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REVIEW ARTICLE

Social Network Analysis in E-Learning Environments: A Preliminary Systematic Review

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Abstract E-learning occupies an increasingly prominent place in education. It provides the learner with a rich virtual network where he or she can exchange ideas and information and create synergies through interactions with other members of the network, whether fellow learners or teachers. Social network analysis (SNA) has proven extremely powerful at describing and analysing network behaviours in business, economics and medicine, but its application to e-learning has been relatively limited. This systematic review of the literature on SNA in e-learning aimed to assess the evidence for using SNA as a way to understand and improve e-learning systems, as well as suggest directions for future research. Most of the 37 studies included in this review applied various methods to analyse interaction patterns in forums involving one-mode networks. Indices of centrality and density were the SNA measures most often used. Although the small number of included studies means that our systematic review should be considered preliminary, the evidence so far strongly suggests that SNA, particularly when combined with content analysis, can provide a detailed understanding of the nature and type of interactions between members of the network, allowing for optimisation of course design, composition of learner groups and identification of learners in danger of dropping out. Future studies should examine two-mode networks and communication channels like chat rooms, wikis, blogs and microblogs. Whenever possible, future studies should also include a quantitative approach that exploits the statistical power of SNA to explain complex systems.

Keywords Social network analysis · SNA · Education · E-learning · Review

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Social network analysis (SNA) aims to study relationships among actors that interact with one another in social networks (Wasserman and Faust 1994). It has generated graphic and mathematical methods of representing human interactions in a social network (Erlin et al. 2008). Relationships between nodes, which can be persons, communities, countries, agencies and companies, are represented graphically, while interactions between actors are represented as paths between nodes (Scott 2000). These relationships can be of many types, such as economic, relational, motivational, communicational, emotional and family based.

As early as 1930, researchers at Harvard were exploring patterns of interpersonal relationships and the formation of cliques. However, it was not until 1954 that Barnes coined the expression 'social network', and not until the 1960s that well-defined methodologies were developed for SNA. Subsequently, SNA quickly developed as an interdisciplinary field, drawing from sociology, psychology and anthropology. It was one of the first non-mathematics disciplines to apply graph theory (Scott 2000).

SNA has been applied to a variety of fields in order to examine the number and characteristics of relationships between actors or elements. One such field is education. Examples of recent advances using SNA to analyse teaching and learning include work by Chang et al. (2010), who studied how different ways to organise peer teams affect communications among team members, as well as the teacher's ability to manage the teams. Ryymin et al. (2008) identified several patterns of relationships connecting teachers in networks: inquirer, collaborator, counsellor and weak socialiser. Moolenaar et al. (2012) correlated characteristics of teacher networks with student achievement, and Merlo et al. (2010) used SNA to detect communities of plagiarisers among students.

Several studies have applied SNA to the specific case of e-learning. For instance, Dradilova et al. (2008) used SNA to examine how learner networks evolve over time; they found that students formed groups based on the type of activities they engaged in. Haythornthwaite (1999) used SNA to show that learners use diverse communication channels to achieve their educational goals. Mansur et al. (2011) found that learners who use wikis as a collaborative tool in e-learning environments can collaborate to greater or lesser degrees depending on how much time they devote to the wiki.

In fact, SNA may be particularly well-suited to studying e-learning (Sie et al. 2012). Most online learning environments are based on Web 2.0 applications that allow learners to collaborate in generating content, giving rise to social networks among learners and between learners and tutors that profoundly influence the learning process. SNA is capable of handling data from numerous communication channels (Garton et al. 1997), including blogs, wikis, forums, chats and e-mails, all of which are common features of e-learning environments and all of which provide valuable information for analysing the social aspects of the learning process. Understanding the social dimension of learning has become the focus of many areas of education research (Dawson 2010), making SNA a tool of central importance.

Despite the relevance of SNA for understanding key questions about e-learning, we are unaware of any systematic review on this question that takes stock of successes in the field and defines key problems for the future. Therefore, we undertook this review with three objectives in mind:

1. to assess whether the application of SNA to e-learning is increasing and explore how these studies have been cited
2. to identify what research questions about e-learning have been addressed using SNA, what SNA measures and network characteristics have been studied most often and what insights we have gained, as well as
3. to identify gaps in the SNA literature on e-learning and suggest directions for future research.

Research Method

This systematic review was carried out according to the recommendations of Kitchenham (2004). These recommendations were adapted from guidelines in other disciplines, mainly medicine, for the purposes of finding, selecting, assessing and summarising evidence about a research question (Staples and Niazi 2007). Based on the recommendations of Kitchenham et al. (2004), we first identified the need for a systematic review, after which we developed a review protocol.

Identifying the Need for a Systematic Review

Prior to carrying out this review, we had come across a few papers applying SNA specifically to e-learning and no systematic reviews or meta-analyses. Nevertheless, we had encountered two reviews indirectly related to SNA and e-learning:

- Sie et al. (2012) reviewed studies that applied SNA to technology-enhanced learning in general, but not specifically to e-learning. Only a few of the studies that they included focused on e-learning.
- Zhao et al. (2011) reviewed studies of SNA published in Chinese literature databases. This review focused on SNA but not specifically on its applications to education.

Neither of these reviews generated substantive insights into how and what SNA can tell us about e-learning outcomes, leading us to pursue this systematic review.

Review Protocol

In order to identify and analyse studies as rigorously and comprehensively as possible, we developed a priori a review focus, literature search strategy and criteria for selecting studies and synthesising data.

Defining the Focus of the Review

Our review of SNA approaches to e-learning was motivated by the widespread use of e-learning because of its advantages for learners and teachers, including global access, self-paced learning, multimedia learning and enhancement of Internet and computer skills (Nichols 2003; Mason and Rennie 2006; Keegan 2002). At the same time, SNA shows potential for advancing e-learning in the same way that it has advanced fields as diverse as computer science (Pham et al. 2011), behavioural science (Hurd et al. 1981; Brenner et al. 1989; Haines et al. 2010), biomedical and life sciences (Kasper and Voelkl 2009; Lusseau 2006; James et al. 2009), business and economics (Prell et al. 2008; Ter Wal and Boschma 2008; Retzer et al. 2012), and face-to-face learning (Carolan and Natriello 2005; Pittinsky and Carolan 2008).

Searching Literature Databases

The following databases were searched in order to identify full-length research articles, conference papers and proceedings that addressed the review objectives: Web of Knowledge, Springerlink, Elsevier Science Direct, IEEE Xplorer, ACM Digital Library and Google Scholar.

Search terms included the terms ‘eLearning’ and ‘e-learning’, which were defined for the purposes of this systematic review as “the application of various technological tools that are either Web based, Web distributed or Web capable for the purposes of education” (Nichols 2003, p. 2). Search strings also included the phrase ‘social network analysis’ and ‘educational context’, ‘education’ and ‘educational settings’. The following search strings were used:

‘Social network analysis’ OR ‘SNA’ AND ‘eLearning’ OR ‘e-learning’
‘Social network analysis’ OR ‘SNA’ AND ‘eLearning’ OR ‘e-learning’ AND ‘education’
‘Social network analysis’ OR ‘SNA’ AND ‘education’
‘Social network analysis’ OR ‘SNA’ AND ‘educational settings’
‘Social network analysis’ OR ‘SNA’ AND ‘educational context’.

Databases were searched in the same way twice, once in January 2012 and again in January 2013. Five new studies not found in the databases in 2012 were found in 2013, highlighting the growing importance of SNA in e-learning, possibly as a consequence of expansion in the e-learning industry, particularly the growth of massive open online courses or MOOCs (Pappano 2012) and other types of e-learning that can provide large datasets for SNA methods.

Study Selection

To be included in this systematic review, studies had to fulfil the following inclusion criteria: (1) they used SNA method(s) to analyse e-learning environment(s), (2) they were published in English and (3) they were published in an electronic format. Our insistence on the electronic format was based on the assumption that information distributed electronically is likely to be more up-to-date and more widely distributed than print information. We included not only journal articles but also conference reports. The latter are useful because they can give a preliminary overview of research presented in journals (Rosmarakis et al. 2005).

Studies were selected through the following steps:

1. Search literature databases using the search terms.
2. Filter out results based on reading titles and abstracts.
3. Retrieve full text of potentially eligible studies.
4. Filter out results based on reading the full text.

After the database searches, 3,185 primary studies were identified and their titles and abstracts were assessed. On this basis, 138 studies were selected for full-text review, which led to the inclusion of 37 studies in the final analysis (Fig. 1).

Results

A total of 37 studies were identified focusing on the use of SNA to analyse interactions in e-learning contexts. The term e-learning includes “online learning, web-based training, virtual universities and classrooms, digital collaboration and technology assisted distance learning” (Keegan 2002, p. 35). Of the 37 studies, 14 examined a learning management system (LMS) or content management system (CMS), both of which generate data that allow in-depth analysis of collaboration and communication of teachers and learners (Littlejohn 2003).

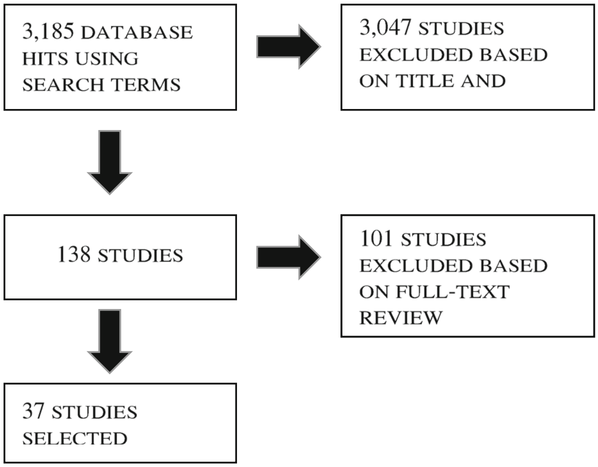

Fig. 1 Description of the study selection process

The types of data analysed from the 37 selected studies are shown in Table 1, and below we discuss the characteristics and results from the studies in greater detail. A more complete summary of the studies can be found in the Appendix.

Frequency of SNA-Based Studies of E-Learning and Their Citation Behaviour

One of the objectives of this systematic review was to assess whether the application of SNA to e-learning is increasing and to explore how such studies have been cited. Based on our final sample of 37 articles, it appears that such studies are being published with increasing frequency (Fig. 2). During the 7-year period of 1999–2005, only 9 studies were published, whereas 13 were published during the 4-year period of 2006–2009, followed by 15 during the 3-year period of 2010–2012. Although the number of studies published per year has fallen over the last 3 years, with seven studies in 2010 giving way to three in 2011 and five in 2012, the overall trend seems to be that the number of studies applying SNA to e-learning is increasing.

These studies have been cited to significantly different extents. Information on the number of citations of the 37 included studies was obtained from Google Scholar (http://scholar.google.es/, accessed on 20 Feb 2013). The 10 most highly cited publications (Table 2) were cited between 37 and 239 times. Seven of the 10

Table 1 Key characteristics of selected papers presented in full in the Appendix

Characteristic	Description
ID	ID number assigned to paper.
Bibliographic reference	Authors and year of publication.
Theoretical approach	The theory or theories on which the study was based.
Method of analysis	Methodologies applied together with SNA in the study.
Sample Size	The number of participants (nodes) in the study.
Main findings	Brief description of the main findings of the study.

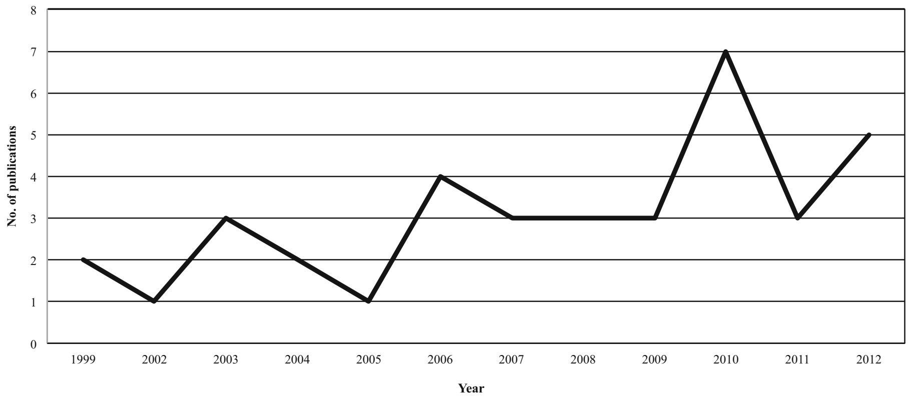

Fig. 2 Number of publications per year that apply SNA to e-learning

publications, including the top 4, are journal papers, while the remaining 3 are conference papers. While to a large extent, the differences in numbers of citations can be attributed to the year of publication, with older studies being cited more, the citation rank of some studies likely reflects factors other than time. For example, the study by Martınez et al. (2003) was published as recently as 2003, but it has already been cited 239 times, whereas the study by Nurmela et al. (1999) was published several years earlier and has been cited 129 times. The study by Haythornthwaite in 1999, published in the same year, has been cited only 42 times.

Among the remaining 27 studies, 11 have been cited fewer than 10 times, probably reflecting the fact that all were published in 2013. The citation rank of all 37 included papers is shown in Table 3.

Table 2 Most highly cited studies in our systematic review

Rank	Author	Number of citations	Title
1	(Martínez et al. 2003)	239	Combining qualitative evaluation and social network analysis for the study of classroom social interactions
2	(Aviv et al. 2003)	235	Network analysis of knowledge construction in asynchronous learning networks
3	(Lipponen et al. 2003)	204	Patterns of participation and discourse in elementary students' computer-supported collaborative learning
4	(Cho et al. 2007)	153	Social networks, communication styles, and learning performance in a CSCL community
5	(Nurmela et al. 1999)	129	Evaluating CSCL log files by social network analysis
6	(de Laat et al. 2007)	85	Investigating patterns of interaction in networked learning and computer-supported collaborative learning: a role for social network Analysis
7	(de Laat 2002)	58	Network and content analysis in an online community discourse
8	(Sing and Khine 2006)	56	An analysis of interaction and participation patterns in online community
9	(Haythornthwaite 1999)	42	Collaborative work networks among distributed learners
10	(Rienties et al. 2009)	37	The role of academic motivation in computer-supported collaborative learning

Table 3 Citation frequencies for all 37 included studies

Number of citations (n)	Number of papers	ID paper
$n>200$	3	S1, S16, S22
$100<n\leq200$	2	S14, S23
$40<n\leq100$	4	S12, S19, S20, S31
$20<n\leq40$	3	S4, S27, S30
$10<n\leq20$	5	S8, S11, S13, S18, S33
$n\leq10$	20	S2, S3, S5, S6, S7, S9, S10, S15, S17, S21, S24, S25, S26, S28, S29, S32, S34, S35, S36, S37
Total	37	

E-Learning Research Topics Analysed by SNA

Analysis of the research topics in the included studies can help us understand the range of e-learning problems to which SNA has been applied. We identified three major topics: (1) evaluation and/or implementation of SNA software tools, (2) identification and analysis of interaction patterns and (3) improvement of e-learning design.

1. Evaluation and/or implementation of SNA software tools: studies in this group focused on implementation of software tools to analyse networks using SNA methods. Studies in this category: [S8], [S26], [S30], [S32], [S34].
2. Analysis of interaction patterns: studies in this group examined patterns of interaction between nodes. This category included several subtopics:

   2.1 Patterns of interaction in information sharing [S3].
   2.2 Patterns of communication in collaborative learning [S2, S5, S12, S16, S23, S37].
   2.3 Patterns of interaction in communicational activities: microblogging [S33], wiki [S21], chat [S29] and forum discussions [S7, S9, S25, S28, S31].
   2.4 Patterns of interaction in construction of knowledge [S1, S13, S36].
   2.5 Patterns of interaction during activity or task completion [S19].
3. Improvement of learning design. This category included the following subtopics:

   3.1 Learning environment [S17].
   3.2 Social learning [S24].
   3.3 Design of discussions [S35].
   3.4 Roles of students [S4, S6, S10, S11, S15, S20, S22] and teachers [S18].
   3.5 Identifying motivations for contributing to the network [S27].
   3.6 Learning performance [S14].

The most frequent research topic was pattern identification analysis (See Table 4). The predominance of this topic can be explained by the availability of large datasets generated by CMS and LMS, forums, chats, blogs and wikis (Greenhow et al. 2009), as well as by the suitability of SNA for identifying relationship patterns among people, groups, organisations and other actors (Wasserman and Faust 1994; Scott 2000). The preponderance of studies

Table 4 Distribution of research topics among included studies

Research topic	No. (%) of studies
Implementation of SNA software tools	5 (14)
Analysis of interaction patterns	19 (51)
Improvement in learning design	13 (35)
Total	37 (100)

examining interaction patterns in e-learning is consistent with the proposal that such research can generate important insights into activities with social connotations (Wellman 1997).

Network Characteristics and SNA Measures Applied to E-Learning

Network Mode

In order to analyse in detail the networks in our included studies, we determined whether the networks were one or two mode. The network mode is defined as "the number of sets of entities on which structural variables are measured" (Wasserman and Faust 1994, p. 34). One-mode networks comprise a single set of nodes interconnected by potentially several types of relationship based on friendship, family and work. Two-mode networks, also called bipartite or affiliation networks, comprise two set of nodes, or one set of actors and one set of events (Wasserman and Faust 1994). Such networks can reveal insights into the interaction between actors and events (Scott 2000).

Of the 37 networks in our systematic review, all but one [S28] was one-mode. Most studies were concerned with relationships between students and between students and teachers.

Node Characteristics and Ties

Networks comprise two main components, nodes and ties (Wasserman and Faust 1994). Ties between nodes serve as links between actors (Scott 2000), such as when one person evaluates another (through forming a friendship, liking or demonstrating respect) or when two people exchange information by talking or sending messages.

Number of Nodes

As a measure of the sampling size in the studies in our systematic review, we examined the numbers of nodes in the analysed networks (Table 5). Since the studies examined specific e-learning courses with defined actors, the boundaries of the SNA came predetermined (Wasserman and Faust 1994). Of the 37 studies, 22 involved 5–50 nodes; 5, 50–100 nodes; 2, 100–200 nodes; and 4, >200 nodes. Four studies did not report the number of nodes in their networks. In all cases, the nodes were individuals, variously identified as students, freshman, college students, university students, bachelor students, engineering students or teachers.

Types of Ties

We applied the taxonomy of Borgatti et al. (2009) to classify the types of relationships analysed in the studies in our systematic review. This taxonomy classifies relationships as 'similarities', 'social relations', 'interactions' and 'flows'.

Table 5 Number of nodes in included studies

No. of nodes	No. of papers	Paper ID
$5<n\leq 50$	22	S1, S2, S3, S6, S10, S12, S13, S14, S16, S17, S18, S19, S20, S21, S23, S24, S25, S28, S30, S31, S35, S37
$50<n\leq 100$	5	S27, S8, S29, S9, S36
$100<n\leq 200$	2	S22, S33
$n>200$	4	S4, S11, S5, S15
No data	4	S32, S7, S34, S26

Similarity relationships emerge when nodes interact simply because they overlap in space and time. Common examples of nodes showing this type of relationship are members of the same school, persons of the same race and people with the same educational level or social status. Social relations between nodes can arise due to kinship or non-familial attachment of an affective or cognitive nature. Examples of nodes linked by social relations are parent and child, friends, classmates, acquaintances and romantic partners. Interaction ties arise through specific behaviours such as sending messages, conversing and writing. Flow ties are the tangible and intangible things that are exchanged in interactions. For instance, opinions are interchanged in a conversation, while money is transferred in a commercial transaction.

Based on this taxonomy, we determined that 33 of 37 studies analysed interaction ties, with the remaining 4 studies failing to provide information about the types of ties analysed (Table 6). Of these 34 studies, 22 focused on communication actions, such as responding to inquiries and using forums, chatting and e-mail. The remaining 11 studies focused on task-solving actions, such as collaboration and joint problem-solving.

SNA Measures

SNA often relies on well-defined measures to provide an important overview of network characteristics (Scott and Carrington 2011; Carolan 2013). For example, power is a fundamental property of networks; generally, actors with more connections enjoy greater power in a relationship network and therefore see a greater proportion of the information flowing through the network (Hanneman and Riddle 2005). SNA attempts to measure power through the composite measure of centrality, which comprises variables such as degree, closeness, and betweenness. Centrality degree is to some extent a power measure, because it shows the proportion of nodes that are adjacent to each node (Freeman 1979). The higher a node's centrality degree, the greater its access to information resources or peers in the network, i.e. the

Table 6 Types of ties analysed

Type of ties	Number of papers	Paper ID
Communicational interactions	22	S4, S8, S10, S12, S13, S17, S19, S20, S21, S22, S23, S24, S25, S27, S28, S31, S32, S33, S34, S35, 36, 37.
Interactions to solve tasks	11	S1, S2, S3, S6, S7, S9, S11, S14, S15, S18, S30
Not reported	4	S5, S16, S20, S29

greater its power and popularity. We found that 14 studies relied mainly on centrality as an indicator of power and prestige.

Closeness is a centrality measure of how quickly one actor can access another. Freeman (1979) has defined closeness as the sum of geodesic distances from one node to all others. Closeness varies inversely with centrality: small closeness values indicate greater proximity to other nodes, whereas larger values indicate greater distances from other nodes. Betweenness indicates how actors mediate the communication among themselves. Actors that are positioned between powerful actors can enjoy more privileges in a network.

Another SNA measure is density, which indicates the number of relationships actually observed in a network divided by the total number of possible relationships. Density is a quantitative way to capture important sociological characteristics such as cohesion, solidarity and membership (Wasserman and Faust 1994). Four studies profiled their networks exclusively based on density measures, while 13 studies combined density and centrality measures.

Two studies used other SNA measures, namely block modeling and cluster analysis. Block modeling uses blocks to represent the relationships among nodes, thereby reducing the complexity of the network representation and simplifying the analysis (Valente 2010). Cluster analysis identifies groups connected by dense ties (Carolan 2013).

Finally, four studies did not specify the SNA measures that they applied. The SNA measures applied in the studies in our systematic review are summarised in Table 7.

SNA Software

In order to understand how researchers have applied SNA to problems in e-learning, we examined which software programs they have used. Our intention was simply to examine trends in software usage, not to promote particular software packages. Of the 37 studies, 23 used existing software tools: UCINET (S3, S4, S11, S15, S16, S17, S18, S20, S21, S23, S24, S27, S35 and S36), GEPHI (S9), GRAPHVIZ (S5), Krackplot (S12), NETMINER (S1, S10 and S13), PAJEK (S28), SAMSA (S22) and SIENA (S32). In another five studies, researchers created their own tools to allow fully customised analysis (S8, S26, S30, S32 and S34). The remaining nine studies did not describe the software systems used (S14, S19, S31, S6, S7, S29, S37, S2 and S25).

The custom-designed programs used in the studies in our systematic review rely on a variety of tools, yet all are based on SNA methods. Lin and Chen (2004), for instance, prototyped a system for analysing virtual tasks performed by teams. The system identifies

Table 7 SNA measures applied in our systematic review

Measures	Number of papers	Paper ID
Centrality	14	S1, S3, S4, S9, S10, S14, S19, S20, S21, S23, S26, S30, S36, S37
Density	4	S24, S31, S32, S33
Density and centrality	13	S2, S8, S11, S12, S13, S15, S16, S17, S22, S25, S27, S29, S35
Blockmodeling	1	S5
Cluster analysis	1	S28
Not reported	4	S18, S6, S7, S34

the relationships among the members and quantifies their strength. Rabbany et al. (2012) developed SNA software that assesses the participation of students in asynchronous discussion forums in online courses. Teplovs et al. (2011) proposed an SNA software tool that assesses user activity in the network, as well as extracts terms used in learner discussions and quantifies their frequency of use. Saltz et al. (2004) created a software tool that visualises a network and analyses its characteristics. Spadavecchia and Giovannella (2010) described a software tool for evaluating and monitoring learning processes using a combination of SNA and CA.

Combination of SNA with Other Methods

Of the 37 studies in our review, 25 applied SNA on its own as the main method for analysing interactions among nodes (Table 8). The remaining studies combined SNA and content analysis (CA), which involves analysing transcripts of interactions. Several researchers routinely combine SNA and CA to examine the quantity and quality of interactions (Erlin et al. 2009; Poon 2006; de Laat 2002).

Results of Included Studies

After exploring the range of research questions and network aspects of e-learning that have been investigated using SNA, we wanted to determine what insights these studies provide for the field.

Patterns of Interaction

Several authors, such as Haythornthwaite (1999), Lipponen et al. (2003) and Chen and Watanabe (2007) examined network patterns on different communication channels during collaborative learning. Haythornthwaite (1999) analysed learner preferences for particular communication channels during collaborative learning; students used various tools, such as Webboard, chat, face-to-face communication and e-mail. Each communication channel served a specific purpose for completing the assigned task: Webboard, chat and face-to-face meetings were used to support group activities, while e-mail was used to advance longer-term activities.

Lipponen et al. (2003) assessed the patterns of discourse and participation of learners in the network. They found that students participated to different degrees, and that participation in all cases tended to be short-lived. Chen and Watanabe (2007) found that learners' physical location and social position influenced the networks they formed. Dradilova et al. (2008) analysed the structures of student groups over time and found that the number of groups increased as they became more involved in course activities.

Corallo et al. (2010) used SNA to assess individual and team progress in an online community. They found that communication flow increased progress and that the quantitative

Table 8 Methodologies applied to the networks in the included studies

Method	Number of papers	Paper ID
SNA alone	25	S2, S3, S4, S5, S7, S8, S9, S10, S11, S12, S25, S14, S17, S20, S21, S22, S23, S24, S26, S28, S29, S30, S33, S35, S37
SNA and CA	12	S1, S6, S13, S16, S15, S18, S19, S27, S31, S32, S34, S36

data provided by SNA was useful for assessing work processes of groups, allowing the detection of isolated learners within groups. These results guided adjustments in the course configuration, curriculum and teacher-student relationship in order to improve learning outcomes.

Nurmela et al. (1999) used log files from an e-learning portal to analyse the collaboration of learners during the preparation of documents. They concluded that log files can allow calculation of the SNA measures indegree (the frequency with which a learner or teacher posts a comment) and outdegree (the frequency with which the posted comment receives a response), providing a quantitative picture of learner participation in a network. Daniel et al. (2008) found that the motivation to share information in a network depends on several factors, such as trust in the recipient, a learning environment that favours cooperation over competition, knowledge sharing that is voluntary and the presence of adequate communication channels.

Still, other authors have focused on using SNA to study interaction patterns during knowledge building in e-learning environments (Aviv et al. 2003; Heo et al. 2010; De Laat 2002; De Laat et al. 2007). Aviv et al. (2003) used SNA and CA to analyse the characteristics of learner interactions and found that careful group design, whether structured or non-structured, can improve the knowledge-building process. De Laat (2002) showed that learner discourse focused on sharing and comparing information, and later work by De Laat et al. (2007) used SNA and CA together to detect learner interaction patterns in networks over time. They identified active and peripheral participants and were able to track changes in these populations over the duration of the course. Martınez et al. (2003) combined several quantitative SNA indicators, such as degree and density, with qualitative methods to measure learner participation and collaboration. Zhang and Zhang (2010) analysed student discussions and observed a low level of knowledge construction and generally superficial learner interactions comprising mostly the exchange of opinions and comparisons. These results highlight the importance of assessing the quality of interactions using CA, given that SNA quantitates the amount of interactions but provides no information about their quality.

E-Learning Contexts

Other studies have focused on interaction patterns in specific contexts, such as wikis (Mansur et al. 2011), microblogs (Stepanyan et al. 2010), chats (Rosen et al. 2011) and forums (Dradilova et al. 2008; Erlin et al. 2008; Gottardo and Noronha 2012; Peng He 2012; Rodríguez et al. 2011; Sing and Khine 2006). For example, Mansur et al. (2011) analysed learner contributions to a wiki using SNA measures such as indegree and outdegree, showing that lack of time can limit the number of contributions.

Stepanyan et al. (2010) used SNA to assess learner microblogging. They found that students showed a homophilic tendency to microblog with learners showing a participation level similar to their own. In their study combining SNA and CA to examine more completely online learner interactions in a forum, Erlin et al. (2009) argued that SNA representations of networks can help teachers understand the social and communicational patterns in online communities.

Gottardo and Noronha (2012) used SNA to study the central actors and group behaviour in learner interactions in forums. Along a similar line, Peng He (2012) used degree measures to identify students who participated actively in the learning forum and those who needed to be encouraged to participate. These findings helped the authors reconfigure their courses to boost participation by less-active learners.

Rodríguez et al. (2011) used SNA to identify forum topics that were more popular and to assess learner interactions in the forums. Their findings should allow instructors to select discussion topics more likely to interest students. Adopting the perspective of teachers rather than learners, Sing and Khine (2006) used SNA to identify patterns of teacher interactions in an online community. The results showed that teachers formed a knowledge-building community in which they actively discussed topics related to integrating technology into education.

This survey of studies applying SNA to e-learning highlights several important insights. One is that SNA can be effective at generating quantitative descriptions of e-learning networks (Paredes and Chung 2012; Haythornthwaite 1999; De Laat et al. 2006; Cho et al. 2007; Buckingham Shum and Ferguson 2012), similar to its quantitative success in numerous other disciplines. Several studies have measured the degree of interaction in learning networks using such measures as indegree, outdegree and learner density. Other studies have used these quantitative analyses to identify isolated and popular learners (Lipponen et al. 2003; Laghos and Zaphiris 2006; Corallo et al. 2010; Dawson 2010; Duensing et al. 2006; Hamulic and Bijedic 2009; Nurmela et al. 1999. These insights should help teachers and e-learning course designers to develop more effective online learning environments, as well as detect learners at risk of dropping out who require additional support (Siemens and Long 2011).

A second insight from this systematic review is that SNA can contribute to our understanding of collaborative learning (Chen and Watanabe 2007; Capuano et al. 2011; Nurmela et al. 1999; Cho et al. 2007; Suh et al. 2005; Rodríguez et al. 2011), since most e-learning activities are designed to be solved in groups (Berge and Collins 1995; Stahl et al. 2006). Studies of SNA in e-learning have so far provided methods for assessing levels of learner participation during group tasks, as well as suggestions for optimising the composition of groups to achieve the most productive collaborations.

A third insight from our systematic review is that combining SNA and CA can provide even deeper analysis of interactions involving learners and/or teachers (Rienties et al. 2009; Sing and Khine 2006; Zhang and Zhang 2010; Aviv et al. 2003; Erlin et al. 2008; Heo et al. 2010; De Laat et al. 2006; De Laat 2002). SNA allows quantitative analysis of these interactions, while CA allows qualitative assessment to provide a more comprehensive picture of interaction quality.

Discussion

The objective of this systematic review was to provide an overview of how SNA has contributed to our understanding of e-learning, as well as suggest directions for future research in this area. The fact that we identified only 37 eligible studies even though our inclusion criteria were fairly general suggests that the application of SNA to e-learning environments is at a very early stage. As a result, any concrete insights that this literature provides should be regarded as preliminary. Given the fact that we see evidence of a gradual increase in the frequency of such publications in the literature (Fig. 2), we believe that SNA-based approaches to e-learning will continue to develop and mature.

SNA has already proven to be an effective technique for analysing e-learning because it is well-suited to understanding technology-dependent processes (Scott and Carrington 2011; Carolan 2013; Sie et al. 2012) and collaborative activities (de Laat et al. 2007; Rienties et al. 2009; Chen and Watanabe 2007; Cho et al. 2007; Nurmela et al. 1999). Using SNA, researchers can visualise and analyse nodes and ties in networks using quantitative measures and graphical representations in order to examine the flows of interactions (Scott and Carrington 2011; Wasserman and Faust 1994). When applied to learning activities, SNA usually aims to identify factors that influence the success or efficiency of the educational process.

Many of these factors are social, consistent with the fact that many e-learning environments are designed based on social learning theory (Bandura and McClelland 1977), which emphasises that learning is socially mediated (Vygotskiĭ 1978; Nonaka and Konno 2005). The relevance of this theory for modern education and professional development is clear given that the ability to work in groups is increasingly valued by educational institutions and employers as a fundamental skill in today's increasingly connected societies, in which complex tasks are handled using decentralised applications and information on the Internet (Centre canadien de gestion & Drucker 1995).

Some studies in our systematic review examined e-learning contexts in which students or users performed collaborative tasks in environments where teamwork was favoured over competition (Lehtinen et al. 1999). In these contexts, the teacher took a secondary role: after he or she provided brief instructions to students about how to achieve their goals, the students collaborated in knowledge construction. Most of the studies were one mode, focusing on student-student and/or student-teacher relationships. This may reflect the fact that most SNA measures focus on one-mode networks, with only a handful intended for use with two-mode networks (Borgatti and Everett 1997; Latapy et al. 2008; Scott and Carrington 2011).

The studies in our review make clear that SNA can deal efficiently with the large amount of data on e-learning systems (Keegan 2002), and that the quantitative measures and graphical representations of SNA can help teachers understand social and communicational patterns in online communities of students (Erlin et al. 2009) and of teachers (Sing and Khine 2006). Finally, the studies have demonstrated the power of combining SNA with CA for a deeper understanding of interactions in an e-learning network in order to improve the learning process (Haythornthwaite 1999; Reuven et al. 2003; Paredes and Chung 2012; Dawson 2010; Teplovs et al. 2011).

The studies in our systematic review focused on a small number of research topics. Below, we discuss each of the research topics that we identified and the relevant contributions of the included studies for the field of e-learning.

Development of SNA Software Tools

Several studies in this systematic review focused on the development of SNA software tools for analysing networks in specific contexts. Some of these software products centre on graphical SNA methods to visualise the social activities of learners in a network primarily using sociograms (Willging 2005). These representations of nodes and their connections can help teachers gain both a global and detailed view of the positions of actors in the network and the flow of connections among them (Nurmela et al. 1999; Erlin et al. 2008; Scott and Carrington 2011).

Lin and Chen (2004) and Saltz et al. (2004) created their own software tools for visualising and analysing learner networks. The software of Saltz et al. (2004) graphically represents students and the direction and number of their interactions. In contrast, the software of Lin and Chen (2004) provides a global view of the learning network and of how the relationships among actors evolve over time. The system builds this network representation by drawing from numerous sources of relational information, including e-mail, chats, discussion boards, file sharings and guest books.

Adopting a different approach, some researchers in this systematic review developed tools that combine SNA and CA methods to gain a complete overview of the quality of learner-learner and learner-tutor interactions. For instance, Rabbany et al. (2012) proposed a software tool that not only assesses user activity in the network but that also extracts terms used by learners in their discussions and measures how often those terms are used. Spadavecchia and Giovannella (2010) proposed a tool for analysing the relationship between how much a learner interacts in the network and his or her emotional state. Teplovs et al. (2011) represent learner interactions using a combination of semantic and social network tools.

These software-based studies aim to provide teachers and instructional designers with immediate results on network interactions that would otherwise take a long time to calculate since they are based on a large amount of data from several communication channels.

Pattern Interaction Analysis

Studies in this category focus on the interaction patterns that emerge from e-learning networks. SNA is ideal for this research topic, since SNA grew out of the desire to identify relational patterns among interacting nodes. Indeed, SNA methodology has matured to include several measures of network connectivity. Measures of centrality, for example, can identify central and isolated learners, as well as learners with the most outgoing and incoming connections. Centrality measures can also assess the extent and strength of group connectivity. Measures of density show the proportion of possible ties that are present in the network. Additional SNA measures, such as analysis of cliques and clusters, provide information about group behaviour in the network (Scott and Carrington 2011; Prell 2011; Borgatti et al. 2013).

Pattern analysis using SNA can generate e-learning best practices by measuring learner preferences for communication channels (Haythornthwaite 1999), determining learner participation levels (Lipponen et al. 2003; Chen and Watanabe 2007) and monitoring collaboration patterns over time (Dradilova et al. 2008) and member contributions within groups (Nurmela et al. 1999).

The studies in our systematic review demonstrate that SNA can be useful for detecting interactions in several communication channels in e-learning environments. Mansur et al. (2011) measured learner participation levels in wiki tools and Stepanyan et al. (2010), participation in microblogging discussions. Most studies in our review focused on interactions in forums. This reflects the fact that all LMS use forum activities to discuss a subject or create a channel of communication among learners and between learners and teachers (Buckingham Shum and Ferguson 2012). The studies in our review that examined forums were interested in identifying popular and isolated learners. The ability of SNA to identify such learners is particularly relevant to e-learning, for which dropout is a problem among students who feel isolated and fail to integrate into the network (Berge and Huang 2004; Levy 2007;

O'Connor et al. 2003; Frankola 2001). The studies in our review have shown that SNA can profile learners, detect those who are active or isolated and recommend short- and medium-term interventions to prevent dropout.

Learning Design Improvement

Designing e-learning courses is a complex process, the success of which depends on numerous factors, including the tutor, instructor, LMS, communicational tools, digital literacy of the learner and the amount of time that learners can dedicate to the tasks (Rosen 2010). Lorenzo et al. (2012), for example, found evidence that massively multi-user online learning (MMOL) systems leads to more connections than LMS.

Social issues among learners play a prominent role in e-learning processes. Yao (2010) found that instructor presence did not impact on the interactivity level of learners, and Laghos and Zaphiris (2006) found that, in a self-taught cause where no teacher was present, learners adopted central positions as de facto teachers, and other learners supported their answers to questions. Duensing et al. (2006) found that the tutorial method influenced the frequency and type of learner interactions. Interestingly, Paredes and Chung (2012) found that network structure characteristics such as density, tie strength and efficiency influenced social learning. Suh et al. (2005) found that popular students showed high interpersonal intelligence and were more active in networks. Similarly, Hamulic and Bijedic (2009) found that successful learners showed higher interaction in the network. This higher interaction is contagious: network members with high academic performance tend to attract other high-performing members (Lin and Chen 2004; Dawson 2010).

Just as social behaviour is determined to a large extent by individual characteristics, Rienties et al. (2009), by applying a combination of SNA and CA, found that learners with high intrinsic motivation contributed discourse at a higher cognitive level in e-learning communication channels. Cho et al. (2007) drew on personality theory to determine that communication styles and pre-existing social networks strongly influenced learner interaction in the network.

Learning Theories Applied in the Studies Reviewed

The studies in our systematic review approached e-learning problems from a variety of theoretical backgrounds, including social learning (S4, S24), social interdependency (S1), collaborative learning (S7, S10, S12, S14, S16, S18 and S23) and project-based learning (S13). All these theories conceptualise social actions that occur among learners; indeed, they share the assumption that knowledge emerges from the social phenomena between collaborators in an environment. These phenomena must be taken into account in order to understand and optimise e-learning because of the many software tools now available and the fact that virtual learning environments focus on social activities such as chats, blogs, forums and group work (Blumenfeld et al. 1991; Lim et al. 2010).

Social interdependence theory of cooperative learning argues that the interaction processes are determined by the design of the relationships among members of a group in the learning environment (Johnson and Johnson 1990). The study of Aviv et al. (2003) stems from this theory and from the constructivist paradigm (Jonassen et al. 1995) for analysing the process of knowledge construction using SNA.

Only one of the studies in our review relied on project-based learning (PjBL) theory [S13]. In this approach, the teacher proposes a common goal to be reached by the members of small groups (Blumenfeld et al. 1991). In this study, SNA helped determine the contribution level of learners in project-based learning tasks.

Finally, the studies in our systematic review overwhelmingly support the idea that collaboration among learners can significantly increase the likelihood of successful learning in an online environment, consistent with earlier work (Aplin 2008). Social theories are key to understanding and optimising such collaboration (Bandura and McClelland 1977), and SNA is ideally suited for analysing interactions among learners in e-learning environments.

The networks in this review involved anywhere between 8 and 839 actors or nodes, which is a reasonable range for many e-learning applications. However, it falls far short of the numbers typical of MMOCs and even of larger introductory courses at public universities, which are increasingly integrating online components. Therefore, future studies should expand the size range of networks to which they apply SNA. Evidence from other fields suggests that SNA will prove quite scalable (Scott and Carrington 2011) and the ability of LMS and CMS to generate significant amounts of data on interactions among network members will ensure an abundance of inputs to feed into the SNA. Indeed, the ease with which interaction data can be collected should hopefully lead to more studies of two-mode networks.

Despite the clear advantages of SNA for analysing network interactions in e-learning environments, it does have limitations. For example, it appears to be useful only for situations in which learning is social, so it may fail to capture processes and variables in individual learners that are invisible at the network level. This highlights the need for combining SNA with non-network-centred methods such as CA. In addition, SNA is fundamentally an observational method that is rarely applied in a prospective, empirical context. While a few studies in our review did include quantitative analyses (Cho et al. 2007; Rienties et al. 2009; Dawson 2010; Stepanyan et al. 2010; Paredes and Chung 2012), a larger number relied mostly on a qualitative approach. Therefore, many authors have used it to perform essentially qualitative, rather than quantitative, analyses of teaching and learning processes in e-learning environments. While a qualitative approach can often reveal the diversity and nuances of network experiences better than a quantitative methodology, it can also fail to provide the detail and rigour necessary for translating the research results into recommendations for action. In addition, qualitative methods do not take full advantage of SNA, which is ideal for statistical analysis because it can handle large, complex datasets. By defining precise research questions and adopting a quantitative approach when appropriate, future SNA studies of e-learning may prove easier to implement into practice than the existing literature.

Conclusions

The objective of this systematic review was to provide an overview of how SNA has contributed to our understanding of e-learning, as well as suggest directions for future research in this area. Only 37 studies were identified after extensive database searches, suggesting that the field is in its infancy and that any insights should be regarded as preliminary. The primary value of this systematic review, then, may well lie in highlighting current knowledge gaps to be filled in the future.

Our findings show that SNA has been used most often to analyse ‘interactions’—according to the taxonomy of Borgatti et al. (2009) among learners in various collaborative work situations. Most of these interactions are of the communicational type: they arise from communication among learners, most often in the form of e-mails, microblogging, wikis and chats. These findings are consistent with the fact that e-learning usually demands collaboration among learners to complete group projects (Lim et al. 2010).

We found that SNA has been used most often to examine patterns of learner communication and collaboration in various situations, such as when discussing, blogging and e-mailing. For example, some studies have tried to identify learners who are influential or isolated, active or inactive; others have examined what forum topics learners prefer to comment on, as well as the communication channels they prefer to use. These studies demonstrate that SNA can provide quantitative insights into learner interactions that can help teachers and course designers (Carolan 2013). Indeed, some studies in our review have sought to generate SNA results that can help prevent learner drop-out, improve the design of class discussions and identify the characteristics of active learners and well-connected ‘stars’ in the group. The studies in our review have pursued these goals using a variety of SNA-inspired software tools.

Most of the 37 studies analysed interaction patterns, reflecting the bias of SNA for examining patterns of social networks in a given context. The contexts in the included studies were mainly one-mode networks, i.e. the nodes were similar to one another (learners and teachers); these networks were built on forums, wikis, microblogs and e-mail. Future research should broaden to include two-mode e-learning networks, which involve two sets of nodes: events and the nodes linked to them. It would be interesting to see how events and the related nodes interact with one another in an e-learning context.

The SNA measures most often examined in e-learning studies are centrality and density, which are important but still fail to capture several variables known to affect learner outcomes, such as subgroup characteristics and structural equivalence. Future studies should incorporate a broader range of network variables.

Although most of the studies in our review relied on SNA alone to analyse learner interactions, several complemented the quantitative approach of SNA with qualitative CA to gain more complete insights. Such combined approaches should become more frequent in the future. Indeed, studies should consider incorporating a range of SNA and non-network learner variables including personality, willingness to communicate, social level, educational level and academic performance.

Studies available so far on SNA in e-learning support the notion that identifying interaction patterns in networks of students and teachers can provide valuable insights into the factors that affect learning success (Paredes and Chung 2012; Buckingham Shum and Ferguson 2012). Future studies should continue to embed SNA philosophy and methods more deeply into e-learning action research by applying it, together with complementary content and semantic methods, to an even wider range of network sizes and types. This future research would do well to focus on precise questions amenable to quantitative analysis in order to exploit the full explanatory power of SNA.

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Appendix

Table 9 Summary of selected studies

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
S1	Aviv et al. 2003	Network analysis of knowledge construction in asynchronous learning networks.	Social interdependence theory of cooperative learning.	Content analysis	37 university students	The use of asynchronic learning networks, whether structured or non-structured, can improve the knowledge construction process.
S2	Corallo et al. 2010	A methodological framework to monitor the performance of virtual learning communities	Collaborative learning	SNA	10 master's students	A framework is proposed for obtaining information about learning at the levels of individuals and groups. The information can help teachers optimise their actions to obtain the best learning outcomes.
S3	Daniel et al. 2008	Social network analysis techniques and implications for information and knowledge sharing in virtual learning communities	Tacit and explicit knowledge	SNA	15 university students	Several factors influence whether members of a network feel motivated or not to share information. These factors include whether the sender trusts the recipient, whether the e-learning environment favours cooperation over competition, whether knowledge sharing is voluntary, and whether adequate channels of communication are available.
S4	Dawson 2010	'Seeing' the learning community: An exploration of the development of a resource for monitoring online student networking	Social learning Social presence	SNA	207 university students	Size and competition differ significantly between networks of high- and low-performing students.
S5	Dradilova et al. 2008	Analysis of relations in e-learning	Small world property of social networks	SNA	839 students	SNA identified clusters of students showing similar activity types. These clusters may correspond to different models of learner behaviour in different systems.

Table 9 (continued)

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
S6	Duensing et al. 2006	Face-to-face and online interactions - is a task a task?	Social interaction Collaborative learning	Discourse analysis	33 lyceum students	Optimising the online learning process by carefully designing tasks and training tutors may help to maximise students' social participation. Tutoring style can strongly influence learner interactions in a network.
S7	Erlin et al. 2008	Integrating content analysis and social network analysis for analysing asynchronous discussion forums	Computer-supported collaborative learning	SNA Content analysis	Not specified	Integrating SNA and content analysis allows analysis of communication transcripts as well as of learner interaction networks. This combined approach can provide quantitative and qualitative insights into networks.
S8	Lin and Chen 2004	Developing and evaluating the social network analysis system for virtual teams in cyber communities	Social network theories	SNA	99 teachers	An SNA system is prototyped that visualises social networks and indicates how they evolve through time.
S9	Gottardo and Noronha 2012	Social networks applied to distance education courses: analysis of interaction in discussion forums	Social network theories Theory of Interaction	SNA	51 students	SNA provides information useful for course coordinators to analyse student and teacher behaviour.
S10	Suh et al. 2005	Identifying peer interaction patterns and related variables in community-based learning	Collaborative learning	SNA	24 middle school students	Students with high intra-personal or verbal-linguistic intelligence were more popular in the network, and students with high interpersonal intelligence were more active and perceived as more friendly. Peer interactions may enhance learning.
S11	Hamulic and Bijedic 2009	Social network analysis in virtual learning community at faculty of information technologies (fit), Mostar.	Social network theories	SNA	293 first-year university students	Successful students were highly active in the network. This study verified the idea that virtual learning communities function as networks.
S12	Haythornthwaite 1999	Collaborative work networks among distributed learners.	Collaborative work	SNA	14 students	They assessed channels of communication that learners used during the learning

Table 9 (continued)

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
						process; learners used channels to engage in diverse types of communication.
S13	Heo et al. 2010	Exploratory study on the patterns of online interaction and knowledge co-construction in project-based learning	Project-based learning Social construction of knowledge	Content analysis	49 undergraduate students	Mutual support and cohesion among team members depends on highly interactive communication.
S14	Cho et al. 2007	Social networks, communication styles, and learning performance in a CSCL community	Communication styles Computer-supported collaborative learning	SNA	31 college engineering students	Communication style and the presence of a pre-existing social network influence social interactions among learners in a network.
S15	Laghos and Zaphiris 2006	Sociology of student-centred e-learning communities: a network analysis	Social network theories	Topic relation analysis	618 students	In a self-taught course in which students worked in pairs, a good relationship within a pair was essential for question resolution and socialisation. One student in the pair took a leading role similar to that of a teacher.
S16	Lipponen et al. 2003	Patterns of participation and discourse in elementary students' computer-supported collaborative learning	Collaborative learning	Content analysis	23 students	Students differed in their level of participation; the authors concluded that much needs to be done to improve the quality of student contributions.
S17	Lorenzo et al. 2012	Studying the effectiveness of multi-user immersive environments for collaborative evaluation tasks	Immersive learning	SNA	21 students	Massively multiuser online learning (MMOL) and a learning management system (LMS) were found to involve different levels of learner interaction. MMOL may be a more appropriate platform for learning experiences like the Convergent Participation Model.
S18	de Laat et al. 2006	Analysing student engagement with learning and tutoring activities in	Collaborative learning	Content analysis	16 students and 2 teachers	Contributions from learner groups were similar to those from tutor groups.

Table 9 (continued)

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
		networked learning communities in a multi-method approach				
S19	de Laat 2002	Network and content analysis in an online community discourse	Collective learning	SNA Content analysis	46 professionals	SNA and CA together can provide a more complete overview of learner interaction. SNA showed relatively dense interaction patterns. CA showed that discourse was focused on comparing and sharing information.
S20	de Laat et al. 2007	Investigating patterns of interaction in networked learning and computer-supported collaborative learning: a role for social network analysis	Collaborative learning	SNA Content analysis	7 students and 1 tutor	SNA and CA together can provide an overview of how learners construct knowledge and of how this process changes over time. The authors measured levels of learner connectivity and engagement.
S21	Mansur et al. 2011	Analysis of social learning network for wiki in Moodle e-learning	SNA theories	SNA	23 users	Lack of time can affect the quantity of contributions to a wiki.
S22	Martınez et al. 2003	Combining qualitative evaluation and social network analysis for the study of classroom social interactions	SNA theories	SNA Content analysis	120 university students, divided in three groups	CA and SNA together can be useful tools for analysing critical issues on learning interactions.
S23	Nurmela et al. 1999	Evaluating CSCL log files by social network analysis	Collaborative learning	NA	18 university students	SNA was found to be an efficient method for evaluating the learning process in a CSCL environment and its social structures.
S24	Paredes and Chung 2012	Modelling learning & performance: a social networks perspective	Social learning Social network theories	SNA	36 undergraduate students	Network structure characteristics such as density, tie strength and efficiency influence social learning.
S25	Peng He 2012	Evaluating students online discussion performance by using social network analysis	Social network theories	SNA	20 students	Level of student activity in an on-line discussion was directly related to their academic performance.

Table 9 (continued)

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
S26	Rabbany et al. 2012	Social network analysis and mining to support the assessment of on-line student participation	Social network theories	SNA	Not reported	An SNA tool is proposed that assesses user activity in the network. It also identifies terms used by learners in their discussions and measures their frequency of use.
S27	Rienties et al. 2009	The role of academic motivation in computer-supported collaborative learning	Motivation in CSCL	Content analysis	82 university students	Highly intrinsically motivated learners made central contributions to the discourse, while extrinsically motivated learners made smaller contributions.
S28	Rodríguez et al. 2011	Exploring affiliation network models as a collaborative filtering mechanism in e-learning	SNA theories	SNA	47 students	Exploratory techniques of SNA can be used to filter collaborative student activities in online forums.
S29	Rosen et al. 2011	Social and semantic network analysis of chat logs.	SNA theories Semantic analysis	SNA	62 participants	SNA and semantic analysis together are effective methods for analysing interactions in multi-user virtual environments.
S30	Saltz et al. 2004	Student social graphs: visualising a student's online social network	SNA theories	SNA	5 students	SNA provides the best possible understanding of learner interactions in a classroom network.
S31	Sing and Khine 2006	An analysis of interaction and participation patterns in online community	Knowledge-building community	Content analysis	11 teachers 1 tutor	Teachers in the study formed a knowledge-building community where they actively discussed topics related to integrating information technology into the classroom.
S32	Spadavecchia and Giovannella 2010	Monitoring learning experiences and styles: the socio-emotional level	SNA theories	SNA Automatic text analysis	Not specified	Two software tools are described for evaluating and monitoring learning processes based on SNA and automatic text analysis.
S33	Stepanyan et al. 2010	A social network analysis perspective on student interaction within the Twitter micro blogging environment	SNA theories	SNA	108 students	Students showing higher reciprocal interaction on a microblog also showed higher achievement scores.

Table 9 (continued)

ID	Authors and publication year	Title	Theoretical background	Method of analysis	Sample size	Main findings
S34	Teplovs, Fujita, and Vatrapu 2011	Generating predictive models of learner community dynamics	SNA theories. Latent analysis	SNA Latent semantic analysis	Not specified	A software tool called Knowledge Interaction and Social Student Modelling Explorer (KISSME) is proposed, which combines SNA and latent semantic analysis to analyse online discourse. This may provide a more complete overview of interactions and their quality.
S35	Yao 2010	Comparing two discussion designs in terms of student online interactions	Constructivism	SNA	45 undergraduates	Learner interaction did not improve when the teachers withdrew from discussions.
S36	Zhang and Zhang 2010	A case study on web-based knowledge construction on a Moodle platform	SNA theories	SNA Content analysis	89 university students	SNA and content analysis were combined to show that the level of knowledge construction was low among learners in the situation analysed.
S37	Chen and Watanabe 2007	A case study of applying SNA to analyse CSCL social network.	SNA theories CSCL	SNA	23 university students	Physical location and social position affect network interactions. Members of the same social position collaborate better than members of different positions.

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