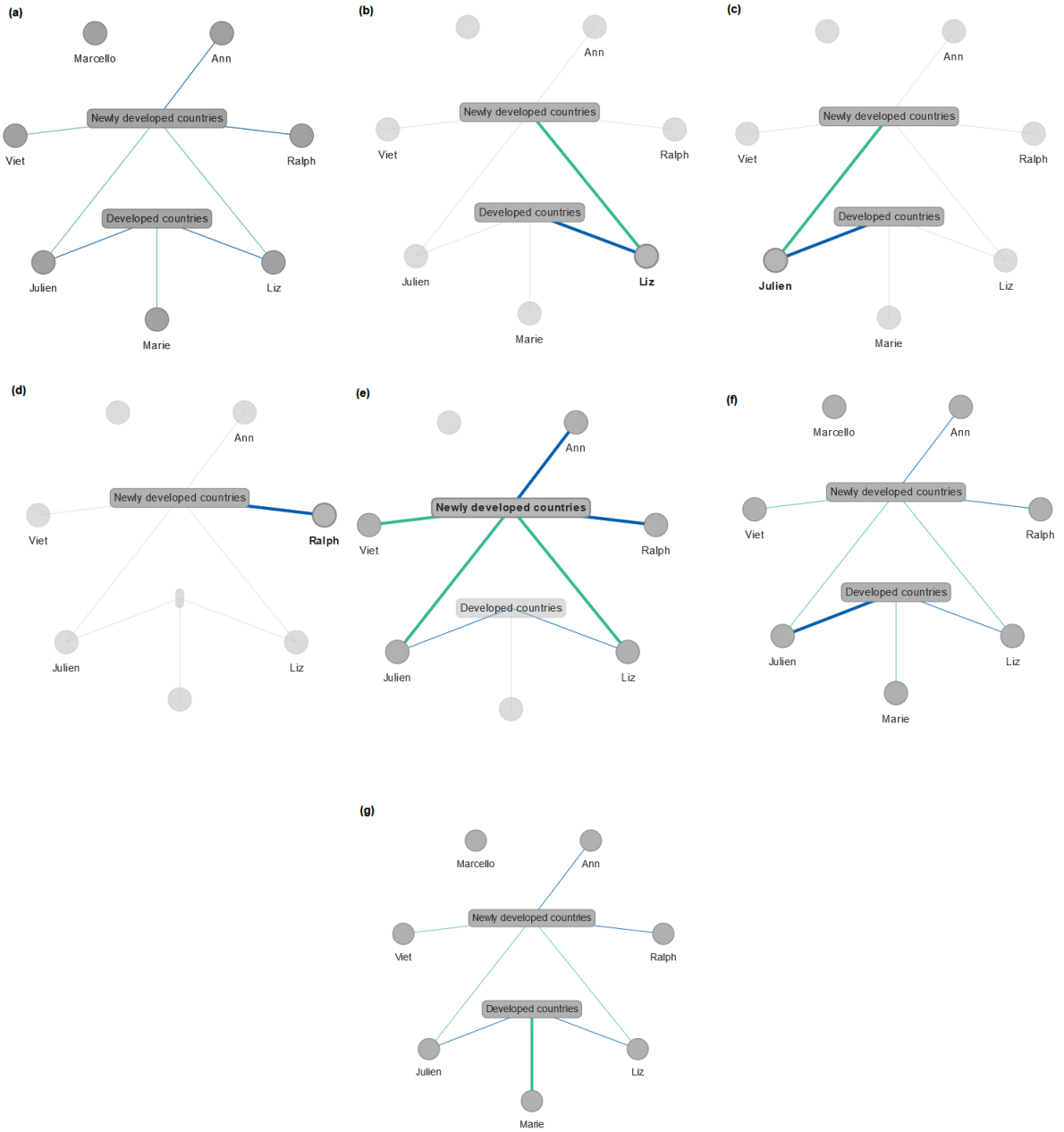


Table C. Sample log files of interactions on the GAT

What user clicks/drags	What user sees	Logged action/information		Annotation label
None	Fig. 4 a	N/A	N/A	N/A
“Liz” node	Fig. 4 b	Click node	“Liz”	Own cognitive info
“Julien” node	Fig. 4 c	Click node	“Julien”	Common stakeholders
“Ralph” node	Fig. 4 d	Drag node	“Ralph”	No common stakeholders
“Newly- Developed countries” node	Fig. 4 e	Click node	“Newly- Developed countries”	Unshared cognitive info
Edge connecting “Julien” and “Developed countries”	Fig. 4 f	Click edge	“Julien—Developed countries”	Same perspective
Edge connecting “Marie” and “Developed countries”	Fig. 4 g	Drag edge	“Marie-- Developed countries”	Different perspective
Reply state: Liz replies to Ralph	-	-	-	Student, unshared cognitive information

Fig. 4 shows (using dummy data) how participants would interact with the elements of the GAT. Table C depicts how these interactions are logged and annotated. These examples show how user “Liz” would interact with the GAT.

- As seen in Figure 4a, Liz and Julien both wrote an economic growth perspective about developing countries in Session 1. Liz and Marie wrote different perspectives about developing countries. Liz and Ralph did not write about the same stakeholders.
- When Liz clicks on the node labelled “Julien” (Figure 4c), she primarily sees social information (i.e., “Julien”), followed by cognitive information related to Julien (i.e., nodes of stakeholders he mentioned and corresponding edges). This action is thus annonated with the label “Common stakeholders”.
- When Liz only clicks on the edge that connects “Julien” and “Developing countries” (Figure 4f), she sees cognitive information first (i.e., Julien perspective, which she shares), with social information (i.e., “Julien”) being less prominent. This action is thus annonated with the label “Same perspective”.
- When Liz clicks on the node “Newly developed countries” (Figure 4e), she primarily sees cognitive information (i.e., a stakeholder she does not mention), followed by social information (i.e., peers that mentioned that stakeholder). This action is thus annonated with the label “Unshared cognitive info”.
- In Session 2, Liz replies to the post of Ralph. Hence, a reply state is appended with the label “Student, unshared cognitive information”.

Appendix D

List of stakeholders

Table D1. List of stakeholders in the no-GAT sequence and frequency of mentions in Session 1

Stakeholder	Number of students who mentioned stakeholder in Session 1 (n=19)
Developed countries	10
Newly-industrialized countries	9
Companies in general	4
Least-developed countries	2
Global organizations or economic unions	2
Island nations	1

Table D2. List of stakeholders in the with-GAT sequence and frequency of mentions in Session 1

Stakeholder	Number of students who mentioned stakeholder in Session 1 (n=18)
Developed countries	15
Newly-industrialized countries	14
Least-developed countries	10
Global organizations or economic unions	8
Countries in general	2

Appendix E

Sample responses for variables analyzed using content analysis

Table E1.

Sample coded responses for multiple-perspective taking

Category	Example (with-GAT sequence)
Dismissal	My perspective still has not changed, as I think that the global economy has to cooperate in order to handle these issues. In the end a global problem stays a problem that has to be solved by global economy.
Local Agreement	I still agree with my own initial answer but while reading the other comments, I can see the valid points that my peers are trying to make about this situation.
Integration	I still agree my statement, because I think my statement overall is good. I think [peer]'s comment is fair, he thinks instead blaming lesser developed countries, all countries need work together. This is a more efficient way. I will add this in my statement.
Withdrawal of initial argument	After I read through the claims of classmates, I got a new perspective. Developed countries and developing countries should help each other especially developed countries should help developing countries as payments to their moralization

Table E2.

Sample coded responses for argumentation quality

Category	Example (no-GAT sequence)
Grounded claims	I believe that tradable permits is indeed the best solution for reducing global carbon emissions. Since a tradable permit system allows a market to direct environmental efforts where a market does not exist, it would be good to have it in newly-industrialized countries because these countries have potential for rapid economic growth.
Claim without grounds	I think it is a good way to reduce global carbon emissions. I'm not sure that they are the best solution, but we can reduce carbon emissions to the amount we expected by tradable permits.

Table E3.

Sample coded responses for argumentation moves

Category	Example (with-GAT sequence)
Counterargument	I completely agree with your statement on that international cooperation is good for solving global warming issue. However, I think it would be stronger to say that instead of blaming lesser developed countries, all countries should work together to find a solution to global warming. Blaming is ineffective
Integration	I agree your point that the support of economic unions is necessary since more countries are involved and we can expect improvements in a large scale. Also, some developed countries need to play a role that spread cleaner and sustainable technologies while newly-industrialised countries and least- developed countries are rushing their development without having those technologies.
Elicitation	You mention that developed country should provide payments to less developed country. How do you think that it would be accomplished?
Non-argumentative move	I agree with your point about car companies because I believe that is something that's underestimated but plays a major role in global warming. (*Note*: Student merely repeats his peer's answer)

Table E4.

Sample coded responses for consistency of Session 2 responses to Session 1 arguments

Category	Example (with-GAT sequence)
Not at all consistent	Session 1 argument: International cooperation isn't necessarily required, however, it could enhance the process of solving global warming. Without international cooperation, it would be possible for developed countries to take measures against global warming individually and therefore not only help solve the problem directly but also influence other countries (not necessarily developed countries) to start taking measures against it as well. Session 2 reply: I agree with your point about car companies because I believe that is something that's underestimated but plays a major role in global warming.
Partially consistent	Session 1 argument: International cooperation is really required because every country required to reduce the carbon emission in order to solve the world common issue. *To get all countries to reduce carbon emission, the United Nation has to impose regulations on industry*. First of all, to set the regulations, developed countries have to agree with the policy to reduce the amount of carbon emission. They also should share their knowledge on clean technology with developing countries because developing countries do not have ability to produce goods with least necessary amount of carbon emission Session 2 reply: *I agree with your idea that international organization or economic unions should set a regulation the amount of carbon emission for every country.* Additionally, I think that developed countries should provide some economic support on developing countries, then their economic growth or development would not be as stagnant.
Fully consistent	Session 1 argument: International cooperation is incredibly important when solving global warming…Newly developed countries find ways to produce clean energy putting them far below their emissions limit. They are then able to trade these permits to larger developed countries for currency or goods. This causes developed countries to not take steps in the direction of solving the problem. If the newly developed countries and larger developed countries worked together to develop the technology for clean energy instead of spending resources to trade permits, both countries would benefit in the long run, And the problem of global warming would be solved sooner. Session 2 reply: Although developed countries have the ability to produce cleaner energy and solve the problem, setting a good example for other countries, but do they? It seems as though the developed countries are making the most emissions damage and paying off newly and nearly developed countries to offset their emissions. In reality, the developed countries are causing the problem more than solving it. (*Note*: Student uses tradable permits in both answers)

Table E5.

Sample coded responses for open-ended comments on L2WAI questionnaire

Category	Example (no-GAT sequence)
Anxious about using English in Economics class	“I always feel nervous in class… because English is not my first language.”

Confident using English in Economics class	“I feel very comfortable writing and speaking in English.”
Slight nervousness due to some language-related concerns	“I don't feel nervous…but sometimes I am afraid that I used some incorrect words”
Anxiety is not due to English proficiency	“I tend to often feel nervous [when writing essays in English]… however this nothing to do with my English skill but rather with my Essay writing skills.”

Appendix F

Usefulness ratings of the GAT

	English A		**English B**		**p-value**
	M	SD	M	SD	Corrected=0.006
1. The GAT accurately represented my answer to the question on Google Classroom.	4.13	.35	3.4	.52	.008
2. The GAT helped me gain a general overview of the stakeholders and perspectives mentioned by my classmates.	4.38	.74	4	.82	.319
3. I was able to see which classmates mentioned the same stakeholders as I did.	4.38	.52	4.1	.57	.334
4. I was able to see which classmates wrote from the same perspective as me.	4.38	.52	4	.47	.140
5. I was able to see which classmates wrote from a different perspective than me.	4.38	.74	4.2	.42	.438
6. I was able to see which classmates mentioned other stakeholders that I did not mention.	4.38	.52	4.1	.99	.731
7. The graphic helped me decide which posts to read.	3.75	1.04	3.4	.84	.426
8. The graphic helped me decide which posts to comment on	3.88	1.13	3.7	.83	.672

6. BIBLIOGRAPHY

References

Asterhan, C. S., & Hever, R. (2015). Learning from reading argumentive group discussions in Facebook: Rhetoric style matters (again). *Computers in Human Behavior*, *53*, 570 - 576. doi: 10.1016/j.chb.2015.05.020

Bakharia, A., & Dawson, S. (2011). SNAPP: A bird's-eye view of temporal participant interaction. In P. Long (Ed.), *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 168–173). New York, NY, USA: The Association for Computing Machinery. doi: 10.1145/2090116.2090144

Becker, R. A., Eick, S. G., & Wilks, A. R. (1995). Visualizing network data. *IEEE Transactions on Visualization and Computer Graphics*, *1*(1), 16-28. doi: 10.1109/2945.468391

Beers, P. J., Boshuizen, H. P. E., Kirschner, P. A., & Gijselaers, W. H. (2005). Computer support for knowledge construction in collaborative learning environments. *Computers in Human Behavior*, *21*(4), 623 - 643. doi: 10.1016/j.chb.2004.10.036

Bodemer, D., & Dehler, J. (2011). Group awareness in CSCL environments. *Computers in Human Behavior*, *27*(3), 1043 - 1045. doi: 10.1016/j.chb.2010.07.014

Bodemer, D., Janssen, J., & Schnaubert, L. (2018). 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* (pp. 351–358). New York, NY: Routledge/Taylor and Francis.

Buder, J. (2011). Group awareness tools for learning: Current and future directions. *Computers in Human Behavior*, *27*(3), 1114 - 1117. doi: 10.1016/j.chb.2010.07.012

Buder, J., & Bodemer, D. (2008). Supporting controversial cscl discussions with augmented group awareness tools. *International Journal of Computer-Supported Collaborative Learning*, *3*(2), 123–139. doi: 10.1007/s11412-008-9037-5

Cadima, R., Ferreira, C., Monguet, J., Ojeda, J., & Fernandez, J. (2010). Promoting social network awareness: A social network monitoring system. *Computers and Education*, *54*(4), 1233 - 1240. doi: 10.1016/j.compedu.2009.11.009

Cain, J., & Policastri, A. (2011). Using Facebook as an informal learning environment. *American Journal of Pharmaceutical Education*, *75*(10). doi: 10.5688/ajpe7510207

Carolan, B. V. (2014). *Social network analysis and education: Theory, methods and applications*. Thousand Oaks, CA: SAGE Publications Ltd.

Cavusoglu, H., Li, Z., & Huang, K.-W. (2015). Can gamification motivate voluntary contributions?: The case of StackOverflow community. In D. Cosley, A. Forte, L. Ciolfi, & D. McDonald (Eds.), *Proceedings of the 18th ACM Conference Companion on Computer Supported Cooperative Work and Social Computing* (pp. 171–174). New York, NY, USA: The Association for Computing Machinery. doi: 10.1145/2685553.2698999

Cela, K. L., Sicilia, M. Á., & Sánchez, S. (2015). Social network analysis in e-learning environments: A preliminary systematic review. *Educational Psychology Review*, *27*(1), 219–246. doi: 10.1007/s10648-014-9276-0

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, *4*(5-6), 318-331. doi: 10.1504/IJTEL.2012.051815

Chen, B., & Bryer, T. (2012). Investigating instructional strategies for using social media in formal and informal learning. *The International Review*

of Research in Open and Distributed Learning, *13*(1), 87–104. Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/1027

Cheng, Y., K., H. E., & L., S. D. (1999). Language anxiety: Differentiating writing and speaking components. *Language Learning*, *49*(3), 417-446. doi: 10.1111/0023-8333.00095

Cheuk, T. (2016). Discourse practices in the new standards: The role of argumentation in common core-era next generation science standards classrooms for English language learners. *Electronic Journal of Science Education*, *20*(3). Retrieved from http://ejse.southwestern.edu/article/view/15860

Churcher, K. M. A., Downs, E., & Tewksbury, D. (2014). Friending Vygotsky: A social constructivist pedagogy of knowledge building through classroom social media use. *Journal of Effective Teaching*, *14*(1), 33–50. Retrieved from https://eric.ed.gov/?id=EJ1060440

Claros, I., Cobos, R., & Collazos, C. A. (2016). An approach based on social network analysis applied to a collaborative learning experience. *IEEE Transactions on Learning Technologies*, *9*(2), 190-195. doi: 10.1109/TLT.2015.2453979

Cormode, G., & Krishnamurthy, B. (2008). Key differences between Web 1.0 and Web 2.0. *First Monday*, *13*(6). doi: 10.5210/fm.v13i6.2125

Dabbagh, N., & Kitsantas, A. (2012). Personal learning environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education*, *15*(1), 3 - 8. doi: 10.1016/j.iheduc.2011.06.002

Dabner, N. (2012). Breaking ground in the use of social media: A case study of a university earthquake response to inform educational design with Facebook. *The Internet and Higher Education*, *15*(1), 69 - 78. doi: 10.1016/j.iheduc.2011.06.001

Dehler-Zufferey, J., Bodemer, D., Buder, J., & Hesse, F. W. (2010). Partner knowledge awareness in knowledge communication: Learning by adapting to the partner. *The Journal of Experimental Education*, *79*(1), 102-125. doi: 10.1080/00220970903292991

de Laat, M., Lally, V., Lipponen, L., & Simons, R.-J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for social network analysis. *International Journal of Computer-Supported Collaborative Learning*, *2*(1), 87–103. doi: 10.1007/s11412-007-9006-4

Dillenbourg, P., Järvelä, S., & Fischer, F. (2009). The evolution of research on computer-supported collaborative learning. In N. Balacheff, S. Ludvigsen, T. de Jong, A. Lazonder, & S. Barnes (Eds.), *Technology-enhanced learning: Principles and products* (pp. 3–19). Dordrecht: Springer Netherlands. doi: 10.1007/978-1-4020-9827-7-1

Dunne, C., & Shneiderman, B. (2009). *Improving graph drawing readability by incorporating readability metrics: A software tool for network analysts* (Tech. Rep.). University of Maryland. Retrieved from `http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.148.3070`

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. doi: 10.1007/s11412-010-9089-1

Engelmann, T., & Hesse, F. W. (2011). Fostering sharing of unshared knowledge by having access to the collaborators' meta-knowledge structures. *Computers in Human Behavior*, *27*(6), 2078 - 2087. doi: 10.1016/j.chb.2011.06.002

Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. *International Journal of Technology Enhanced Learning*, *4*(5-6), 304-317. doi: 10.1504/IJTEL.2012.051816

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

Friedkin, N. E., & Johnsen, E. C. (1997). Social positions in influence networks. *Social Networks*, *19*(3), 209–222. doi: 10.1016/S0378-8733(96)00298-5

Friesen, N., & Lowe, S. (2012). The questionable promise of social media for education: connective learning and the commercial imperative. *Journal of Computer Assisted Learning*, *28*(3), 183-194. doi: 10.1111/j.1365-2729.2011.00426.x

Golanics, J., & Nussbaum, E. (2007). Enhancing online collaborative argumentation through question elaboration and goal instructions. *Journal of Computer Assisted Learning*, *24*(3), 167-180. doi: 10.1111/j.1365-2729.2007.00251.x

Greenhow, C., & Askari, E. (2017). Learning and teaching with social network sites: A decade of research in K-12 related education. *Education and Information Technologies*, *22*(2), 623–645. doi: 10.1007/s10639-015-9446-9

Greenhow, C., Gibbins, T., & Menzer, M. M. (2015). Re-thinking scientific literacy out-of-school: Arguing science issues in a niche Facebook application. *Computers in Human Behavior*, *53*, 593—604. doi: 10.1016/j.chb.2015.06.031

Greenhow, C., & Lewin, C. (2016). Social media and education: Reconceptualizing the boundaries of formal and informal learning. *Learning, Media and Technology*, *41*(1), 6-30. doi: 10.1080/17439884.2015.1064954

Gunawardena, C. N., Hermans, M. B., Sanchez, D., Richmond, C., Bohley, M., & Tuttle, R. (2009). A theoretical framework for building online communities of practice with social networking tools. *Educational Media International*, *46*(1), 3-16. doi: 10.1080/09523980802588626

Hmelo, C. E., Nagarajan, A., & Day, R. S. (2000). Effects of high and low prior knowledge on construction of a joint problem space. *The Journal of Experimental Education*, *69*(1), 36-56. doi: 10.1080/00220970009600648

Hmelo-Silver, C. E. (2003). Analyzing collaborative knowledge construction: multiple methods for integrated understanding. *Computers and Education*, *41*(4), 397 - 420. doi: 10.1016/j.compedu.2003.07.001

Hou, H.-T., Wang, S.-M., Lin, P.-C., & Chang, K.-E. (2015). Exploring the learner's knowledge construction and cognitive patterns of different asynchronous platforms: comparison of an online discussion forum and Facebook. *Innovations in Education and Teaching International*, *52*(6), 610–620. doi: 10.1080/14703297.2013.847381

Janssen, J., & Bodemer, D. (2013). Coordinated computer-supported collaborative learning: Awareness and awareness tools. *Educational Psychologist*, *48*(1), 40-55. doi: 10.1080/00461520.2012.749153

Janssen, J., Erkens, G., & Kirschner, P. A. (2011). Group awareness tools: It's what you do with it that matters. *Computers in Human Behavior*, *27*(3), 1046 - 1058. doi: 10.1016/j.chb.2010.06.002

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. doi: 10.1080/00461520.2016.1158654

Jeong, H., Hmelo-Silver, C. E., & Yu, Y. (2014). An examination of CSCL methodological practices and the influence of theoretical frameworks 2005–2009. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 305–334. doi: 10.1007/s11412-014-9198-3

Jones, C. (2015). *A network of network theories.* Cham: Springer International Publishing.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! the challenges and opportunities of social media. *Business Horizons*, *53*(1), 59 - 68. doi: 10.1016/j.bushor.2009.09.003

Kellogg, S., Booth, S., & Oliver, K. (2014). A social network perspective on peer supported learning in MOOCs for educators. *The International Review of Research in Open and Distributed Learning*, *15*(5), 264–289. Retrieved from `http://www.irrodl.org/index.php/irrodl/article/view/1852`

Kirschner, P. A. (2015). Facebook as learning platform: Argumentation superhighway or dead-end street? *Computers in Human Behavior*, *53*, 621 - 625. doi: 10.1016/j.chb.2015.03.011

Kirschner, P. A., & Erkens, G. (2013). Toward a framework for CSCL research. *Educational Psychologist*, *48*(1), 1-8. doi: 10.1080/00461520.2012.750227

Knoke, D., & Yang, S. (2008). *Quantitative applications in the social sciences: Social network analysis* (2nd ed.). Thousand Oaks, California: SAGE Publications Ltd.

Kollar, I., Fischer, F., & Hesse, F. W. (2006). Collaboration scripts: A conceptual analysis. *Educational Psychology Review*, *18*(2), 159–185. doi: 10.1007/s10648-006-9007-2

Kopcha, T. J. (2012). Teachers' perceptions of the barriers to technology integration and practices with technology under situated professional development. *Computers and Education*, *59*(4), 1109 - 1121. doi: 10.1016/j.compedu.2012.05.014

Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in Human Behavior*, *19*(3), 335–353. doi: 10.1016/S0747-5632(02)00057-2

Lambropoulos, N., Faulkner, X., & Culwin, F. (2011). Supporting social awareness in collaborative e-learning. *British Journal of Educational Technology*, *43*(2), 295–306. doi: 10.1111/j.1467-8535.2011.01184.x

Law, N. (2005). Assessing learning outcomes in CSCL settings. In T. Koschmann, D. D. Suthers, & T.-W. Chan (Eds.), *Proceedings of the 2005 Conference on Computer Support for Collaborative Learning: The next 10 years!* (pp. 373–377). International Society of the Learning Sciences. Retrieved from `http://dl.acm.org/citation.cfm?id=1149293.1149342`

Law, N., Yuen, J., Wong, W. O. W., & Leng, J. (2011). Understanding learners' knowledge building trajectory through visualizations of multiple automated analyses. In S. Puntambekar, G. Erkens, & C. Hmelo-Silver (Eds.), *Analyzing interactions in CSCL: Methods, approaches and issues* (pp. 47–82). Boston, MA: Springer US. doi: 10.1007/978-1-4419-7710-6-3

Leitão, S. (2000). The potential of argument in knowledge building. *Human Development*, *43*(6), 332–360. doi: 10.1159/000022695

Leite, L., Dourado, L., & Morgado, S. (2015). Sustainability on earth Webquests: Do they qualify as problem-based learning activities? *Research in Science Education*, *45*(1), 149–170. doi: 10.1007/s11165-014-9417-y

Liao, Y.-W., Huang, Y.-M., Chen, H.-C., & Huang, S.-H. (2015). Exploring the antecedents of collaborative learning performance over social networking sites in a ubiquitous learning context. *Computers in Human Behavior*, *43*, 313–323. doi: 10.1016/j.chb.2014.10.028

Lin, J.-W., Mai, L.-J., & Lai, Y.-C. (2015). Peer interaction and social network analysis of online communities with the support of awareness of different contexts. *International Journal of Computer-Supported Collaborative Learning*, *10*(2), 139–159. doi: 10.1007/s11412-015-9212-4

Lin, K.-Y., & Lu, H.-P. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior*, *27*(3), 1152 - 1161. doi: 10.1016/j.chb.2010.12.009

Lin, P.-C., Hou, H.-T., Wu, S.-Y., & Chang, K.-E. (2014). Exploring college students' cognitive processing patterns during a collaborative problem-solving teaching activity integrating Facebook discussion and simulation tools. *The Internet and Higher Education*, *22*, 51–56. doi: 10.1016/j.iheduc.2014.05.001

Lipponen, L. (2002). Exploring foundations for computer-supported collaborative learning. In G. Stahl (Ed.), *Proceedings of the Conference on Computer Support for Collaborative Learning: Foundations for a CSCL Community* (pp. 72–81). Boulder, Colorado: International Society of the Learning Sciences. Retrieved from `http://dl.acm.org/citation.cfm?id=1658616.1658627`

Lipponen, L., Hakkarainen, K., & Paavola, S. (2004). Practices and orientations of CSCL. In J.-W. Strijbos, P. A. Kirschner, & R. L. Martens (Eds.), *What we know about CSCL: And implementing it in higher education* (pp. 31–50). Dordrecht: Springer Netherlands. doi: 10.1007/1-4020-7921-4-2

Llorens Cerdà, F., & Capdeferro Planas, N. (2011). Facebook's potential for collaborative e-learning. *International Journal of Educational Technology in Higher Education*, *8*(2), 197–210. doi: 10.7238/rusc.v8i2.963

Lotsari, E., Verykios, V. S., Panagiotakopoulos, C., & Kalles, D. (2014). A learning analytics methodology for student profiling. In A. Likas, K. Blekas, & D. Kalles (Eds.), *Artificial intelligence: Methods and applications* (pp. 300–312). Cham: Springer International Publishing. doi: 10.1007/978-3-319-07064-3-24

Ludvigsen, S. (2016). CSCL towards the future: The second decade of ijCSCL. *International Journal of Computer-Supported Collaborative Learning*, *11*(1), 1–7. doi: 10.1007/s11412-016-9230-x

Madge, C., Meek, J., Wellens, J., & Hooley, T. (2009). Facebook, social integration and informal learning at university: 'it is more for socialising and talking to friends about work than for actually doing work. *Learning, Media and Technology*, *34*(2), 141-155. doi: 10.1080/17439880902923606

Manca, S., & Ranieri, M. (2013). Is it a tool suitable for learning?: A critical review of the literature on Facebook as a technology-enhanced learning environment. *Journal of Computer Assisted Learning*, *29*(6), 487-504. doi: 10.1111/jcal.12007

Mason, L., & Scirica, F. (2006). Prediction of students' argumentation skills about controversial topics by epistemological understanding. *Learning and Instruction*, *16*(5), 492 – 509. doi: 10.1016/j.learninstruc.2006.09.007

Meishar-Tal, H., Kurtz, G., & Pieterse, E. (2012). Facebook groups as LMS: A case study. *The International Review of Research in Open and Distributed Learning*, *13*(4), 33–48. Retrieved from `http://www.irrodl.org/index.php/irrodl/article/view/1294`

Ángel Hernández-García, González-González, I., Jiménez-Zarco, A. I., & Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. *Computers in Human Behavior*, *47*, 68 - 80. doi: 10.1016/j.chb.2014.10.038

Norman, D. A. (1999). Affordance, conventions, and design. *Interactions*, *6*(3), 38–43. doi: 10.1145/301153.301168

Noroozi, O., Weinberger, A., Biemans, H. J., Mulder, M., & Chizari, M. (2012). Argumentation-based computer supported collaborative learning (ABCSCL): A synthesis of 15 years of research. *Educational Research Review*, *7*(2), 79 - 106. doi: 10.1016/j.edurev.2011.11.006

Paavola, S., & Hakkarainen, K. (2009). From meaning making to joint construction of knowledge practices and artefacts: A trialogical approach to CSCL. In *Proceedings*

of the 9th International Conference on Computer Supported Collaborative Learning (Vol. 1, pp. 83–92). Rhodes, Greece: International Society of the Learning Sciences. Retrieved from `http://dl.acm.org/citation.cfm?id=1600053.1600066`

Phielix, C., Prins, F. J., & Kirschner, P. A. (2010). Awareness of group performance in a CSCL environment: Effects of peer feedback and reflection. *Computers in Human Behavior*, *26*(2), 151 - 161. doi: 10.1016/j.chb.2009.10.011

Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015a). Blending Facebook discussions into seminars for practicing argumentation. *Computers in Human Behavior*, *53*, 605 - 616. doi: 10.1016/j.chb.2015.04.006

Puhl, T., Tsovaltzi, D., & Weinberger, A. (2015b). A long-term view on learning to argue in Facebook: The effects of group awareness tools and argumentation scripts. In O. Lindwall, P. Häkkinen, T. Koschmann, P. Tchounikine, & S. Ludvigsen (Eds.), *Exploring the material conditions of learning: The Computer Supported Collaborative Learning (CSCL) Conference 2015,* (Vol. 1, pp. 110–118). Gothenburg, Sweden: International Society of the Learning Sciences, Inc. doi: 10.22318/cscl2015.167

Rambe, P. (2012). Constructive disruptions for effective collaborative learning: Navigating the affordances of social media for meaningful engagement. *Electronic Journal of E-Learning*, *10*(1), 132–146. Retrieved from `https://eric.ed.gov/?id=EJ969451`

Razak, N. A., & Saeed, M. A. (2014). Collaborative writing revision process among learners of English as a foreign language in an online community of practice. *Australasian Journal of Educational Technology*, *30*(5), 580 – 599. Retrieved from `https://ajet.org.au/index.php/AJET/article/view/786`

Scheuer, O., Loll, F., Pinkwart, N., & McLaren, B. M. (2010). Computer-supported argumentation: A review of the state of the art. *International Journal of Computer-Supported Collaborative Learning*, *5*(1), 43–102. doi: 10.1007/s11412-009-9080-x

Schreurs, B., Teplovs, C., Ferguson, R., de Laat, M., & Buckingham Shum, S. (2013). Visualizing social learning ties by type and topic: Rationale and concept demonstrator. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge* (pp. 33–37). Leuven, Belgium: The Association for Computing Machinery. doi: 10.1145/2460296.2460305

Sha, L., Teplovs, C., & van Aalst, J. (2010). A visualization of group cognition: Semantic network analysis of a CSCL community. In J. L. Polman et al. (Eds.), *Proceedings of the 9th International Conference of the Learning Sciences* (Vol. 1, pp. 929–936). Chicago, Illinois: International Society of the Learning Sciences. Retrieved from `http://dl.acm.org/citation.cfm?id=1854360.1854479`

Shih, R.-C. (2011). Can Web 2.0 technology assist college students in learning english writing? integrating Facebook and peer assessment with blended learning. *Australasian Journal of Educational Technology*, *27*(5). doi: 10.14742/ajet.934

Shum, S. B., & Ferguson, R. (2012). Social learning analytics. *Journal of Educational Technology and Society*, *15*(3), 3–26. Retrieved from `http://www.jstor.org/stable/jeductechsoci.15.3.3`

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, *57*(10), 1380-1400. doi: 10.1177/0002764213498851

Simonneaux, L. (2011). Students' reasoning on socioscientific issues and socially acute questions. In D. J. Boerwinkel & A. J. Waarlo (Eds.), *Genomics education for decision-making: Proceedings of the second invitational workshop on genomics education* (Vol. 2, pp. 73–83). Utrecht, the Netherlands: Freudenthal Institute for Science and Mathematics Education.

Simonneaux, L., & Simonneaux, J. (2009). Students' socio-scientific reasoning on controversies from the viewpoint of education for sustainable development. *Cultural Studies of Science Education*, *4*(3), 657–687. doi: 10.1007/s11422-008-9141-x

Smith, E. E. (2016). A real double-edged sword: Undergraduate perceptions of social media in their learning. *Computers and Education*, *103*, 44–58. doi: 10.1016/j.compedu.2016.09.009

Spada, H., Meier, A., Rummel, N., & Hauser, S. (2005). A new method to assess the quality of collaborative process in CSCL. In T. Koschmann, D. D. Suthers, & T.-W. Chan (Eds.), *Proceedings of the 2005 Conference on Computer Support for Collaborative Learning: The next 10 years!* (pp. 622–631). Taipei, Taiwan: International Society of the Learning Sciences. Retrieved from `http://dl.acm.org/citation.cfm?id=1149293.1149375`

Stahl, G., Koschmann, T., & Suthers, D. (2005). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (Vol. 2, pp. 409–426). Cambridge, United Kingdom: Cambridge University Press. doi: 10.1017/CBO9780511816833.025

Stahl, G., Ludvigsen, S., Law, N., & Cress, U. (2014). CSCL artifacts. *International Journal of Computer-Supported Collaborative Learning*, *9*(3), 237–245. doi: 10.1007/s11412-014-9200-0

Strijbos, J.-W., Martens, R. L., Jochems, W. M., & Broers, N. J. (2007). The effect of functional roles on perceived group efficiency during computer-supported collaborative learning: A matter of triangulation. *Computers in Human Behavior*, *23*(1), 353 - 380. doi: 10.1016/j.chb.2004.10.016

Suthers, D. D. (2001). Towards a systematic study of representational guidance for collaborative learning discourse. *Journal of Universal Computer Science*, *7*(3), 254–277. doi: 10.3217/jucs-007-03-0254

Suthers, D. D. (2003). Representational guidance for collaborative inquiry. In J. Andriessen, M. Baker, & D. Suthers (Eds.), *Arguing to learn: Confronting cognitions in computer-supported collaborative learning environments* (pp. 27–46). Dordrecht: Springer Netherlands. doi: 10.1007/978-94-017-0781-7-2

Suthers, D. D., Dwyer, N., Medina, R., & Vatrapu, R. (2010). A framework for conceptualizing, representing, and analyzing distributed interaction. *International Journal of Computer-Supported Collaborative Learning*, *5*(1), 5–42. doi: 10.1007/s11412-009-9081-9

Suthers, D. D., Vatrapu, R., Medina, R., Joseph, S., & Dwyer, N. (2008). Beyond threaded discussion: Representational guidance in asynchronous collaborative learning environments. *Computers and Education*, *50*(4), 1103 - 1127. doi: 10.1016/j.compedu.2006.10.007

Tess, P. A. (2013). The role of social media in higher education classes (real and virtual): A literature review. *Computers in Human Behavior*, *29*(5), A60 - A68. doi: 10.1016/j.chb.2012.12.032

Thelwall, M. (2009). Social network sites: Users and uses. *Advances in Computers*, *76*, 19 - 73. doi: 10.1016/S0065-2458(09)01002-X

Tsovaltzi, D., Dutta, N., Puhl, T., & Weinberger, A. (2017). Group and individual level effects of supporting socio-cognitive conflict awareness and its resolution in large SNS discussion groups: A social network analysis. In B. K. Smith, M. Borge, E. Mercier, & K. Y. Lim (Eds.), *Making a difference: Prioritizing equity and access in CSCL, 12th International Conference on Computer Supported Collaborative Learning (CSCL)* (Vol. 1, pp. 247–254). Philadelphia, PA: International Society of the Learning Sciences. doi: 10.22318/cscl2017.35

Tsovaltzi, D., Judele, R., Puhl, T., & Weinberger, A. (2015). Scripts, individual preparation and group awareness support in the service of learning in Facebook: How does cscl compare to social networking sites? *Computers in Human Behavior*, *53*, 577 - 592. doi: 10.1016/j.chb.2015.04.067

Tsovaltzi, D., Puhl, T., Judele, R., & Weinberger, A. (2014). Group awareness support and argumentation scripts for individual preparation of ar-

guments in Facebook. *Computers and Education*, *76*, 108 - 118. doi: 10.1016/j.compedu.2014.03.012

van Aalst, J. (2009). Distinguishing knowledge-sharing, knowledge-construction, and knowledge-creation discourses. *International Journal of Computer-Supported Collaborative Learning*, *4*(3), 259–287. doi: 10.1007/s11412-009-9069-5

van Aalst, J., & Chan, C. K. K. (2007). Student-directed assessment of knowledge building using electronic portfolios. *Journal of the Learning Sciences*, *16*(2), 175-220. doi: 10.1080/10508400701193697

Vasilescu, B., Serebrenik, A., Devanbu, P., & Filkov, V. (2014). How social Q and A sites are changing knowledge sharing in open source software communities. In S. Fussell, W. Lutters, M. R. Morris, & M. Reddy (Eds.), *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work and Social Computing* (pp. 342–354). New York, NY, USA: The Association for Computing Machinery. doi: 10.1145/2531602.2531659

Veletsianos, G., & Navarrete, C. (2012). Online social networks as formal learning environments: Learner experiences and activities. *The International Review of Research in Open and Distributed Learning*, *13*(1), 144–166. Retrieved from `http://www.irrodl.org/index.php/irrodl/article/view/1078`

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500-1509. doi: 10.1177/0002764213479363

Wang, C.-M. (2012). Using Facebook for cross-cultural collaboration: The experience of students from Taiwan. *Educational Media International*, *49*(1), 63-76. doi: 10.1080/09523987.2012.662625

Wang, Q., Woo, H. L., Quek, C. L., Yang, Y., & Liu, M. (2011). Using the Facebook group as a learning management system: An exploratory study. *British Journal of Educational Technology*, *43*(3), 428-438. doi: 10.1111/j.1467-8535.2011.01195.x

Wang, S. S., Moon, S.-I., Kwon, K. H., Evans, C. A., & Stefanone, M. A. (2010). Face off: Implications of visual cues on initiating friendship on Facebook. *Computers in Human Behavior*, *26*(2), 226 - 234. doi: 10.1016/j.chb.2009.10.001

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

Wever, B. D., Schellens, T., Valcke, M., & Keer, H. V. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers and Education*, *46*(1), 6 - 28. doi: 10.1016/j.compedu.2005.04.005

Wise, A. F., Hausknecht, S. N., & Zhao, Y. (2014). Attending to others' posts in asynchronous discussions: Learners' online "listening" and its relationship to speaking. *International Journal of Computer-Supported Collaborative Learning*, *9*(2), 185–209. doi: 10.1007/s11412-014-9192-9

Zafar, S., Safdar, S., & Malik, B. (2014). Online behaviour of students in a new blended learning course: An experience report. In *Proceedings of 2014 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)* (p. 387-394). Wellington, New Zealand: Institute of Electrical and Electronics Engineers, Inc. doi: 10.1109/TALE.2014.7062569