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Social network analysis for technology-enhanced learning: Review and future directions

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Abstract

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Keywords

social, network, analysis, technology-enhanced, future, learning:, directions, review

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Social Network Analysis for Technology-Enhanced Learning: Review and Future Directions

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Abstract: By nature, learning is social. The interactions by which we learn from others inherently form a network of relationships among people, but also between people and resources. This article gives an overview of the potential social network analysis (SNA) may have for social learning. It starts with an overview of the history of social learning and how SNA may be of value. The core of the paper outlines the state-of-art of SNA for technology-enhanced learning (TEL), by means of four possible types of SNA applications: visualisation, analysis, simulation, and interventions. In an outlook, future directions of SNA research for TEL are provided.

Keywords: social network analysis, technology-enhanced learning, social learning, literature review, roadmap

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1 Introduction

When we learn socially from peers, we implicitly form a relationship with these peers. Social networks that specifically aim at learning are also called *learning networks* (Sloep et al., 2012). Personal Learning Environments (PLEs) can cater to learning networks, as they provide learners with the opportunity to exchange information and knowledge with peers for their own sake (Mott, 2010).

The relationships and interactions between individual learners in learning networks and PLEs can be analysed using Social Network Analysis (SNA). The integration and adoption of technological tools in the educational process has created even more opportunities to exploit SNA-based tools. By character, these tools open up the possibility to track, monitor, and build profiles of learners to guide interventions. They allow us to understand the role of social networks in learning and provide a perspective to research how people learn, what they learn, and in particular with and from whom they learn. To date, however, Technology-enhanced Learning (TEL) research has

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not fully utilised the potential of SNA. In this article, we show how TEL can take the next step towards utilising the full potential of SNA.

Before elaborating on SNA, it is important to take a look at how the concept of social learning came about (Section 2). Afterwards, we provide an explanation of some basic jargon used in SNA. Next, we show how SNA can assist social learning. Following this, we discuss the present state of SNA for social learning by going over recent research in the field of TEL that uses SNA (Section 3). Subsequently, we sketch some future directions for SNA for social learning (Section 4). Finally, we present our conclusions (Section 5).

2 The Past of SNA for TEL: Social Learning and SNA

2.1 Social Learning

According to Bandura and Vygotsky, people learn with and from others by example or through observation (Bandura, 1977; Vygotsky, 1978). Social interaction supports the development of cognition in young learners. The notion of the *zone of proximal development* (Vygotsky, 1978) is well established in the field of education and learning, and may even have value for social learning. Knowledge that rests within peers can fill in the zone of proximal development (i.e. those who have slightly more advanced knowledge or skills than the learner), and can thus be of more significance than mere experts in the field.

Constructivist theory (Bruner, 1966) describes learning as a process of constructing new ideas and concepts from known concepts, by an individual learner or by several learners collaborating. Social interactions lead learners to articulate their tacit knowledge, engage in collaborative knowledge building (Scardamalia & Bereiter, 2006) and evaluate their own and others' ideas critically.

Since the rise of the Internet, several changes have occurred in the learning landscape. That is, their learning is not constrained by taking class, as they can easily find information on the Internet. More importantly, the order in which they acquire information is more chaotic than it used to be (Siemens, 2005). As a response to these changes, George Siemens (2005) presented the notion of *connectivism*. Some of its main principles are (Siemens, 2005): learning is a process of connecting specialised nodes (e.g. individuals) or information resources, ability to see connections between fields, ideas and concepts, and decision-making is itself a learning process.

As the relevance of social interactions for learning became more recognised, several researchers in the field of education also started to investigate the affordances of different social constructions for learning (Lave & Wenger, 1991; Sloep et al., 2012). For example, *situated learning* (Lave & Wenger, 1991) states that social interactions and the resulting learning are defined by the activity engaged in by the learner, the context (network) in which the learner is situated and the culture the learner acts in. SNA can be used to identify these contexts, structures and relationships, in order to understand, intervene or re-design learning strategies. Also, visualising these structures allows for the use of social proxies, i.e. abstract representation of individuals (nodes) whose progress or

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activities can be followed and translated into direct own activities (Erickson, 2004). But how does SNA exactly work?

2.2 Social Network Analysis

Social Network Analysis has already a long research tradition. Many publications have been written and for novices the amount of literature can be overwhelming. SNA applied on citation networks can come to help.

A literature search for social network analysis was conducted using Thomson Reuters Web of Knowledge (February 2012). The topic search included the key terms “social network analysis”, “network analysis” in combination with “technology-enhanced learning”, “TEL”, “e-learning”, “social science”, “educational science”, “psychology”, “computer science”, and “information science”. 133 papers matched the search query containing 5693 references. A co-citation analysis was applied to find papers, which are highly consented in the field (White, 2011, p. 277). Co-citation analysis is a tool to identify important documents on a topic by identifying papers, which are often cited together. The following graph represents the pruned result of this analysis, highlighting only documents, which are most frequently cited together.

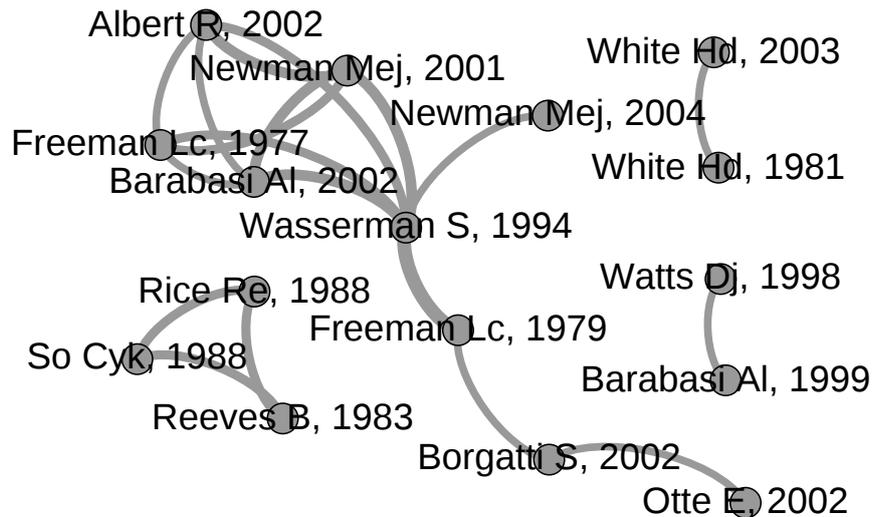


Figure 1 Co-citation network for SNA in TEL literature.

The results could be grouped into four categories. The first group is about collaboration patterns of researchers (Barabasi et al., 2002; Newman, 2001, 2004). The second group is mainly on SNA techniques, metrics (Freeman, 1977, 1979; White, 1981, 2003), and properties (Albert & Barabasi, 2002; Barabasi & Albert, 1999; Watts & Strogatz, 1998). The third group is about analysing citation patterns of journals (Reeves & Borgman, 1983; Rice, et al., 1988; So, 1988). The last group contains introductory texts on SNA (Otte & Rousseau, 2002; Wasserman & Faust, 1994) and software (Borgatti, et al., 2002).

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These papers can be seen as a primer on SNA. Especially the papers on collaboration are close to the research area of Technology-Enhanced Learning and might stimulate the discussion of parallels between research networks and learning networks.

2.2.1 Network data collection

Before we start analysing a social network, we need to have appropriate social data at hand. To collect such data, two main methods of data collection exist (Garton, Haythornthwaite, & Wellman, 1997; Chung & Davis, 2005). First, we have *sociocentric networks*, or whole networks, which focus on the interactions between people on a network level. In other words, it studies structural patterns of interactions in a network, with the specific aim to generalize these to other networks. In practice, this often means that we monitor real-world data of human interactions, such as email traffic, Twitter followers and retweets, Facebook contacts, and so on and so forth.

Second, we have *egocentric networks*, which focus on the networks of individuals. Construction of an ego network can be performed in two ways. First, we simply ask one or more participants to identify their contacts. If we ask those contacts whether they are related or not, we have an ego network with *alters*. Second, we have the *snowball* method. For each participant, ask for his or her contacts. For each of these contacts, ask about his or her contacts. Data collection is continued until a stopping criterion is met, such as the number of hops by one person, or the total amount of nodes in the network.

When we construct networks of people that know each other, people that are friends, or give advice, or any other form of direct contact, we can construct a so-called one-mode network. In a one-mode network, an edge between person A and B is for instance a friendship relationship. If we focus on what tools people use, we can construct a two-mode network. To illustrate this, we provide the following example: Person A and B do not know each other, so we cannot construct a one-mode network using their relationship. They do, however, browse the same Internet forum β . Person A is now linked to that forum β , and so is person B, resulting in the two-mode relationships $\{A, \beta\}$ and $\{B, \beta\}$. If we consider the relationships to be transitive, we can replace two-mode relationships $\{A, \beta\}$ and $\{B, \beta\}$ by the one-mode relationship $\{A, B\}$, allowing us to analyse the network using ordinary SNA metrics, which will be discussed in the following paragraph.

2.2.2 Metrics

Three main levels exist on which we can use social network analysis metrics for analysis. Firstly, we can analyse the whole network. We can study how many links are formed, as opposed to the total number of links that are possible, also known as *density*. We can use density to study how well connected a network is; How well do people know each other? Also, the extent to which a network revolves around a few persons (centralization) can be measured. Often, we prefer not to have a network be dependent on few persons, so we tend to decentralize the network.

Secondly, we can study the network on the community level. We analyse the number of subnetworks within a network, also known as *connected components*. Such

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components have weaker links between them than among their individual members. Connected components, or clusters, often share a certain meaning, an interest, or a practice. They are sometimes referred to as communities of practice (Lave & Wenger, 1991). One way to detect community structures is *block modelling*, which analyses two-mode data about individuals and their affiliation to detect underlying interaction patterns. For instance, data about learners and forum topics can be analysed to detect underlying communities of interest (Rodríguez, Sicília, Sánchez-Alonso, Lezcano, & Garcia-Barriocanal, 2011).

Thirdly, we can study social networks from an individual level. Degree centrality measures the popularity of an individual by counting the number of relationships one has. Betweenness centrality (Brandes, 1994) tells us to what extent someone is 'needed' in terms of information flow: How often is someone in-between two other people? Closeness centrality provides information about how easy someone can reach others; how many hops in the network does it take (on average) to reach someone?

2.3 Four types of SNA applications

When one wants to apply SNA to study social learning, four types of SNA applications can be distinguished. These four types, which increase in complexity respectively, comprise 1) network visualisation, 2) network analysis, 3) simulation, and 4) network interventions.

Network *visualisation* can be done in several ways. As shown in section 2.2.1, we can construct either a one-mode network that consists of merely individuals, or a two-mode network that consists of individuals and, for instance, the tools that they use to learn. A network can be visualised by a so-called *sociogram* (Moreno, 1934) in which we connect nodes (individuals) by means of edges (relationships). The edges may be directed (person A learns from B, but not the other way around) or undirected (persons A and B learn from each other, so no distinction). In practice, network visualisation is often combined with network analysis.

Network *analysis* is the mathematical analysis of interactions, relationships, positions in the network, and the network itself. As shown in 2.2.2, we can apply the analysis on three levels: the network level, the community level, and the individual level. For instance, one can analyse the position of individuals in a knowledge exchange network, to identify authoritative individuals in that network.

Also, *simulation* may be a welcome step before a network intervention. Interventions may be time and money consuming, and it may pay off to design a computer simulation of the learning context at hand, to see how learners would behave during a future intervention. Also, existing data and analysis about learners and their interactions can be used to extrapolate behaviour.

After an initial analysis of a social network in a learning context, activities can be set up to change the structure of the network. Network *interventions* can be undertaken in order to increase the number of connections in a network, to strengthen certain types of ties between learners, or to support learners (nodes in the network) with personalised information triggering network actions. Social Network Analysis here acts as a diagnostic tool to understand the network structure, in order to create more value from it through an

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intervention. Namely, Social Network Analysis may be part of a larger system, for example, graph- or network-based recommender systems, as we will show later on.

Though not necessarily a type of SNA application, network *data collection* can be seen as a pre-step in the process of applying SNA. It is important that one consider the way data is collected. Will the network be collected from an egocentric perspective, aiming to generalise individual behaviour across networks? Or is data rather collected from a sociocentric perspective, to study group behaviour and structure, or information flow? Anyhow, when collecting data, it is crucial to approximate reality as good as possible. For instance, ‘friendship’ is an intangible and subjective concept, and people may not always recall all their friends when you ask them. Hence, a sociocentric method such as collecting one’s Facebook friends may be worth considering as an alternative to an egocentric method.

3 Present state of SNA for TEL

SNA has already a long-standing tradition, whereas analysing learning networks by means of SNA is still in its infancy (Haythornthwaite, 2011). However, we can already pinpoint some results from research that applies this method in the learning context. For each of the four SNA applications, we discuss current research, what they comprise, and what their findings are.

3.1 Visualisation

Learning Management Systems (LMSs) may be especially suited to monitor the interaction of students. Their log files and fora provide the opportunity to construct social networks from a sociocentric perspective (Brooks, Panesar, & Greer, 2006; Chatti, Jarke, Indriasari, & Specht, 2009; Dawson, 2010; De Laat, Lally, Lipponen, & Simons, 2007; Duensing, Stickler, Batstone and Heins, 2006; Heo, Lim, & Kim, 2010; Merlo, Ríos, Álvarez, L’Huillier, & Velásquez, 2010; Mödritscher, Taferner, Soylyu, & De Causmaecker, 2011; Nuankhieo, Tsai, Goggins, & Laffey, 2007; Posea et al., 2006; Wild & Ullmann, 2012), as one can monitor online interaction between students. This is in contrast with the egocentric perspective (De Laat et al., 2007; Martínez et al., 2003) in which students report, obviously constrained by their memory, about their interactions with other students. Messages and replies on fora in LMSs allow for the extraction of directed edges between network nodes (e.g. person A learns from person B) (Rodríguez et al., 2011; Duensing et al., 2006; Posea et al., 2006). Table 1 provides an overview of how and where data was collected in the abovementioned studies, and how they were represented.

Table 1 Overview of network data collection methods, sources, and edge and network types.

study	data collection	source	edge type	network type
Brooks et al. (2006)	sociocentric	iHelp collaborative annotation tool	undirected	one-mode
Chatti et al. (2009)	sociocentric	Plone content management system	undirected	one-mode
Dawson (2010)	sociocentric	/ Blackboard	directed	one-mode

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De Laat et al. (2007)	egocentric sociocentric/ egocentric	WebCT logs	directed	one-mode
Duensing et al. (2006)	sociocentric	Lyceum	undirected	one-mode
Heo et al. (2010)	sociocentric	generic LMS logs	directed	one-mode
Martínez et al. (2003)	sociocentric/ egocentric	BSCW logs	undirected	one-mode
Merlo et al. (2010)	sociocentric	course documents	undirected	one-mode
Mödrtscher et al. (2011)	sociocentric	several Wikis	undirected	one-mode / two-mode
Nuankhieo et al. (2007)	sociocentric	Sakai resources and discussion board	directed	one-mode
Posea et al. (2006)	sociocentric	Moodle forum	directed	one-mode
Rodríguez et al. (2011)	sociocentric	Dokeos forum	directed	two-mode
Wild & Ullmann (2012)	sociocentric	TELeurope.eu / Elgg	undirected	one-mode

Notably, sometimes an egocentric approach may add value to a sociocentric method to act as triangulation (De Laat et al., 2007; Martínez et al., 2003). Also, a vast amount of relationships that are extracted from the network data are displayed as undirected relationships. The majority of research mentioned hereinbefore studies one-mode interactions between students, whereas recent studies point out that it may be interesting to study two-mode relationships as well, to identify core discussion topics (Rodríguez et al., 2011; Wild & Ullmann, 2012), for instance.

3.2 Analysis

Network visualisation is often combined with its analysis to identify interaction patterns among students in online learning systems (Heo et al., 2010; Corallo, De Maggio, Grippa, & Passiante, 2008; De Laat et al., 2007; Posea et al., 2006; Martínez et al., 2003), analyse sense of community and social ability among students (Nuankhieo et al., 2007) and to identify groups and topics of discussion (Rodríguez et al., 2011). Studies that merely analyse networks, rather than also visualising them, include those that study student interactions (Dawson, Macfadyen, Lockyer and Mazzochi-Jones, 2011; Dawson, 2010; Yao, 2010; Hamulic & Bijedic, 2009; Aviv, Ehrlich, Ravid, & Geva, 2003), student achievement (Moolenaar, Slegers, & Daly, 2012; Lomi, Snijders, Steglich, & Torló, 2011; Cho, Gay, Davidson, & Ingraffea, 2007), networking patterns (Capuano, Laria, Mazzoni, Pierri, & Mangione, 2011; Mödrtscher, Taferner, Soyly and Causmaecker, 2011; Ryymin, Palonen and Hakkarainen, 2008; Klamma, Spaniol, Cao, & Jarke, 2006), and communities (Merlo et al., 2010; Reffay and Chenier, 2002).

Table 2 provides an overview of the network analysis methods and findings for each of the studies mentioned in the current subparagraph. With respect to the metrics that are being employed, we see a tendency toward the use of individual-level metrics

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such as degree, betweenness, closeness and eigenvector to identify *how* interactions take place, in order to map these to student achievement. Interestingly, little attention is given to *what* learners are talking about: only Rodríguez et al. (2011) focus on the discovery of core discussion topics in a learning network.

On the community level, group cohesion is studied by identifying cliques and clusters, but many research performed in this area dates back to an era in which social media were not yet used (Aviv et al. 2003; Reffay & Chenier, 2002). In current times (2012), social media are finding their way to the (virtual) classroom, and research is necessary to study how the change in Internet use influences social learning (Siemens, 2005).

Recent initiatives focus on structural properties of the network, such as its density, centralization and reciprocity, to study student performance. Fascinatingly, An et al. (2009) and Yao (2010) present contrasting findings on whether teachers have a positive influence on student interactivity. This may be due to tutoring style; An et al. hint towards a change of teacher feedback style yielding different results. Also, Yao points out that *what* students discuss may influence student interaction, in line with the study by Rodríguez et al. (2011).

Table 2 Overview of network analysis methods and findings.

study	metrics	findings
Moolenaar et al. (2012)	density, centralization	density affects teachers' perceptions of collective efficacy
Capuano et al. (2011)	eigenvector, degree, (flow) betweenness, closeness, neighbourhood centrality	n/a
Dawson et al. (2011)	degree, betweenness, closeness, eigenvector	weak correlations between interview score and closeness and eigenvector values
Lomi et al. (2011)	degree, betweenness, reciprocity	students perform similarly to their peers' average; students that perform similarly are more likely to form friendship and advice ties
Mödritscher et al. (2011)	PALADIN software	detection of 'conversationalist' and 'pioneer' interaction patterns
Rodríguez et al. (2011)	block modelling	core forum topic threads (m-slices)
Dawson (2010)	degree	high-performers make more connections than low-performers; scholars connect to peers of similar academic standing; teachers take more often part in high-performer networks than low-performer networks.
Heo et al. (2010)	density, flow betweenness	high density affects communication, cohesion and mutual support
Merlo et al. (2010)	connectivity	detection of textual copy communities
Yao (2010)	density, centralisation, share, reciprocity	student interactivity drops after teacher withdrawal; change of discussion design did not change relative

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An et al. (2009)	density, centrality, share, reciprocity	student contribution presence of a teacher hinders student interaction
Chatti et al. (2009)	degree, closeness, betweenness	several network visualisations
Ryymin et al. (2008)	density, degree	four teacher networking patterns: counsellor, inquirer, collaborator and the weakly social.
Cho et al. (2007)	degree, betweenness, closeness, structural holes	communication style is reflected in ego network structure
De Laat et al. (2007)	degree	interaction patterns change over time
Nuankhieo et al. (2007)	density, centralisation	small groups of 3-4 individuals share more information and knowledge than dyads; small group activity yields higher sense of community and social ability
Klamma et al. (2006)	degree, closeness, betweenness, structural holes	identification of the <i>troll</i> role, a person that “aims at drawing attention and starting useless discussions”
Posea et al. (2006)	density, closeness, eigenvector, centralisation	n/a
Aviv et al. (2003)	cliques, bridges, role groups, eigenvector centrality, degree, density	high cohesion exists in structured asynchronous learning networks
Martínez et al. (2003)	density, centralisation	a mixed methods approach can be used to identify networking patterns
Reffay & Chenier (2002)	cliques, clusters	hierarchical cluster analysis is a useful pre-step in cohesion analysis using cliques

3.3 Simulation

Sie, Bitter-Rijpkema and Sloep (2011) focus on the combination of SNA with utility-based recommender systems to inform themselves about the value of future connections in innovation networks. Based on extensive literature review, they present an exploratory simulation of networked innovation.

Wild and Sigurdarson (2011) use a simulation approach to simulate the impact of management facilities on learning networks in a higher education blogosphere. They take the use of simulation a step further in that it is based on trial data and general data about the blogosphere. They studied how a change in learning practice and technology would affect the structure of higher educational networks, and found that density and reciprocity within the blog network increased. Yet, the missing link is how simulation can be used to inform interventions. Moreover, predictions may be used to inform interventions in real-time or to extrapolate current networking behaviour (Steglich, Snijders, & West, 2006).

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3.4 Interventions

In non-formal learning contexts, such as the workplace, SNA can be used to promote network awareness and to uncover hidden connections in the organisation. It can be used to promote awareness, give feedback and prompt reflection. An example of this provides research by Steiny and Oinas-Kukkonen (2007), who analyse interactions and collaborations between employees in order to support managers for better organisational decision making (regarding constitution of teams, and distribution of responsibilities). Jo (2009) showed that feeding back the identification of communities of practice positively influenced the interactions in a social network of programmers.

Network analysis can also offer insight into people's information seeking behaviour. Su, Huang and Contractor (2010) conclude that proactive information seeking rather than unsolicited information receiving is more appreciated in teamwork. In a follow-up study, Su and Contractor (2011) show that social network connections influence information seeking from databases and human knowledge sources.

Breuer, Klamma, Cao and Vuorikari (2009) use SNA to investigate the structure of the large eTwinning network of schools and schoolteachers through the online eTwinning platform. The investigation shows that although the network is huge, only a fraction of the members is actively connecting on the platform. Fetter, Rajagopal, Berlanga, Sloep and Cao (2011) present an intervention that creates ad-hoc groups of teachers to increase connections in the eTwinning network, and thereby to decrease the dependency on a few, active participants in the network (decentralization). The initial analysis of the network resulted in the development of tools that support individual teachers (nodes in the network) to change their networking activities on the platform. Similarly, Corallo et al. (2008) successfully intervene in the learning process by analysing interactions and planning intermediate meetings accordingly.

Sie, Drachsler, Bitter-Rijkema and Sloep (2012) present a first prototype of the CoCooN system that connects scholars to new co-authors. Small-scale evaluation shows that connecting to powerful (betweenness centrality) and similar peers (keyword similarity) that can persuade other network members eases cooperation.

As shown above, social network analysis provides numerous opportunities to visualise, analyse, simulate and intervene in social learning networks. Below, we give an overview of what value SNA currently has for TEL:

- make learners aware of valuable peers, knowledge and resources by means of diverse visualisation techniques and network-based recommender systems
- identify experts, hubs, and decrease dependency of learners on them, by using individual metrics such as degree, betweenness, closeness, and eigenvector centrality
- identify (effective and efficient) communities by means of clique detection and closeness measures
- promote efficient communication/learning by means of closeness measures and network-level measures such as share and reciprocity

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- reduce workload on experts / teachers by automatically bringing learners into contact with other, relevant learners and resources
- guide and inform assessment of learners
- increase cohesion and sense of community
- prediction and extrapolation of social learning behaviour
- provide relevant feedback for both teachers and learners, to inform learning actions or interventions in the learning process

4 Future Directions of SNA for TEL

The previous sections hint that SNA is currently not being used to its full potential. When collecting data, for instance, a challenge is to identify intangible relationships. One can, for instance, triangulate network data using content analysis (Heo et al., 2010; An et al., 2009; Aviv et al., 2003; De Laat, 2002) to identify *what* learners talk about. Another method to analyse what learners discuss is block modelling (Rodríguez et al., 2011), which uses two-mode learner-topic data.

To give more meaning to what learners discuss, one may want to enrich the data that one has. Semantic techniques such as RDF allow one to spell out what a relationship γ between learner A and B comprises. Consequently, Semantic Web techniques help one make sense of the network data and types of networks, and can help distinguish *from whom* learners learn and *what* learners learn, and *enrich existing data* (Barrat, Cattuto, Szomszor, Van den Broeck, & Alani, 2010). Ereteo, Gandon, Corby and Buffa (2008) show how such a distinction is made, and how networks can be analysed through SNA-based SPARQL queries. Moreover, a recent update of SPARQL, version 1.1 (Prud'hommeaux & Seaborne, 2012), allows for property paths. Such property paths may be useful in computing network variables that include path lengths, such as closeness and betweenness. Besides, they may be more efficient than the calculations by Ereteo et al., but this needs further investigation.

As George Siemens (2005) indicates, Internet use has changed, and it is necessary that we deal with this changing landscape with respect to social learning. Social media may add a new dimension to community-level metrics such as cohesion, share and reciprocity. Extracting friends or colleagues from Facebook and LinkedIn, respectively, may deal with a challenge that egocentric network elicitation currently faces. That is, one can extract all contacts from Facebook (thereby bypassing cognitive limitations in recalling contacts), present them to the learner, which then tells which of them are learning contacts. Access to data in these social networks may open up possibilities for analysing non-formal learning, but also bridge the gap between formal learning and non-formal learning by bringing formal learners into contact with valuable peers from their non-formal social, learning network. In turn, such enhancements may affect network characteristics such as cohesion, as they may foster learners' *sense of community* (Rovai, 2002).

When using social data on the web, one has to be aware that what one measures actually reflects what one wants to know. For example, people often make the distinction

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between Facebook for private use and LinkedIn for professional use. Although both social graphs may say something about a person in general, a professional network such as LinkedIn may say more about professional learning, as colleagues are more likely to be in one's (professional) LinkedIn network than one's (private) Facebook network.

It is, however, not wise to retrieve this information 'freely' from the Web without participants' consent. Some people are not aware that technology can be used to monitor one's behaviour, and others may not even know that their information is out on the Web for others to be viewed. These and other considerations are reported in a recently EU-funded initiative called DataTEL (<http://www.teleurope.eu/pg/groups/9405/datatel/>).

To date, a vast majority of current research focused on the reporting and analysis of learner interactions within LMSs. This may guide tutors to changing their teaching style, or make learners aware of their own and peers' position in the network. Though, to make optimal use of SNA for TEL, research needs to deal with the changing behaviour of learners, as De Laat et al. (2007) suggest. Real-time interventions may offer a solution, and may be shaped into so-called *network-based recommender systems*, in order to recommend learning actions, resources, or valuable peers (Sie et al., 2012; Mödritscher & Law, 2010; Posea & Trausan-Matu, 2010).

Learners' behaviour may change over time, so one needs to be aware that interventions driven by learners' actions over the past five years may yield disapproval, whereas interventions based on recent behaviour may not. In recommender systems, such *time-drift* is a known issue when building a profile or user model and it may distort recommendations. We should keep in mind that the user profile that we build may not be an genuine representation. A natural answer is time-dependent SNA (Steglich et al., 2006), but up till now, no research in the field has been reported using this.

Current approaches to measure interactions between students are mainly limited to extracting their interactions from LMSs. On the longer term, research may need to embrace new methods to more accurately collect learning network data. Sensor devices to monitor behaviour, emotions and perception open up ways of conducting SNA research in learning and education. Apart from aiding conversational agents (Vertegaal, Slagter, Van der Veer, Nijholt, 2001), one can use eye-tracking equipment to monitor facial expression; the attitude towards topics or individuals can be determined during virtual meetings. This allows one to construct force fields of attracting and repelling attitudes (Lewin, 1941) and conflicting emotions in an online collaborative learning environment. For instance, by measuring the attitude of person A towards person B using eye-tracking or facial recognition devices, one can construct a directed, weighted relationship $\{A,B,<weight>\}$ denoting the positive or negative attitude. Aggregating a multitude of these attitudes will result in a network of attitudes. Putting learners together that have a similar attitude may boost collaborative and social learning in collaborative learning environments. Particularly, learning networks may profit from such attitude monitoring.

Radio frequency identification (RFID) employs small chips that may be put on or in devices, tangibles or people to identify their presence. Near Field Communication (NFC) is an extension of RFID in that it can actively detect presence and communicate with other NFC-enabled devices. NFC and RFID can, for instance, monitor interactions during a conference (Barrat et al., 2010; Reinhardt, Messerschmidt, & Nelkner, 2011,

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Zirn, 2012) to construct networks of people that have the same social presence. Currently, NFC is being integrated into mobile phones by an increasing number of manufacturers. NFC allows us to monitor the interactions between people, and see when they meet, to form a social network that is based on actual face-to-face interaction data. In combination with online presence monitoring, we can construct an extensive view of social interactions (*ubiquitous social network analysis*) when people learn. Also, NFC, RFID, and sensor devices may provide additional methods for triangulation.

All in all, the current article provides an elaborated outlook for SNA for TEL on both the short and longer term. Table 3 sums up the future of SNA for TEL by presenting a roadmap.

Table 3 Overview of future work for SNA for TEL. The type of improvement can be data collection (d), visualisation (v), analysis (a), simulation (s), or intervention (i).

future work	type
more predictive analysis and extrapolation to save time/money	s
more interventions driven by SNA	i
block-modelling and content analysis to identify <i>what</i> learners talk about	v,a
semantic techniques to identify <i>from whom</i> learners learn, <i>what</i> learners learn, and <i>enrich data</i>	v,a
collecting network data from social network sites to <i>triangulate</i> or enrich data	d
real-time interventions, e.g. <i>network-based recommender systems</i>	i
<i>time-dependent</i> SNA	a,s
more accurate and unobtrusive collection of network data by means of <i>sensor devices</i> or <i>Near Field Communication</i>	d

5 Conclusion

The current article describes how Social Network Analysis (SNA) can assist social learning. The changing learning environment (e.g. non-linear learning, the use of social media) poses new challenges that can be addressed by SNA. In the field of Technology-enhanced Learning (TEL), SNA as a research method has taken off, but mainly in the form of visualisation and analysis. In general, the authors propose an increase in the use of network simulations to predict or extrapolate behaviour, and interventions driven by SNA.

Current use of SNA for social learning focuses mainly on the visualisation and analysis of one-mode learner-learner interactions, whereas two-mode learner-topic or learner-object relationships may tell us more about what learners are learning. Also, community-level research dates back to 2003, an era in which social media were not integrated in peoples' daily lives. Therefore, the authors argue for a new investigation of community characteristics such as cohesion and bridge roles in networked learning.

The future of SNA for TEL comprises a variety of improvements over current research. First, the abovementioned research gap suggests that research focus on the use of, for instance, block-modelling to identify *what* learners learn. Semantic techniques may assist in identifying what learners learn, but may also make clear *from whom*

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learners learn (*sense making*). Research should try to *enrich data* or *triangulate data* using techniques such as content analysis and collecting data from social networking sites. The authors propose more use of real-time interventions and time-dependent SNA may solve some of the time-drift challenges that current network-based recommender systems may face. Finally, on the longer term, we may use sensor devices and Near Field Communication to more accurately and unobtrusively monitor the relationships between individuals.

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