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Abstract

In this article we want to understand in more detail how learning networks emerge in online networked learning environments. An adage in Networked Learning theory is that networked learning cannot be designed; it can only be designed for. This adage implicitly carries the idea that networked learning is seen as learning in which information and communication technology is used to promote (emergent) connections between learners and their peers, learners and tutors and learners and learning resources. Emergence entails a self-organizing component. However, there is no comprehensive understanding of how self-organizing network effects occur in networked learning environments, how they influence possible learning outcomes and how these network effects can be enhanced or frustrated by the design elements of different networked learning environments. By means of a review we investigate how the three most known self-organizing network effects occur in networked learning environments, namely preferential attachment, reciprocity and transitivity. Results show that in most studies self-organizing network effects are significantly present. Moreover we found important (design) elements related to the people, the physical environments and the tasks of the learning networks that could influence these self-organizing network effects. Studies that looked at learning outcomes are limited. Based on the review study future research directions for the field of Networked Learning are addressed.

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Review

How do Online Learning Networks Emerge? A Review Study of Self-Organizing Network Effects in the Field of Networked Learning

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Abstract: In this article we want to understand in more detail how learning networks emerge in online networked learning environments. An adage in Networked Learning theory is that networked learning cannot be designed; it can only be designed for. This adage implicitly carries the idea that networked learning is seen as learning in which information and communication technology is used to promote (emergent) connections between learners and their peers, learners and tutors and learners and learning resources. Emergence entails a self-organizing component. However, there is no comprehensive understanding of how self-organizing network effects occur in networked learning environments, how they influence possible learning outcomes and how these network effects can be enhanced or frustrated by the design elements of different networked learning environments. By means of a review we investigate how the three most known self-organizing network effects occur in networked learning environments, namely preferential attachment, reciprocity and transitivity. Results show that in most studies self-organizing network effects are significantly present. Moreover we found important (design) elements related to the people, the physical environments and the tasks of the learning networks that could influence these self-organizing network effects. Studies that looked at learning outcomes are limited. Based on the review study future research directions for the field of Networked Learning are addressed.

Keywords: networked learning; online learning networks; self-organizing network effects; literature review

1. Introduction

In this article we wanted to understand in more detail how learning networks emerge online. An adage in Networked Learning theory is that networked learning cannot be designed; it can only be designed for [1]. This adage implicitly carries the idea that networked learning is seen as learning in which information and communication technology (ICT) is used to promote (emergent) connections between learners and their peers, learners and tutors and learners and learning resources [2,3]. These connections or ties result in learning networks. Learning networks are seen as the central phenomena for inquiry in Networked Learning research [1]. We follow Goodyear and Carvalho's [1] definition of learning networks and see learning networks as "providing educational contexts [formal, non-formal or informal including learning in the wild] where certain pedagogical interactions take place and where people are exchanging views and experiences related to knowledge and knowing" [1] (p. 264).

Our interpretation of learning networks is closely related to the post digital approach [4]. Learning networks are perceived as a collection of ties between people or between people and learning objects [5].

Although not all learning networks emerge online, for this article we only incorporated learning networks that emerge through the use of some sort of computer mediated communication [6]. Online learning networks can consist of all types of online learning resources like online learning resources (people and objects) present in formal (e.g., discussions in an online learning environment), non-formal (learning resources in a university massive open online course (MOOC)) and informal learning environments, including learning resources in the wild (e.g., Youtube videos). We look at learning networks as a result of human activity [1]. This excludes for example learning relations (i.e., chatbots) between learning objects, Artificial Intelligence (AI) or machine learning. We focus not only on educational silos but we focus also on a world of hybrid learning environments and digital learning in society [4,7]. Learning networks can emerge in teams, groups, communities or in ego-networks in education, organizations and society. They can be ad-hoc or long term.

In philosophy, emergence is defined as: “the arising of novel and coherent structures, patterns and properties during the process of self-organization in complex systems” [8] (p. 49). If we translate this definition to the emergence of learning networks, self-organization implies that learning ties between learners and their peers, or learners and their instructor or learners and their learning objects are at least partly, the result of a process of self-organization. The process of self-organization in (learning) networks is well described in social network theory. Self-organizing network effects are endogenous network effects that are inherent at all types of social networks [9]. According to Lusher and Robins [9] networks can organize themselves into certain patterns because the existence of some ties encourages other ties to come into existence. They describe self-organizing network effects as endogenous effects because the networked effects arise from within the network. Self-organizing network effects are mechanisms or processes that are at play in a network. Self-organizing network effects are perceived as the micro-structures that explain the emergence of ties. Self-organizing network effects are not the same as macro structures like cohesiveness or density [10]. Density is not a self-organizing network effect in itself but refers to the proportion of ties in a network. The same argument holds for network centralization. Network centralization refers to the degree in which a network is centered on a few ties. Self-organizing network effects are the effects that refer to the process where ties emerge because of the existence of other ties [9].

Three well known self-organizing network effects are preferential attachment, reciprocity and transitivity [9]. Preferential attachment is a process in which tie formation is distributed among learners or learning objects according to the amount of online learning ties these learners or learning objects already have [11]. Preferential attachment is also referred to as “cumulative advantage”, “the rich get richer”, and the “Matthew effect” [12]. The process of preferential attachment generates networks with power-law in-degree distributions resulting in networks that consist of a few hubs with highly connected participants [13]. Preferential attachment is seen as a mechanism to explain the growth of the world wide web [11].

Reciprocity reflects the tendency of individuals to reciprocate a learning tie. Reciprocity measures a form of mutual engagement [9]. Networks that have a high proportion of reciprocal ties result in balanced and dense networks. In this article we focus on actual reciprocal learning behavior, for example through social interaction such as a reply to a message in a discussion forum. This means that we exclude investigations in related concepts like anticipated reciprocity referring to research where participants share knowledge because they anticipate reciprocity. This also excludes the general norm of reciprocity, referring to the idea that people in a group (universally) agree that people should help those who have helped them [14]. Anticipated reciprocity and the general norm of reciprocity are more about culture than actual behavior. In this review we only focus on actual reciprocal learning ties.

Transitivity refers to the self-organizing effect in which learners tend to form groups. Transitivity, also known as network closure, triangulation or network clustering, refers to the tendency of people to connect with a person who is already connected to a connection, or a friend of a friend [9]. Transitivity refers to the tendency of people to form small group-like structures. Like reciprocity, a high proportion

of transitive ties result in cohesive networks. Figure 1 provides a visual representation of preferential attachment, reciprocity and transitivity.

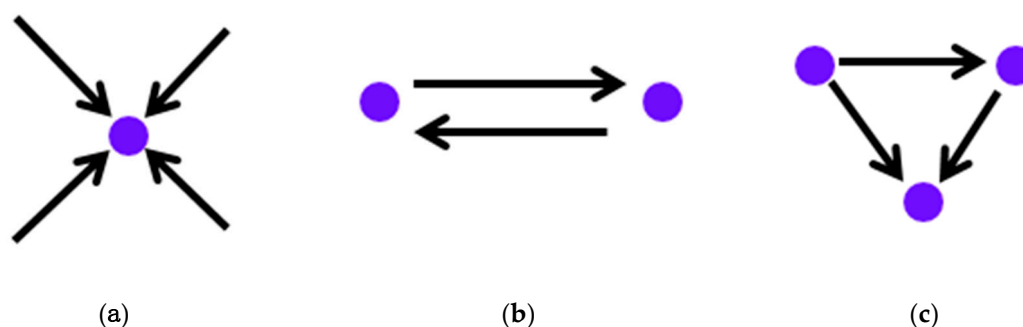


Figure 1. Graphical representation of preferential attachment, reciprocity and transitivity. (a) Preferential attachment; (b) reciprocity; (c) transitivity.

Self-organizing network effects in the field of Networked Learning are seen as important mechanisms described within the theoretical foundations of Networked Learning and related fields like social learning. For example, reciprocity is a prerequisite for mutual engagement, an important factor to promote learning according to theoretical foundations of social learning like the theory of communities of practice [15] and community of inquiry [16]. According to the theoretical foundations of Connectivism, preferential attachment could lead to unbalanced networks where learners who are capable of building great profiles will more easily gain more access to other learners [17]. This is particularly true in designs that promote learning at scale, such as massive open online courses (MOOC)s. However, a more in depth understanding of how these self-organizing effects occur in online learning networks is lacking to support these important theoretical notions.

Research in the field of face-to-face networks demonstrated that the presence of reciprocal tie formation can be an important condition for learning [18] because networks with a lot of reciprocal ties can create a strong inward focus that enhances deeper learning [19] and the development of tacit knowledge [20]. On the other hand reciprocated ties appear less productive for innovation and outward focus [21]. Granovetter's [22] seminal work on the strength of weak ties shows that innovative information is more likely to come from non-reciprocated and infrequent ties. This tension between cohesive network structures and the need for weak ties to generate innovative knowledge remains unresolved, not in the least for online learning networks.

These theoretical notions trigger several questions concerning the design of networked learning environments like: Are there self-organizing network effects present in online learning networks? And if so, how are these self-organizing network effects triggered? How do self-organizing network effects influence the emergence of learning networks and learning outcomes? Do self-organizing network effects occur differently in formal settings with small student groups than for example in informal contexts like MOOCs? To answer these questions, the following research questions were addressed: (1.1) How are self-organizing network effects defined in the field of Networked Learning? (1.2) How do self-organizing effects occur in networked learning environments. (2) What factors affect self-organizing network effects? (3.1) How do self-organizing network effects influence learning networks? (3.2) What is the influence of self-organizing network effects on learning outcomes? By answering these research questions we aimed to unravel the possible tension between the components of the design of learning environments (the people, the set and the purpose), the learning network and the network self-organizing effects.

To answer these research questions, we performed a review of empirical results of Networked Learning research and related fields like Computer Supported Collaborative Learning (CSCL) and online learning focused on self-organizing network effects. First, we set clear boundaries for our review study. Second, we describe in detail our search and selection process. Third, we summarize the studies

and provide the results. We will generate future research directions by assessing where Networked Learning research currently is.

2. Materials and Methods

2.1. Search and Identification Process

We performed a literature review following the PRISMA guidelines to report our results systematically. PRISMA stands for preferred reporting items for systematic reviews and meta-analyses [23]. We accessed the search engines ScienceDirect, ERIC and Web of Science to find relevant articles. ScienceDirect is a large and general database from Elsevier. ScienceDirect claims to cover over 25% of the world's science, technology and medicine full text and bibliographic information. ERIC focuses more specifically on education literature for scholarly research. Web of Science is a publisher independent database with a multidisciplinary focus. We also searched all conference papers from the Networked Learning Conference from January 1998–May 2019. We used the search terms self-organizing network effects, endogenous network effects, preferential attachment (or cumulative advantage or the rich get richer or Matthew effect), reciprocity, transitivity (or network closure or network clustering). Each term was combined once with networked learning, once with CSCL and once with online learning + social to limit the search to online learning networks. To exclude non-human networks we combined the search with the following exclusion: NOT neural. To avoid overlap within the same database we included NOT for each term already used. The search covered literature published between January 1998 and May 2019. We chose to start the search from 1998 because 1998 is coined as the start of the field Networked Learning [1]. ERIC and Web of Science only searches titles, abstracts and keywords, and Science Direct also searches full texts, therefore we extended our search in ERIC and Web of Science with the following key words: “networked learning” OR “online learning” OR CSCL AND “social network analysis”. Moreover, we searched 87 articles from the review study of Dado and Bodemer [24] who performed a review study on social network analysis in the field of CSCL and online learning until 2015. The results of the search are presented in Appendix A.

2.2. Screening and Selection Process

The title and abstract as shown by the search engines were checked against the criteria for inclusion and exclusion to select possible relevant publications. Titles and abstracts were checked by a single reviewer with advice from other authors. Supplementary references were included based on a search of the reference lists from key papers. The results are presented in Figure 2.

To set these boundaries of our review study, in the screening phase 413 publications were judged against the following criteria for inclusion. The number of publications that were excluded on each criterion is shown in parentheses after the criterion: (a) the article reported on an empirical study (e.g., we excluded theoretical articles without empirical data) (123), (b) the article focused on online learning networks of humans (e.g., we excluded inter organizational networks) (16), (c) the article focused on online learning ties directly collected within the online learning environment (e.g., we excluded learning networks created based on self-reported ties in surveys) (20), (d) the study focused on formal, non-formal or informal learning activities (e.g., we excluded articles without any online learning component in it) (35), (e) the article focused on self-organizing network effects (e.g., we excluded articles that focused on anticipated reciprocity) (110).

In the eligibility phase we judged the 109 articles on a full text read on the final criterion (g) the study provided insights into the definition of network self-organizing effects, factors that influenced network self-organizing effects, or influence of self-organizing effects on learning networks and learning outcomes (81). Using these criteria, 28 publications of the total of 413 were included in the review.

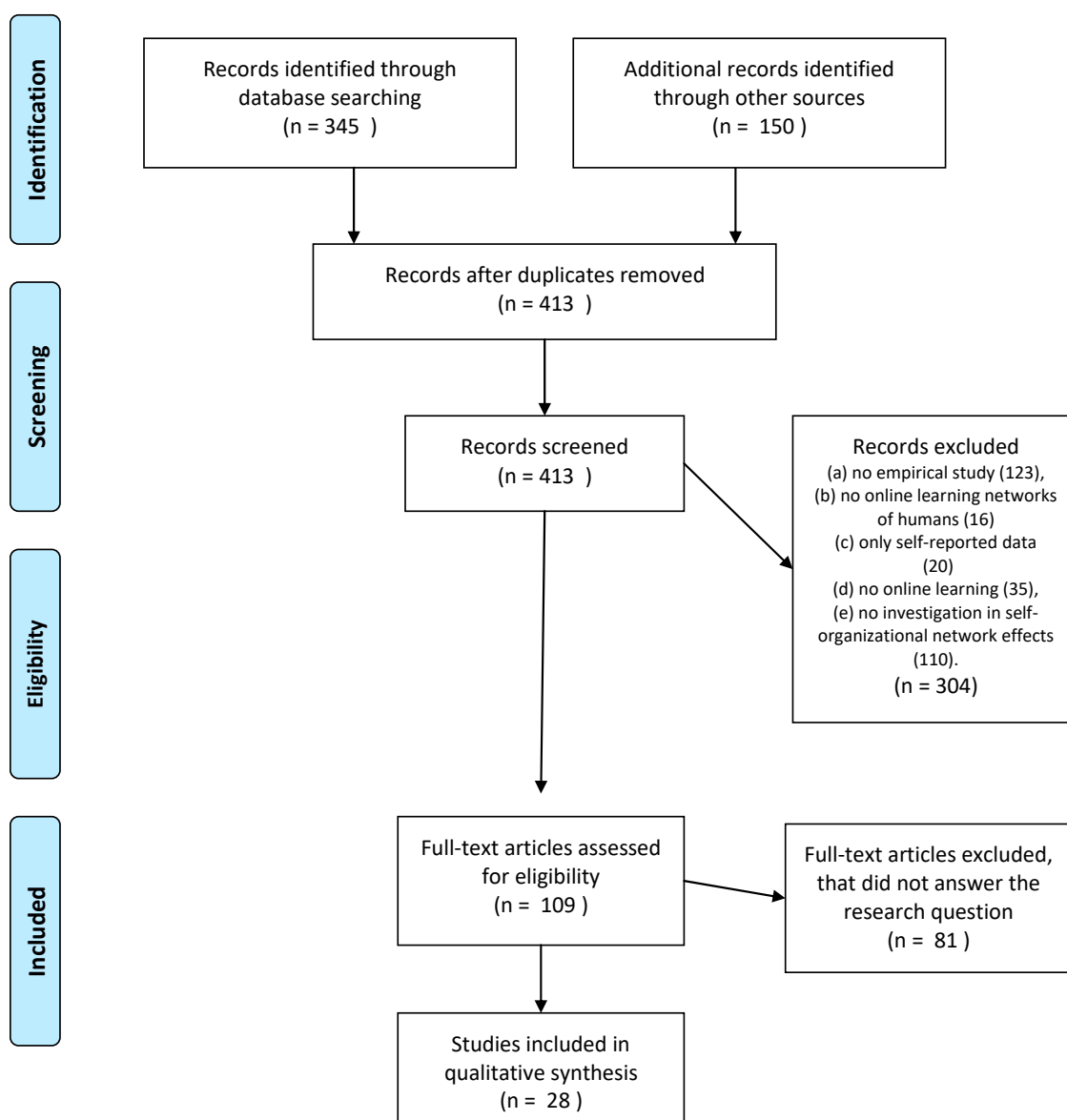


Figure 2. Results of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) systematic review process.

2.3. Summarizing the Studies

To summarize the results of the review study we created a table (Table 1). To create this overview we followed Goodyear and Carvalho's [1] architectural perspective on learning networks and described for each learning network first the people including the type and number of learners or participants in the online learning networks and their roles in the learning networks (students, teachers. Second, the physical setting including the type(s) of technology used; third, the task or the purpose of the learning network.

The table also contains an overview of the (emergent) activity including the type of learning ties under investigation (discussion threads, links; referrals; comments etc.). In this table we also looked at the self-organizing network effects under investigation and if the article looked at the nature of these self-organizing effects, the antecedents (e.g., structure of learning environment, roles, tasks) or the consequences (e.g., learning outcomes) of self-organizing network effects.

2.4. Data Analysis

First, we looked at the different learning networks presented in the articles and looked closer at the methodology used to collect the data on learning ties in an online learning environment. Second, we looked at the nature of self-organizing network effects. We looked at the definition of preferential attachment, reciprocity and transitivity and we looked to see if these self-organizing network effects were present in the learner networks of the different studies. We included the statistical measure by which self-organizing effects were measured. For more advanced statistical analysis, only the results of the final statistical models were reported. If two or more learning networks were compared, we included the statistical measures for each learning network or each subset of the learning network.

Second, we looked at the factors or antecedents related to the self-organizing network effects under investigation. The factors that could influence self-organizing network effects were categorized into three main factors based on Goodyear and Carvalho's [1] architectural perspective on learning networks namely (1) factors related to the people and their roles in the learning networks (2) factors related to the physical setting including the type(s) of technology used; (3) factors related to the task or the purpose of the learning network. To determine which factor belonged to which category the original operationalization and descriptions of the authors of the publications was matched against the description of Goodyear and Carvalho [1]. To further examine the relation of the factors on self-organizing network effects we indicated for each factor if it was positive or negative.

Third, we looked at the consequences (learning outcomes) related to self-organizing network effects. We only found six studies that reported on the possible learning outcomes, therefore forming categories was not possible or needed.

Finally, based on these findings we constructed an overview of how learning networks emerge online based on the nature of self-organizing network effects, what factors could stimulate or hamper learning networks to emerge and described the possible consequences.

2.5. Appraising the Studies

Learning networks and self-organizing network effects gained increased attention in the field of Networked Learning and related fields recently. Eleven articles were published between 2006 and 2013. Seventeen articles were published between 2014 and 2019. The studies were conducted throughout the world. Ten studies were from Europe (one UK, two Finland, one Germany, one in Germany together with Spain, and three in Spain, from which one was in collaboration with Colombia). Six studies were from Australia from which one was in collaboration with UK, Denmark and United States. One study was from Israel. Two studies were from Canada, from which one was in collaboration with the Netherlands and the United States. Three studies were from China. One study was from Thailand. Five studies were from the United States.

Following Goodyear and Carvalho's [1] architectural perspective on learning networks we first summarized the people including the type and number of learners or participants in the networked learning environments and their roles in the learning networks (students, lifelong learners). Ten studies involved between 16–21 participants, five studies involved between 36 and 48 participants, four studies involved between 51 and 68 participants, one study reported on 138 and 99 participants, one study reported on 392 and 99 participants, one study included 1915 participants and one study around 33527 participants. One study reported on two groups, one of 8317 participants and one group of 65975 participants. One study compared six different learning networks with sizes varying between 506–8 participants. Three studies were unclear about the actual number of participants and only reported on the amount of online learning ties under investigation. Seventeen studies involved students from a university, two studies involved pupils from primary or secondary education and nine studies involved lifelong learners.

According to the physical setting and the type(s) of technology used, 19 studies were conducted in a formal learning setting at a formal educational institution like a university, five learning networks took place in a non-formal learning context and three learning networks took place in an informal learning

context, like learning in the wild. One study compared learning networks in a formal, non-formal and informal learning context. If we looked at the technology used we saw that 16 studies investigated online learning networks on a VLE (Virtual Learning Environment), five studies investigated learning networks in a MOOC environment, five studies studied learning networks in a social networking site (SNS) (e.g., Twitter), and one online special interest group. The study which compared formal, non-formal and informal contexts only included discussion boards.

Third, we described the task or the purpose of the learning network. Although most studies reported elaborate on the overall purpose of the learning network, we only focused on the feature if participating in the learning network was compulsory or not. In nine studies participating in the learning network was explicitly mentioned as compulsory. One study compared three discussion forums from which two were compulsory and one was not [25]. One study compared one compulsory and one not compulsory discussion forum [26]. Other important features related to self-organizing network effects were included in the analysis of the antecedents or outcomes of self-organizing network effects.

We also included information about how the studies helped us to answer our research questions in Table 1. All studies helped us to define the nature of self-organizing network effects. Only three studies helped us to understand more about preferential attachment. Reciprocity occurred in 21 articles. Transitivity was investigated by 12 studies. From these studies only two studies looked at the three self-organizing network effects simultaneously. Of the 28 studies 17 studies focused on antecedents that influence self-organizing effects and six articles also looked at the consequences of self-organizing network effects and learning networks.

Concerning quality issues we identified three main issues with regard to the quality of the reviewed studies [27]. First, the method of how the data was collected and harvested from the logbooks was not always described in detail. In this way it was sometimes unclear how the authors defined the selected online learning ties. This is described in detail in the Results section. The second matter concerns the generalization of the conclusions of some articles. All but four studies investigated one online learning network or one course. The third issue dealt with the strength of the claims made in the conclusions of the articles. All but three studies used cross-sectional data instead of dynamic network data. Often, self-organizing network effects are only used to describe the state of the learning network under investigation and the data presented are descriptive of nature. For these studies causal relationships between antecedents and self-organizing network effects can only be inferred based on theory. The quality issues concerning causality were mapped for each article in Table 1. If the study reported on one learning network and the analysis was only descriptive the quality concerning causality was rated low. If the study compared two or more learning networks (different learning networks or the same network in different sequences) in a descriptive manner the quality concerning causality was set to medium. If the study reported on one network but used more advanced statistical analysis like Exponential random graph models (ERGMs) the quality was set to high. If the study used dynamic data analysis methods, the quality was set to very high. We want to emphasize that these quality issues only relate to answering our research questions. The quality issues are not about the overall quality of the studies selected in our review.

Table 1. Overview of the included studies.

General Information		People*	Physical Setting			Task
Study	Country	#	Context	Level	Type of Technology Used	Comp.
An, Shin, and Lim (2009) [28]	US	18 (L), 18 (L), 20 (L)	Formal	Unknown	VLE BB WebCT	x
Aviv, Erlich and Ravid (2005) [10]	Israel	19 (L), 1 (T), 18 (L), 1 (T)	Formal	Unknown	VLE	x/-
Chen, Chang, Ouyang and Zhou (2018) [29]	US	20 (L), 19 (L)	Formal	Undergraduate	VLE Canvas	
Claros, Cobos and Collazos (2016) [30]	Spain, Colombia	18 (L)	Formal	Undergraduate	VLE Local	x
Esteve Del Valle et al. (2018) [31]	Canada; USA, Netherlands;	8317 (L), 65,975 (L)	LIW	NA	SNS Reddit	
Engel, Coll and Bustos (2013) [32]	Spain	21 (L), 1 (T)	Formal	Postgraduate	VLE Moodle	x
Gašević, Joksimović, Eagan and Shaffer (2019) [33]	Australia, UK, Denmark, USA	Unknown	Non-formal	NA	MOOC Coursera	
Haya, Daems, Malzahn, Castellanos and Hoppe (2015) [34]	Spain and Germany	40 (L)	Formal	Undergraduate	Open-source social platform Elgg	
Hurme, Palonen and Järvela (2006) [35]	Finland	16 (L) and 1 (T)	Formal	Secondary Education	VLE Knowledge Forum	
Jan (2018) [26]	Australia	138 (L), 1 (T); 99 (L), 1 (T)	Formal and non-formal	Undergraduate	Moodle	x/-
Jan and Vlachopoulos (2018) [25]	Australia	20 (L), 1 (T)	Non-formal	NA	Moodle	x
Jordan (2016) [36]	UK	55 (L)	LIW	NA	SNS Academia.edu or ResearchGate and Twitter	
Kellogg, Booth and Oliver (2014) [37]	US	Unknown	Non-formal	NA	MOOC Google CourseBuilder	
Lin, Mai and Lai (2015) [38]	Taiwan	58; 59	Formal	Undergraduate	VLE local	x
Mayordomo and Onrubia (2015) [39]	Spain	16 (L)	Formal	Undergraduate	VLE Local	
Ouyang and Scharber (2017) [40]	US	20 (L), 1 (TA), 1 (T)	Formal	Graduate	SNS Ning	x
Pham, Cao, Petrushyna and Klamma (2012) [41]	Germany	Unknown	LIW	NA	SNS eTwinning	
Schwier and Seaton (2013) [42]	Canada	506 (L), 82 (L), 12 (L), 8 (L), 18 (L), 8 (L)	All	NA	Discussion Boards	x
Shu and Gu (2018) [43]	China	51 (L), 1 (TA), 1 (T)	Formal	Undergraduate	SNS Baidu Post Bar	x
Stepanyan, Mather and Dalrymple (2013) [44]	UK	44 (L), 7 (T)	Non-formal from university	NA	MOOC Local	
Timmis, Gibbs, Manuel and Barnes (2008) [45]	UK	68 (L)	Formal	Undergraduate	E-SIG	
Toikkanena and Lipponen (2011) [46]	Finland	392 (L), 99 (L)	Formal	Primary and Secondary	VLE Synergeia	
Uddin and Jacobson (2013) [47]	Australia	34 (L)	Formal	Master	VLE BB WebCT	
Uddin, Thompson, Schwendimann and Piraveenan (2014) [48]	Australia	39 (L)	Formal	Master	VLE BB WebCT	
Vercellone-Smith, Jablokowa and Friedel (2012) [49]	US	21 (L)	Formal	Graduate	VLE Moodle	x
Vu, Pattison and Robins (2015) [50]	Australia	33,527 (L)	Non-formal	NA	MOOC Coursera	
Yang, Li, Guo and Li (2015) [51]	China	48 (L)	Formal	Undergraduate	VLE Local	x
Zhang, Skryabin and Song (2016) [52]	China	1915 (L)	Formal	Undergraduate	MOOC XuetangX	

Table 1. Cont.

Overview of the included studies Continued								
Study	Learning Ties	Self-Organizational Network Effects**					Causality	
	Type of Learning Ties	PA	RP	TR	Nat.	Ant.	Con.	Causality
Ana, Shin and Lim (2009) [28]	Forum messages		x		x	x		medium
Aviv, Erlich and Ravid (2005) [10]	Forum messages	-	x	x	x	x		high
Chen, Chang, Ouyang and Zhou (2018) [29]	Forum messages		x	x	x	x		medium
Claros, Cobos and Collazos (2016) [30]	Video, documents and comments		x		x			very high
Esteve Del Valle et al. (2018) [31]	Forum messages		x	x	x	x		high
Engel, Coll and Bustos (2013) [32]	Forum messages		x		x	x	x	low
Gašević, Joksimović, Eagan and Shaffer (2019) [33]	Forum messages		x		x	x		very high
Haya, Daems, Malzahn, Castellanos and Hoppe (2015) [34]	Comments on videos and votes		x		x		x	low
Hurme, Palonen and Järvelä (2006) [35]	Computer notes and replies		x		x		x	medium
Jan (2018) [26]	Forum messages		x	x	x	x		low
Jan and Vlachopoulos (2018) [25]	Forum messages		x	x		x		low
Jordan (2016) [36]	Followers		x	x	x	x		low
Kellogg, Booth and Oliver (2014) [37]	Forum messages		x		x	x		high
Lin, Mai and Lai (2015) [38]	Forum messages		x		x			medium
Mayordomo and Onrubia (2015) [39]	Documents and comments		x		x		x	low
Ouyang and Scharber (2017) [40]	Forum messages		x	x	x	x		low
Pham, Cao, Petrushyna and Klamma (2012) [41]	Project collaboration, blog and blog comment, wall messaging and contact lists	x		x	x			high
Schwier and Seaton (2013) [42]	Forum messages		x		x	x		low
Shu and Gu (2018) [43]	Forum messages		x	x	x	x		low
Stepanyan, Mather and Dalrymple (2013) [44]	Forum messages	x	x	x	x			very high
Timmis, Gibbs, Manuel and Barnes (2008) [45]	Forum messages, MSN, Skype				x			low
Toikkanena and Lipponen (2011) [46]	Forum messages		x		x		x	medium
Uddin and Jacobson (2013) [47]	Emails within VLE				x			very high
Uddin, Thompson, Schwendimann, and Piraveenan (2014) [48]	Emails within VLE		x	x	x	x		high
Vercellone-Smith, Jablokowa and Friedel (2012) [49]	Forum messages		x		x	x		medium
Vu, Pattison and Robins (2015) [50]	Forum messages, quiz submission and dropout events.				x			very high
Yang, Li, Guo and Li (2015) [51]	Documents and Comments		x		x		x	low
Zhang, Skryabin and Song (2016) [52]	Forum messages	x	x	x	x	x		very high

3. Results

3.1. Types of Online Learning Ties and how the Online Learning Ties are Selected and Collected

3.1.1. Types of Online Learning Ties

First we looked at types of online learning ties in the different articles. An overview can be found in Table 1. Discussion threads, replies posts or comments of an online forum—forum messages—were investigated as online learning ties in 17 of the 28 articles. One additional study used online forum messages together with conversations on MSN, and Skype. Another study focused on online forum messages, and several other learning network events. Three studies from the same main author used email communication in a VLE. Two studies investigated learning ties based on who uploaded online documents in a VLE and the comments related to the documents. Another study used posted videos and text-based resources and the comments made on the resources. One study used comments on posted videos and voting on posted videos. One study used followers on social networking sites. One study used comments on blogposts, wall messages and project collaboration ties.

3.1.2. Methods to Select Online Learning Ties for Research Purposes

The importance of the use of online forum messages as object of investigation in the field of Networked Learning was such that we gathered more detailed information on the identification and selection of online learning ties based on forum messages. Based on the review of 17 articles focused on forum messages we distilled five important choices made by researchers when selecting learning ties derived from online forum messages. The first three choices are related to the boundaries of the learning networks under investigation. First, researchers made a choice concerning the type of network (one-mode, two-mode, projected two-mode networks or personal networks) they wanted to investigate. Were they interested in online learning ties amongst students or amongst students and resources? Or both? The second choice related to the level of aggregation. Did researchers merge different forums into one learning network? Did researchers select only a sample of the discussion forum? Third, researchers needed to make choices about the participants involved (peer network or teacher included). The fourth and fifth choice linked to the content of the ties. Researchers made decisions about what makes a reply a learning tie and they considered what to do with the strength of a learning tie.

Concerning the first choice, we found three types of networks. All 17 studies that used forum messages reported on one-mode networks. From which 16 were participant–participant networks and one study focused on a group–group network. Two studies also reported on two-mode networks referring to threads–participant network [40,46]. These networks shed a light on the amount of threads participants are involved in. These two studies [40,46] also reported on projected two-mode networks referring to a network that results from the projection of two-mode networks into a participant–participant network where ties represent the number of discussion threads the participants are both involved in.

The second choice concerns the level of aggregation. We found four levels relevant for the selection of online learning ties. The first level is the online discussion forum. The second level refers to the discussion threads within the discussion forum, also termed the initial post or the start of a new discussion topic. An initial post or thread will never be a reply to another post. The third level refers to posts. Within discussion threads participants can post messages, often termed posts. These posts can be a reply to the initial post. A reply to another post, which is not the initial post, is termed a comment and situates on the fourth level. On the fourth level we can also consider quotes within a post specifically referring to another post. If the quote is written within a reply to a post, two learning ties are possible. The message with the quote can be considered as a reply to the post or the post is considered as a learning tie to the post the quote refers to, or both. Analyzing the 17 articles that used discussion forums, we see a lot variation in the depth of reporting on the aggregation performed

to create the investigated learning networks. The main issue we encountered is that articles did not explicitly mention if initial posts (or threads) are perceived as learning ties, a known issue in the field of Networked Learning [53]. Messages posted to initiate a new discussion thread have no relational direction because they will never be a reply as mentioned explicitly by two studies [32,44]. The decision to include initial posts has profound implications on the measurement of reciprocity and transitivity. Six studies do not mention threads or initial posts. Three studies define learning ties as the combination of posts and replies without specification about the initial posts [29,32,37]. Two studies explicitly include initial posts in the aggregation as the sum of threads and comments or replies [28,43]. Four other studies explicitly focus on reply networks only, but do not explicitly state why. Some studies aggregate on the forum level and create one learning network from different forums. Twelve studies create a learning network for each forum to answer a specific research question about the differences between the forums [25,26,28,29,31,32,37,38,42,46,49].

The third choice concerning the boundaries of the learning network refers to the people included. This choice is mostly focused on the question of whether to include forum posts from teachers or facilitators or not. This choice is mostly based on the research question. For example one study [32] included ties of the teacher because they focused on questions related to distributed teaching presence. If the research question focused on the learning behavior of peers, the posts of teachers are avoided in the design of the course or excluded afterwards for analysis.

The fourth choice of what type of reply is a learning tie is both informed by theoretical considerations and more practical ones. For example Reference [33] used the general rule that each message is considered as being directed to the previous one. Three studies used content analysis of the transcripts of the messages to decide in detail to whom the message replied to. The study of Engel, Coll and Bustos [32] was specifically focused on the issue on how to operationalize reply messages. The study compared two techniques to determine a reply network. They compared learning networks based on the technological method of the export of the reply network directly from the log file of the VLE's database and a nominal method based on content analysis of the transcripts. The authors of the study concluded that log file data based on the design of the often simple structure of a forum with the restricted options to open a new chain of discussion, reply to a message and comment on the replies, undervalue the quantity and the extent of the relations that the participants establish. A possible solution could be to use the quote function in messages which give the opportunity to refer to specific participants of the discussion forums in a comment or reply, however, none of the studies in our review used this function to select online learning ties. Another possibility to provide more transparency in the collected data is to explicitly mention if reply-to-all messages are included in the learning network or not like for example References [42,49].

The strength of a tie was mostly defined by the frequency of replies in one-mode networks [26,29,33,49]. In the study of Shu et al. [43] a specific formula is used to determine the strength of the tie. For two-mode networks the frequency of contributions in a thread is used to determine the tie strength e.g., Reference [43]. In more than half of the studies online learning networks are used without any information on the strength of the tie, like for example frequency or intensity.

3.1.3. Methods to Collect Online Learning Ties

Data on learning ties are collected automatically, based on export of logbooks of the technology used, or nominally through a content analysis of the transcripts of the learning ties in the learning networks as presented in Table 1. Most studies that collect data technologically only report that they extracted data from log files. Two studies are more specific about the data collection. The study from Jordan [36] uses Pajek [54] to extract data. Pajek is a program specifically for analyzing and visualizing very large networks [54]. The study of Vu, Pattison and Robins [50] uses the methodology of relational event models. This study is dedicated to fully explain the relational events model (REM) in detail. It is particularly interesting for the field of Networked Learning because the study used a MOOC discussion forum as an example. REM is a methodology to collect network data in sequences and

based on events that happen in a certain point of time between a participant and an event. The events can include many features of a MOOC or VLE like looking at a video, replying to a post, writing a blogpost [50]. The study of Vu, Pattison and Robins [50] is the only paper that occurred in our review that used REM in the field of Networked Learning and looked at self-organizing network effects. In the following section we dive more into the nature of self-organizing network effects. We start with describing the definition, the findings and how self-organizing network effects are analyzed in online learning networks.

3.2. Nature of Preferential Attachment, Reciprocity and Transitivity and How They are Analyzed

3.2.1. Preferential Attachment

Considering three self-organizing network effects under investigation, preferential attachment occurred the least. Two studies [44,52] conducted in a MOOC actually mentioned preferential attachment and used the definition of Barabási and Albert [11]. Preferential attachment is defined as a process in which participants accumulate new ties in proportion to the number of ties they already have. Therefore the development of networks resembles a multiplicative process, which is known to give power-law distributions [11]. The study conducted in the e-Twinning environment, an European online portal environment created to stimulate collaboration amongst educational professionals, did not mention but described preferential attachment as the presence of power-law degree distribution indicating that super connectors (or hubs) exist [41]. All three studies are conducted in an open discussion environment.

In all three studies the investigated processes related to preferential attachment are positive and significant. In the two studies performed in the MOOC preferential attachment is based on the activity (outdegree) of the participants indicating that participants who are active become even more active over time [44,52]. The study performed in the e-Twinning environment [41] reported presence of preferential attachment based on undirected learning networks, indicating that participants with more ties become even more connected without taking into account the direction of the tie. Looking at the results of the studies we can only conclude that preferential attachment occurred in open discussion environments. Participants who are actively involved become even more active over time.

Based on the results, the following suggestions are formulated by the authors. Super connectors may play an important role to ensure connectivity, to share of information, and for behavior cascading in networks [41]. Participants have more power in the network because they have access to many resources and these participants are likely to play a key role in the discussion forums [52]. However, preferential attachment can also have a negative side [52]. The authors pointed that preferential attachment in an educational setting, particularly in an open discussion space where some participants acquire a dominant position, may not be desirable, making the engagement of less active participants even less likely [52]. The super active participants can dominate the discussion and there is a danger that when these super active participants drop-out of the course, the discussion is discontinued [52]. For designers of networked learning environments it is key to take the possible process of preferential attachment into account to increase the robustness of sustainable MOOCs [52].

3.2.2. Reciprocity

Reciprocity is the most prevalent self-organizing network effect in our studies. Twenty-four of the 28 studies looked into the nature of reciprocity. When we look at the definition of reciprocity we found a lot of variation of the same two main parts of the concept of reciprocity (Table 2). The first part considers the dyad level of reciprocity and describes reciprocity as a two-way relationship in which a participant receives a response from the participant they have sent to. Three studies only used this simple description [28,32,41]. The second part refers to the individual level or to the group level. Some studies described reciprocity on the individual level. Reciprocity was for example described as a reflection of a participants' connection level with the group [40]. On the individual level reciprocity

is also seen as a structural property that measures the tendency of actors to reciprocate initiated ties more frequently than the ties that would occur by chance [33,37,44,51,52]. Studies that investigated reciprocity as a structural property used more advanced analysis techniques like ERGM and dynamic social network analysis (SNA). Other studies focused more on the group level and define reciprocity as the proportion of reciprocal ties in a network [10,25,26,34–36,38,46], or the level of cohesion of the learning network [30,43]. Four studies used reciprocity as part of another concept. The study of Schwier and Seaton [42] investigated the S/R ratio (ratio sent/to received messages) and described this ratio as reciprocity. Another study used the core–periphery measure [49] of Borgatti and Everett [55] to identify participants who have a high proportion of reciprocal ties. One study saw reciprocity as an important feature of the different types of coordination and organization forms like jigsaw, with lower reciprocity and chain and star organizations which involve higher reciprocity [39]. Another study sees reciprocity as part of ritual communication [45]. One study only mentioned reciprocity in the results section without a definition [29].

Table 2. Overview of use of definitions of reciprocity.

Definition on the Level of the Dyad	Reference Number of Study
Reciprocity is a two-way relationship in which a participant receives a response from the participant they have sent a response to.	[28,32,41]
Definition on the Level of the Individual	
Reciprocity is seen as a reflection of a participants' connection level with the group.	[40]
Reciprocity is seen as a structural property that measures the tendency of actors to reciprocate initiated ties more frequently than the ties that would occur by chance.	[10,33,37,44,51,52].
Definition on the Level of the Group	
Reciprocity is the proportion of reciprocal ties in a network.	[25,26,34–36,38,46]
Reciprocity is the level of cohesion of the learning network.	[30,43]
Four studies used reciprocity as part of another concept.	[39,42,49]
No clear definition.	[29]

Twelve studies found a positive tendency towards reciprocity within the learning networks, or a proportion of reciprocal ties higher than 50%. This means that in most studies participants tend to learn in reciprocal learning relationships online. Two studies reported to find around 40% of the learning ties reciprocal for email traffic [47] and followers on social networking sites [36]. Five studies reported low reciprocal learning ties from which one was a large-scale MOOC [37] and three formal courses on a VLE with around 20 students [26,32,43], one study reported low reciprocity on a VLE with 59 and 58 students, and one non-formal course with 20 students [25].

Most studies considered reciprocity as an important indication of collaborative or social or networked learning. Reciprocity can give an indication that participants do not only use the platform to express their own ideas, but also use it to respond to other messages [52]. Reciprocity is considered as a vital important part of sharing the cognitive processes at a social level [52]. Other authors see reciprocity as an indication of symmetry in the learning environment which could be related to a uniform distribution of efforts and contributions by participants [30] or engagement [34]. Lin, Mai and Lai perceive reciprocity as an indication that peer relations within the learning network are more bilateral and stable [38]. According to Jan and Vlachopoulos [25] reciprocity (and transitivity), implicate overall power dynamics within the community. According to these authors a network with low transitivity and high reciprocity indicates that the network is dominated by a few central nodes that are actively engaging with one another and control the flow of the network. This claim differs with most studies who perceive a high proportion of both reciprocity and transitivity as an indication of cohesion within a network. Forming reciprocal learning ties is considered one of the defining characteristics of networks emerging from online interactions [32]. Reciprocity is only measured on the dyad level and does not provide insights into the depth of conversations. The study of Schwier

and Seaton provide an alternative way to look at reciprocity to give more depth to the measure [42]. They refer to Wiley's approach based on an unpublished working draft of the author. This approach proposes to calculate a mean reply depth based on the sum of the replies where the value of each level of reply increases. If replies are only happening within a reciprocal dyad, this could also have a downside. According to Toikkanen and Lipponen, the value of conversations suffers if pupils are only engaged in reciprocal one-on-one conversations. Better conversations were held in larger groups [46].

Insights in group-level self-organizing network effects could help to get more insights into the networked learning activities on a group level. In the following paragraph we try to understand more about transitivity in learning networks.

3.2.3. Transitivity

In our review study, the self-organizing network effect transitivity or network clustering appeared in 11 studies. One study did not provide a definition [29]. In three studies transitivity referred to the occurrence of triples or triads in a network. Triads are small groups of three ties that are all connected at least in one direction. The studies calculated the proportion of triads in the overall learning network [36,40]. In seven other studies, the definition of transitivity referred to the tendency among two participants to be connected if they already share a tie to the same participant (Table 3).

Table 3. Definition of transitivity.

Transitivity is the tendency among two participants to be connected if they already share a tie to the same participant.	[10,31,41,43,44,48,52]
Transitivity is the occurrence of triads in a network.	[25,36,40]
No clear definition.	[29]

Four studies reported a positive and significant transitivity effect [31,41,44,52]. One study reported a positive transitivity effect for one forum, characterized by a cooperative learning design and found no transitivity effect for another forum characterized by a Q and A structure [10]. One study reported a high proportion of triads (0.82) in the network [40]. One study compared four different learning contexts and found a proportion of (0.26; 0.42; 0.30; 0.49) of triads in the learning network [43]. Another study compared three types of discussion fora amongst the same students, one with a central role of the tutor, one with a peripheral role of the tutor and one with no role of the tutor. The proportion of transitivity was respectively 22.6%; 9.2%; 11.4% [25]. Another study compared learning networks based on conversations held at a website dedicated to project work, a contact list, a blog website and wall messaging networks in the e-Twinning community [41]. Only the learning network based on the project work website yielded a positive and significant transitivity effect. One study investigating transitivity effect for email communication did not find a significant transitivity effect in the learning network under investigation [48]. Studies relate a positive transitivity effect to an interactive, cohesive and equally distributed learning community [40]. According to Zhang, Skryabin and Song [52] and according to Stepanyan, Mather and Dalrymple [44] transitivity may lead to cohesive subgroups optimal to generate trust and cooperation. However, transitivity may also have a downside, transitive relations may be negatively correlated to innovation in a competitive environment [44]. Subgroups could make learning robust within larger networks like MOOCs. According to Zhang, Skryabin and Song [52] transitivity has also a positive outcome on the individual level. In learning networks with a positive transitivity effect, participants are more likely to receive stimuli from multiple peers. Learning ties connected to different clusters might help to provide an individual with a variety of information sources [52]. To get more insights into these relationships we needed to look more into the possible consequences of self-organizing network effects. But first we looked at the research methods to analyze self-organizing network effects and dove into the antecedents or the factors that influence self-organizing network effects.

3.2.4. Research Methods to Analyze Self-Organizing Network Effects

In Table 4 we provide an overview of the different research methods used to analyze self-organizing network effects. Based on our review we found four types of methods to analyze self-organizing network effects. First, we found the method based on social network analysis (SNA) with a focus on the description of the learning network under investigation. Social network analysis is described in detail in almost all reviewed studies. Social network analysis is a method to investigate social structures based on graph theory. Learning networks are perceived as nodes (individual actors, people, or things within the network) and the ties, edges, or links (relationships or interactions) that connect them. Based on these network structures statistical programs like UCINET calculate basic SNA measures like reciprocity or the proportion of triads in a network. Social networks are also often visualized to make interpretation of the results easier. Visualization is often done based on multidimensional scaling. Second, learning networks are analyzed in a descriptive way based on a qualitative content analysis. Based on a thorough reading of the transcripts researchers determine the sender, the receiver(s) and the direction of a learning tie. According to the study of Engel, Coll and Bustos [32] the qualitative content analysis yields better results than the technological approach based on log book data. Based on the results of the qualitative content analysis, authors often use SNA software to calculate basic SNA metrics. A third method to analyze self-organizing network effects is a more advanced statistical analysis like exponential random graph models, especially designed to analyze social network data [9]. ERGMs provide a statistical approach to network modeling that account particularly for tie interdependence in network structures. ERGMs are for cross-sectional networks to model both local structures (e.g., reciprocity and transitivity) and other characteristics of nodes and or edges [50]. ERGMs determine the statistical likelihood of a learning tie in terms of parameters (e.g., reciprocity, transitivity) associated with these patterns. Estimates can be interpreted similar to logistic regression analysis. A fourth method is dynamic social network analysis for time-stamped networks. Two techniques are found to measure dynamic networks. Relational event models, described in the study of Vu, Pattison and Robins [50] and stochastic actor-oriented models which are suitable for panel network data. [52].

Table 4. Overview of methods of analysis for self-organizing network effects.

Study	Analysis Method
An, Shin and Lim (2009) [28]	Descriptive SNA
Aviv, Erlich and Ravid (2005) [10]	Advanced SNA simulation models using ERGM
Chen, Chang, Ouyang and Zhou (2018) [29]	Descriptive SNA and qualitative content analysis
Claros, Cobos and Collazos (2016) [30]	Dynamic SNA
Esteve Del Valle et al. (2018) [31]	Advanced SNA ERGM
Engel, Coll and Bustos (2013) [32]	Descriptive SNA with visualization
Gašević, Joksimović, Eagan and Shaffer (2019) [33]	Advanced SNA with ERGM and ENA (epistemic network analysis)
Haya, Daems, Malzahn, Castellanos and Hoppe (2015) [34]	Descriptive SNA with qualitative content analysis
Hurme, Palonen and Järvela (2006) [35]	Descriptive SNA with multidimensional scaling technique and qualitative content analysis
Jan (2018) [26]	Descriptive SNA with snapshots over time
Jan and Vlachopoulos (2018) [25]	Descriptive SNA and qualitative content analysis with illocutionary unit
Jordan (2016) [36]	Descriptive SNA
Kellogg, Booth and Oliver (2014) [37]	Advanced SNA with ERGM, Blockmodeling and qualitative content analysis
Lin, Mai and Lai (2015) [38]	Descriptive SNA with snapshots over time
Mayordomo and Onrubia (2015) [39]	Descriptive SNA with qualitative content analysis
Ouyang and Scharber (2017) [40]	Descriptive SNA with Opsahl's tuning parameter
Pham, Cao, Petrushyna and Klamma (2012) [41]	Advanced SNA

Table 4. Cont.

Study	Analysis Method
Schwier and Seaton (2013) [42]	Descriptive SNA with qualitative content analysis with transcript analysis tool (TAT)
Shu and Gu (2018) [43]	Descriptive SNA, content analysis and thematic analysis
Stepanyan, Mather and Dalrymple (2013) [44]	Dynamic SNA
Timmis, Gibbs, Manuel and Barnes (2008) [45]	Descriptive SNA with qualitative content analysis
Toikkanena and Lipponen (2011) [46]	Descriptive SNA
Uddin and Jacobson (2013) [47]	Dynamic SNA
Uddin, Thompson, Schwendimann and Piraveenan (2014) [48]	Advanced SNA simulation models using ERGM
Vercellone-Smith, Jablokowa and Friedel (2012) [49]	Descriptive SNA and automated linguistic analysis
Vu, Pattison and Robins (2015) [50]	Dynamic SNA with relational event models
Yang, Li, Guo and Li (2015) [51]	Descriptive SNA method and LSA (lag sequence behavior)
Zhang, Skryabin and Song (2016) [52]	Dynamic SNA

3.3. Antecedents Related to Preferential Attachment, Reciprocity and Transitivity

Sixteen studies focused on possible factors that may influence self-organizing network effects. We divided the factors into three main categories following Goodyear and Carvalho's [1] architectural perspective on learning. First, we described factors related to the people in the learning network. Second, we looked at factors related to the physical setting of the learning network including the type(s) of technology used. Third, we looked at factors related to the task or the purpose of the learning network. The learning outcomes are tackled in the next section, when we consider possible consequences of online learning networks.

3.3.1. Antecedents Related to the People and Their Roles in Learning Networks

Concerning the people in the network we found two types of factors to influence self-organizing network effects, individual and tie level characteristics. First, two studies demonstrate that individual differences have an effect on the formation of reciprocal learning ties. For example, the study of informal learning networks of academics [36] found significant differences in network structure according to personal characteristics of participants, such as job position and subject area. Academic social networking sites showed significant differences according to subject area. Significant differences in reciprocity in Twitter networks were found in relation to job position, with PhD students showing highest reciprocity and professors the lowest. In another study, adaptive individuals, referring to individuals who tend to place greater value on group conformity, tend to be more involved in reciprocal learning ties [49]. Concerning roles the study on the formation of online learning ties in Reddit [31] found that being a moderator increases the likelihood of forming online learning ties. The results of the effect of other roles like being a gold member or having a high number of Karma points are inconclusive. A third type of factor related to people is the investigation in characteristics on the tie level, referring to the well-known concept of homophily. Homophily refers to the tendency of people to interact with others who are similar to themselves [56]. If we look at individual differences we see the universal tendency of people to learn from others who are similar to themselves in interests and perspectives [33] and top-performing students are more likely to learn with other top-performers [49]. Concerning roles the opposite is found, in one study, namely students did not prefer to form ties amongst peers [52]. Online learning ties in this study tend to be heterophilic (student with teacher).

3.3.2. Factors Related to the Physical Setting

We considered two types of factors related to the physical setting, namely technology related factors and not-technology related factors. Only the study of Jordan [36] specifically looked at different types of technology used, namely follower networks on Twitter and academic Social Networking

Sites (SNS). The extent of clustering and reciprocity was found to be significantly higher in academic SNS than in Twitter personal networks. Fewer tendencies for reciprocity and transitivity on Twitter could suggest that Twitter may allow better circulation of information through weak ties, according to the authors. Another technology related factor we found in our review concerned the forum feature of Moodle. According to Engel, Coll and Bustos [32] Moodle, offers a typical forum structure in which contributions are nested in chains. Participants have only two options; either reply to a specific contribution or open a new chain of discussion. The authors argue that due to this technological feature, analyses based on logs of the forum undervalue the quantity and the extent of the learning ties that the participants form [32]. However, nominal analysis of the same forum data reveals more in depth knowledge construction and more reciprocal learning ties. Based on these results the conclusion could also be made that despite the restricted functionality of the Moodle forum, participants are able to establish reciprocal and coherent learning networks. Second, we looked at factors which are not technology related. Three studies were conducted to specifically look at the influence of differences in learning contexts on the formation of (online) learning ties. Shu and Gu [43] explicitly looked at the differences between online and face-to-face student–group interactions in a blended learning course. They found that learning networks in a blended learning environment are more centralized around the teacher. In an online environment peers tend to form more reciprocal learning ties amongst themselves. Lin, Mai and Lai [38] have set-up an experimental setting to compare the amount of learning ties in two different learning settings. In the first learning setting the researchers created social awareness amongst the students, giving information about who is friends with whom, and the helping activity of the students. The second learning setting created a knowledge awareness context, providing information about the prior knowledge and expertise of the students. Results showed that the social awareness context resulted in a higher proportion of reciprocity and reciprocity accelerated faster over time.

The study of Schwier and Seaton [42] compared online learning ties in formal, non-formal and informal online learning environments. They found that online learning ties tend to be reciprocal in formal and non-formal learning contexts and less reciprocal in informal learning contexts. On an individual level, they also found that reciprocity did not vary across individuals in the formal group as much as it did for individuals in the non-formal group. Schwier and Seaton [42] explain the difference in the informal, formal and non-formal learning contexts based on the different instructions and tasks in the courses, rather than the specific context. We elaborate on their explanation in the following paragraph which is dedicated to summarizing the factors that could influence self-organizing network effects related to the task or purpose of the learning networks.

3.3.3. Factors Related to the Task or Purpose of the Learning Network

We found three factors related to the task or purpose of the course to influence self-organizing network effects. The first important factor is the degree of compulsory participation in the formation of online learning ties. According to Schwier and Seaton [42] the proportion of reciprocal learning ties was lower in the informal learning context due to its voluntary and casual nature. This notion was confirmed in another study which explicitly investigated the impact of different types of instructor moderation varying in the degree in which students were voluntary posting or not [28]. The study found that letting students voluntarily post feedback to their peers' initial postings was not very productive. The discussion board became very instructor-centered. When the instructor intervened too much, the reciprocal interactions amongst peers decreased. The most optimal facilitator strategy seemed to provide a ground rule for a minimum number of replies with a minimum of active contributions of the teacher. Another factor related to the role of the instructor is to offer well designed topics for interaction with high expectation formulated to the participants. According to the study of Schwier and Seaton well defined questions are defined as "multi-level questions that ask open-ended questions that explore several related aspects of the overall topic. Often these questions encourage the student to relate their answer to their experiences" [42] (p. 11). According to Aviv et al. [10] the specific role of the tutor to reply to questions in a Q and A forum triggered more reciprocal relationships between

student and tutor in the forum. Reciprocity was not significant in another forum where no specific roles were set. On the other hand, the forum with a special focus on cooperative learning, where students had the task to cooperate to come to a collective solution, there was a significant transitivity effect. This transitivity effect was not found in the Q and A forum [10]. The study of Jan [26] compared two different courses where forum posting was compulsory or not. However, the two courses also differed in student population, duration and type of facilitation. There is no investigation in which this factor is the reason for the differences in transitivity or reciprocity.

Jan and Vlachpolous [25] also looked at differences in reciprocity and transitivity in three different set-ups of discussions amongst the same students and course. In the first discussion set-up the tutor had a central role, in the second the tutor had a peripheral role and in the third discussion there was a base group where the tutor had no role. Discussion 1 was dominated by the tutor and a small number of students. Reciprocity was lowest in discussion 1 indicating that even though students were actively participating in the discussion, they were not responding to one another. Transitivity was highest in group 1. Reciprocity is highest in the base group, transitivity the lowest. Another study found that giving students the opportunity to interact in a base group, stimulates interactions amongst students beyond more task-specific forums [40]. Another study examined the extent to which a social learning analytics (SLA) tool facilitated conceptual and social engagement in online discussion [29]. The idea is that a visualization of the learning network could give students insights into their networked learning behavior and position in the network. These insights could stimulate students to alter their networked learning behavior. However, the study did not find any significant effect of the use of the SLA-tool.

3.4. Consequences of Preferential Attachment, Reciprocity and Transitivity

Only six studies reported on possible consequences related to self-organizing network effects, focusing only on reciprocity. Therefore we did not find any investigation on the (learning) outcomes related to preferential attachment or transitivity. On the individual level, the study of Hurme, Palonen and Jävelä [35] showed positive and significant correlations between metacognitive skills, especially monitoring, and that the student pairs seem to regulate their own understanding in reciprocal interaction. The study of Toikkanen and Lipponen [46] showed the opposite results. In their study reply reciprocity negatively correlates with students' meaningfulness of the course. Toikkanen and Lipponen, explained this finding by fact that the value of conversations suffer if pupils only engaged in reciprocal one-on-one conversations. They found a positive correlation between reading reciprocity (reading each other's contributions) and pupils' understanding of the course.

We found four studies that reported on learning outcomes related to reciprocity on group level. The study of Haya et al. [34] did not find any correlation between teams with a high ratio of reciprocal ties and high ratings, indicating that highly engaged students did not benefit. We want to remark that the ratings were based on the quality of the video uploaded by the teams and the engagement measured by the comments and voting of the teams on other videos. The study of Mayordomo and Onrubia looked at learning outcomes at the group level [39]. They found that groups with a low-mark lack reciprocity among the group members in the work process. The lack of reciprocity refers to the finding that participants carry out their own work without taking into consideration the parts developed by others. Yang, Li, Guo and Li [51] also found different types of collaboration amongst low and high performing groups, however, they did not make correlations with reciprocity. Engel, Coll and Bustos found that [32] the higher the reciprocity index, in combination with other SNA measures like indegree, outdegree and centralization, the more likely is it that the network has a high degree of distribution of teaching presence [32].

To conclude, based on the results of our review study we created a preliminary conceptual model (Figure 3) summarizing the findings of this review study. The model shows the factors (identified in the reviewed studies) that influence self-organizing network effects related to the people, the physical environment and the task or purpose of the learning network. The lines indicate the relations between factors, self-organizing network effects and consequences.

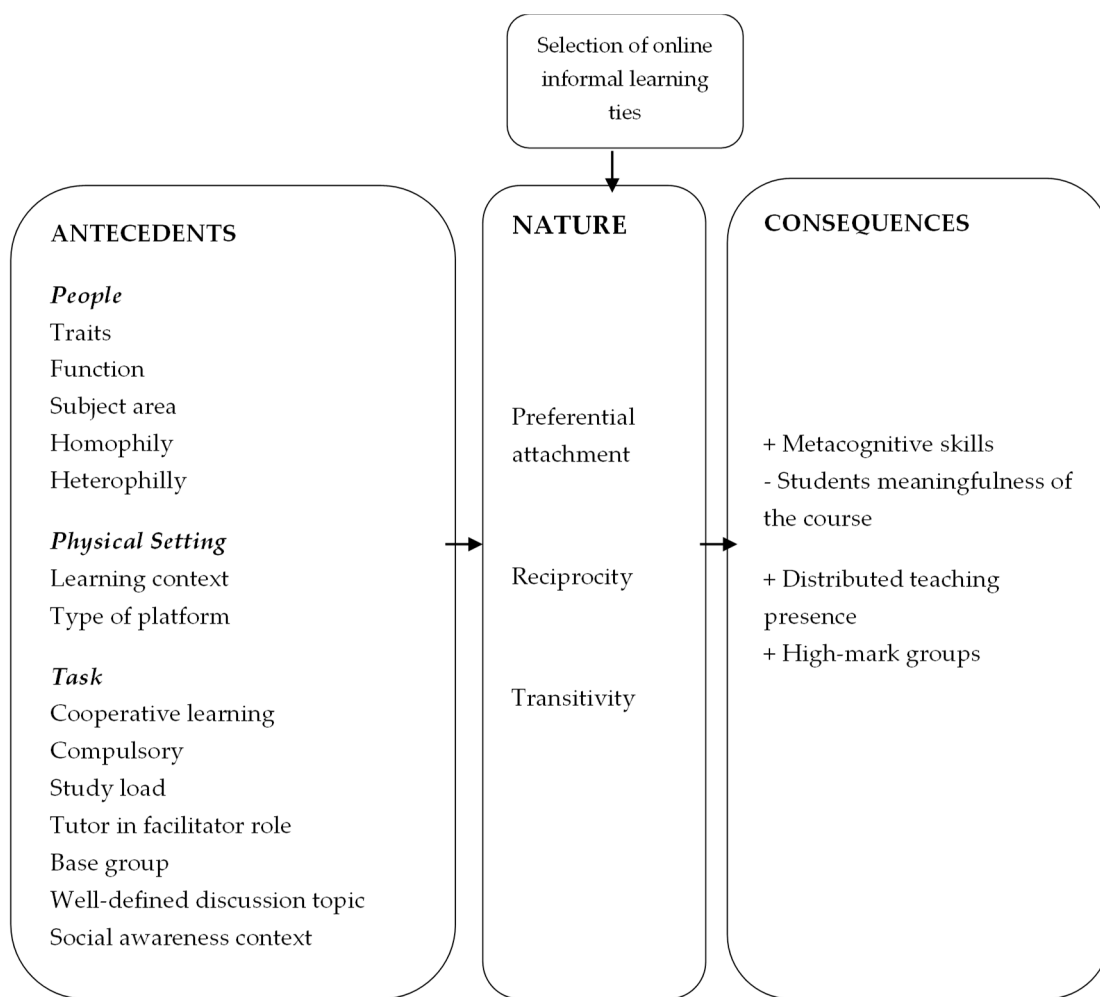


Figure 3. Conceptual model: overview of the relationship between antecedents related to the people, the physical setting and the task and self-organizing innovative behavior and possible consequences.

4. Discussion

In this article, we explored how learning networks emerge online by looking closer at the nature, antecedents and consequences of self-organizing network effects in online learning networks. A literature review was conducted and yielded 28 publications that met the criteria for inclusion. With the literature review we found answers for the following research questions related to the nature of self-organizing network effects: (1.1) How are self-organizing network effects defined in the field of Networked Learning? (1.2) How do self-organizing effects occur in networked learning environments. Second, we looked into the antecedents of self-organizing network effects and asked the following research question: (2) what factors affect self-organizing network effects? Third, we looked at the consequences of self-organizing network effects: (3.1) How do self-organizing network effects influence learning networks? (3.2) What is the influence of self-organizing network effects on learning outcomes? By answering these research questions we unraveled possible relations between the components of the design of learning environments (the people, the set and the purpose), the learning network and the network self-organizing effects, as depicted in the conceptual model presented in Figure 3.

To understand self-organizing network effects in the field of Networked Learning we first looked into the types of online learning ties that were investigated in the 28 studies. We found that the majority of the studies looked into learning networks based on forum messages derived from an online discussion board, two studies looked into email traffic of a VLE, two studies looked at the posting

of documents and comments on the documents, three studies looked at several networked learning activities and one study looked at followers on social network sites.

Looking at the online learning ties in more detail and how they were analyzed, we encountered two methodological issues that need to be considered when interpreting the results of the study. First, we looked more in depth into the selection of forum messages of online learning ties and although the features of online forums are rather limited, we found a lot of variation in the choices made by the researchers and sometimes the choices made were not so clear. For our qualitative review study these variations did not have huge implications on the results. However, for future research, it is necessary to get more detailed information into the way online learning ties are selected. These decisions could have an effect on the outcome results of the different self-organizing network effects. To provide more clarity in the different selection possibilities of online learning ties we have included a short guideline in the practical implications at the end of the article. Second, the field of Networked Learning and related fields are still in the exploratory stage when it comes to the investigation of self-organizing network effects. Most studies are focused on one learning network, or compare two or three learning networks. Moreover the statistical methods used to look specifically into self-organizing network effects are often descriptive. Therefore the results and the conceptual model need to be looked at from this exploratory perspective.

In what follows we will discuss the results in more detail for each research question. This reflection generates future research questions for the field of Networked Learning. These questions are intertwined within our reflections. We will end this paper with some practical implications. These practical implications also need to be read in the context of the exploratory state of the studies reviewed in this article.

4.1. How do Self-Organizing Network Effects Occur in the Field of Networked Learning?

The definitions of the three self-organizing network effects are comparable in all studies. Preferential attachment is defined as a process in which participants accumulate new ties in proportion to the number of ties they already have. Reciprocity is defined as a two-way relationship in which a participant receives a response from the participant they have sent to. Some studies add an individual level component to the definition referring to the proportion or the tendency of actors to reciprocate initiated ties more frequently. On the group level reciprocity refers to the overall cohesion of the learning network. In most studies transitivity refers to the tendency among two participants to be connected if they already share a tie to the same participant.

Self-organizing or endogenous network effects are never explicitly described as self-organizing or emergent. In the field of Networked Learning and related fields preferential attachment, reciprocity and transitivity are mostly described as descriptive features of how a participant learns (in reciprocal relationships or not), what the learning network looks like, or how the learning network evolves over time.

The main interest of the 28 studies was to look into reciprocity and/or transitivity to investigate the overall cohesion of the learning network. The overall cohesion of the network is seen as an indication if participants learn collaboratively or not. Reciprocity is a good indicator for cohesion because it is not dependent on the size of the network like the more often used measure density [46]. Seeing reciprocity mainly as an indicator of the cohesion of the learning network is in our perspective rather limited. From a self-organizing perspective, it is also very interesting to look in more detail in the process of reciprocity in itself. How do participants form reciprocal ties? When does reciprocity start and when does it stop? If we get more insights into the process itself it will also become easier to identify the possible factors that affect reciprocity. Our review analysis showed that social network analysis is often combined with content analysis. An interesting avenue could be to do a more systematic and integrated analysis of SNA and content analysis to make it possible to understand the process of self-organization in more depth.

A highlight in our review study was to ascertain that in the majority of the studies reviewed, reciprocity and transitivity are significantly present in both small and large learning networks in formal, non-formal and informal contexts. Preferential attachment is also significantly present in the three studies where preferential attachment was investigated in an informal context. In smaller formal student groups, reciprocity and transitivity processes are related to dense and cohesive student groups. In large learning networks, participants form smaller cohesive subgroups due to transitivity and reciprocity effects.

Another important finding of our review was the limited amount of studies that investigated the concept preferential attachment. An unexpected finding was that only three studies looked into preferential attachment. The difference between active participants and lurkers is a well-known issue in online (learning) networks. Preferential attachment could yield very interesting insights into why some participants become more active or more popular within a learning network. This is an interesting research question to unravel, also, because preferential attachment has been proven an interesting process to understand the growth of the internet [11]. Translation of these findings into the field of Networked Learning seems very interesting because learning networks in networked learning environments are mainly built on connections between people and people and objects.

4.2. What Factors Affect Self-Organizing Network Effects? (Antecedents)

Related to the second research question, we found factors related to the people, the physical environment and the task of the learning networks. An overview can be found in Figure 3.

What is very interesting is that we found positive and significant evidence that self-organizing network effects occurred in most of the learning networks under investigation, regardless of the number of participants or the number of ties, or the learning context. Five studies did not find significant results concerning self-organizing network effects.

We found studies with significant reciprocity effects in formal, non-formal and informal environments. If a study did find differences in different learning contexts, the differences are explained by the different instructions and tasks in the courses, rather than differences in context. For example, interaction must be intentionally designed into the learning network or it is unlikely to emerge both in small formal learning networks as in large and informal learning networks like MOOCs.

If we look at the antecedents related to the task it seems that based on the studies we investigated, the task or purpose provided at the beginning of the learning activity by the instructor is an important trigger for the formation of online learning ties. But once “the party has started”, no direct interference is necessary to keep the party going. These results make us wonder if self-organizing network effects are at a certain point in time purely self-organizing. If we get more insights into processes of reciprocity and transitivity and preferential attachment we could investigate this hypothesis in more detail. This idea could relate to some sort of tipping point in the learning networks where self-organizing network effects take over. An interesting future research question could be to investigate if a tipping point exists and what tasks are needed to get to this tipping point.

Results confirm that the people involved in the learning networks need to be taken into account. People differ in their networked learning behavior based on job function, role and subject area. The review outcomes show that participants are more inclined to form learning ties with others who are similar to themselves concerning performance and socio demographics. If teachers are visibly present in the learning network, participants are more likely to form learning ties with the teacher or facilitator, rather than with peers.

4.3. How do Self-Organizing Network Effects Influence Learning Networks and Possible Learning Outcomes? (Consequences)

The studies that focus on the consequences of self-organizing network effects are very limited. The review indicated that being involved in a high proportion of reciprocal ties lead to better metacognitive skills. If these reciprocal relations are only situated in one-to-one conversations learning

outcomes (amongst children) become negative. Reciprocal relationships occur in groups with high learning outcomes and reciprocity is seen as an indicator of distributed teacher presence. The studies that looked at the consequences only focused on reciprocity.

More research is needed to investigate the effects on learning outcomes due to the process of preferential attachment and transitivity. Transitivity can give more insights into the learning activities on a group level. Both individual and group level learning outcomes need to be integrated into the studies to understand more about the possible learning outcomes. Reciprocity and transitivity can lead to cohesive groups with many strong and reciprocal ties. An interesting research avenue could be to investigate the tension between the need for a dense connected group to transfer tacit knowledge and the need for weak ties to generate innovative information. The most well-known theory of strength of weak ties is often used as a statement to claim that weak ties are needed to get novel information [22]. More research is needed about possible learning outcomes and self-organizing network effects to verify this theory in the field of Networked Learning. For example, is it possible that weak ties are less present in learning networks in small student groups and more in larger learning networks with many possible weak ties between subgroups? And how do the processes of reciprocity and transitivity allow the existence of weak ties? It could be interesting to investigate if online learning networks that emerge in small formal student groups are less innovative than interconnected subgroups that emerge in a MOOC.

As a final conclusion we want to state that according to the findings of this review study we can say the following concerning the adage of networked learning that networked learning cannot be designed; it can only be designed for: Online networked learning environments can be used to promote emergent relations between learners and their peers, learners and tutors and learners and learning resources. The people, the set and the design can influence the emergence of learning networks. Self-organizing network effects are significantly present in learning networks which gives the impression that online learning ties emerge or self-organize due to the presence of the learning ties that are already present. With the review we aimed to expand the current understandings of Networked Learning and introduced the perspective of self-organization to look at learning networks and how antecedents can influence self-organizing processes in learning networks.

4.4. Limitations of the Study

Our search procedure was carried out as a manual search of a specific set of search engines and conference papers. Other search engines may yield different results. As described in the result section, the geographical coverage is rather limited. This may be due to the choice of the databases, although the databases used are not limited in geographical scope. Thus, our results must be qualified as applying only to systematic literature reviews published in the journals accessible by ScienceDirect, Web of Science and ERIC, and the conference papers of the Networked Learning conference. Due to the specific scope of the Special Issue dedicated to understanding more about Networked Learning, the choices made seem relevant for the scope of the Special Issue.

A second limitation concerns the choice of self-organizing network effects preferential attachment, reciprocity and transitivity. We do not suggest that reciprocity, preferential attachment and network closure are the only self-organizing network effects, although they are generally considered in the network literature. Moreover, we did not look at macro-structure measures like density, as they are not perceived as self-organizing network effects [10]. Self-organizing network effects may result in cohesion or centralization of a network. The density of a network is a possible result of self-organizing network effects. Moreover, although density is often used as a measure to describe a learning network, researchers in the field of Networked Learning agree that density is a dubious measure because it is so dependent on network size [9]. This limitation of the review study possibly explains the low number of articles that look at the outcomes of learning activities. Measures like centrality and cohesion are more often used to relate with learning outcomes. Possibly, self-organizing network effects are the mechanisms that can be influenced by the people, the design and the set. These self-organizing network effects result in a certain amount of cohesion within a network. However, we claim that correlations

between learning outcomes and cohesion or density are difficult to interpret if there are no insights in the mechanisms that underlie the density or cohesion of a network.

A third limitation of this study refers to any claims about quality. Self-organizing network effects are about the process of learning, the way people self-organize in different learning network structures. Understanding these self-organizing mechanisms could inform designers about possible consequences of their design choices on these self-organizing network effects. However, we cannot and do not make claims about the quality of learning, purely based on these self-organizing network effects. Making claims about the quality of learning needs to be cautious. First because the data about learning outcomes we have found is so limited but foremost because making claims about learning quality purely based on self-organizing network effects present in an online learning network, without investigation into the content of what is learnt, is not advised.

4.5. Practical Implications

We advise that future articles use clear and more detailed descriptions of the choices made regarding the boundaries of the learning network and the content of the learning network, namely the type of network (one-mode, two-mode, projected two-mode networks or personal networks), the level of aggregation and the participants involved (peer network or teacher included). Concerning the content researchers need to make the choice about what makes a reply a learning tie and whether to include the strength of a learning tie or not. These choices can have profound influences on the final result concerning the three self-organizing network effects. We advise to use these choices as a set of principles included in the method section of studies in the field of Networked Learning that investigate self-organizing network effects or other important SNA measures. Providing detailed information of the choices made in the selection process of informal learning ties makes it possible for future researchers to perform integrative studies in the field of Networked Learning. Meta-analysis studies are especially needed in the field of Networked Learning. Most studies using SNA and content analysis are mostly based on case-study research, therefore more integrative studies could help the field of Networked Learning to develop theory on learning, teaching, learning networks and social structures.

For learning architects that design for learning networks to emerge, we would provide the following guidelines based on the results of the review study. Based on the review study we can state that the following triggers worked in the learning networks under investigation. Provide clear and well-structured opening questions. Make participation in the learning network compulsory to a certain extent as an incentive to promote interaction and network development. For example course design instruction that each participant contributes at least two posts or two comments on documents/posts. Provide enough study load and design open exploratory questions so participants are triggered to learn from others through dialogue. Provide a base group discussion forum at the beginning of a course where participants can get to know each other and ask general questions. Embed learning activities such as peer-review to avoid that a moderator/teacher, facilitator becomes too central in the discussions.

However, as pointed out several times, claims about causality cannot be made based on the results of the review study. These design guidelines are suggestions and based on the results of case-study research. Possibly in other contexts other triggers could work. To conclude, learning architects are advised to design for learning networks to have the possibility to emerge. If learning architects design triggers suitable for the specific context, self-organizing network effects may happen and as a result learning networks emerge.

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Appendix A

Table A1. Search Results.

Review	
ScienceDirect	
"networked learning" AND "self-organizing network effects" (endogenous network effects)	1
"online" AND "self-organizing network effects" (endogenous network effects)	0
"online" AND "self-organizing network effects" (endogenous network effects)	0
"networked learning" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect) NOT "neural" NOT agent-based Type: Research Article	3
"networked learning" AND "reciprocity" NOT "neural" NOT agent-based Type: Research Article	31
"networked learning" AND "transitivity" (network closure, network clustering) NOT "neural" NOT agent-based Type Research Article	13
"online learning" AND "social" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect) NOT "neural" NOT agent-based	8
"online learning" AND social AND "reciprocity" NOT "neural" NOT agent-based	85
"online learning" AND social AND "transitivity" (network closure, network clustering) NOT "neural" NOT agent-based	14
"CSCL" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect) NOT "neural" NOT agent-based	2
"CSCL" AND "reciprocity" NOT "neural" NOT agent-based	14
"CSCL" AND "transitivity" (network closure, network clustering) NOT "neural" NOT agent-based	21
ERIC	
"networked learning" AND "self-organizing network effects" (endogenous network effects)	
"online" AND "self-organizing network effects" (endogenous network effects)	
"online" AND "self-organizing network effects" (endogenous network effects)	
"networked learning" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	0
"networked learning" AND "reciprocity"	2
"networked learning" AND "transitivity" (network closure, network clustering)	0
"online learning" AND "social" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	1
"online learning" AND "social" AND "reciprocity"	8
"online learning" AND "social" AND "transitivity" (network closure, network clustering)	1
"CSCL" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	0
"CSCL" AND "reciprocity"	3
"CSCL" AND "transitivity" (network closure, network clustering)	0
("Networked learning" OR "online learning" OR CSCL) AND ("social network analysis")	39
WebofScience	
"networked learning" AND "self-organizing network effects" (endogenous network effects)	0
"online learning" AND "self-organizing network effects" (endogenous network effects)	0
"CSCL" AND "self-organizing network effects" (endogenous network effects)	0
"networked learning" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	0
"networked learning" AND "reciprocity"	3
"networked learning" AND "transitivity" (network closure, network clustering)	0
"online learning" AND "social" AND "AND" preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	1
"online learning" AND "social" AND "reciprocity"	10
"online learning" AND "social" AND "transitivity" (network closure, network clustering)	1
"CSCL" AND "preferential attachment" (accumulative advantage, rich get richer, Matthew Effect)	0
"CSCL" AND "reciprocity"	2
"CSCL" AND "transitivity" (network closure, network clustering)	0
TS=("Networked learning" OR "online learning" OR CSCL) AND TS=("social network analysis")	82
Networked Learning Conference	
preferential artachment (OR accumulative advantage, rich get richer, Matthew Effect) OR reciprocity OR transitivity (OR network closure OR network clustering)	61
Review Study Bodemer and Dado	
	89
	495

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