

2025, Vol. 12, No. 3, 701–726

https://doi.org/10.21449/ijate.1586688

journal homepage: https://dergipark.org.tr/en/pub/ijate

Research Article

Investigation of higher education level social network analysis studies in educational sciences

Akça Okan Yüksel¹^{*}, Sibel Somyürek²

¹Middle East Technical University, Rectorate Office, Department of Computer Education and Instructional Technologies

²Gazi University, Faculty of Education, Department of Computer Education and Instructional Technologies

ARTICLE HISTORY

Received: Nov. 17, 2024 Accepted: Mar. 14, 2025

Keywords:

Social network analysis, Content analysis, Educational sciences, Higher education.

Abstract: In this study, we conducted a holistic analysis of educational studies on social network analysis (SNA) in higher education. To this end, articles published in Web of Science between 2010 and 2020 on social network analysis at higher education level in the field of educational sciences were analyzed using content analysis. A systematic review of available literature using the PRISMA flowchart was conducted. The key terms used to search for relevant publications were "Social Network Analysis" and "SNA"; "higher education", "post-secondary education", "third-level", "tertiary education", "graduate", "undergraduate", "post-graduate", "postgraduate". Studies in the "education, educational research," and "educational sciences" categories were filtered, as our goal was to examine studies related to education. A total of 75 relevant publications were selected based on the predefined selection criteria. The publication year of the reviewed studies, application fields, software tools, data analysis methods, data collection tools, structural characteristics of metrics, learning environments, and interaction tools in the learning environment were analyzed. The results provide suggestions for future research, emphasizing the need for a diverse approach in selecting SNA metrics. Our findings also emphasize the strong potential of SNA practices in the learning process and offer an insight into SNA practice at the higher education level in terms of determining interaction and engagement in the learning process and ultimately maximizing learning outcomes.

1. INTRODUCTION

A social network is a map of ties between nodes labelled as actors (Scott, 2000). The actors to whom an individual is connected are defined as the social relations; said differently, these are contacts of that individual. Examples of social networks include friendships between students at school, family relationships, human resources structures of companies, and classroom interactions of students. According to Wasserman and Faust (1994), a social network is a group of individuals and the relationship(s) among them. The field that examines the relationships and structures between these social networks is Social Network Analysis (SNA). SNA is a new but rapidly expanding interdisciplinary field that draws from various disciplines such as sociology, mathematics, statistics, and computer science (Bandyopadhyay *et al.*, 2011). In general, SNA

^{*}CONTACT: Akça Okan YÜKSEL 🖾 akca@metu.edu.tr 🖃 Middle East Technical University, Rectorate Office, Department of Computer Education and Instructional Technologies, Ankara, Türkiye

The copyright of the published article belongs to its author under CC BY 4.0 license. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/

can be defined as a set of methods used to determine the characteristics of relationships in a social network. The general aim of SNA is to determine the position of an actor in a social network by predicting behavioral outcomes such as performance and beliefs, partly by identifying the opportunities or obstacles it will face (Borgatti *et al.*, 2013).

SNA involves the mathematical structures describing the relationships between actors, as well as the organizational situation consisting of links and actors. SNA differs from the individualbased approaches that dominate educational research or any other research within the social and behavioral sciences. Specifically, what makes this analysis different is that, in addition to focusing on the individual, it treats the relationships connecting the individual to others as central and important (Carolan, 2013). Accordingly, SNA is not only an analytical method, but also an approach that encompasses a range of theories, models, and practices expressed as relational concepts and processes (Haythornthwaite, 1996).

SNA can also be defined as the process of qualitative and quantitative analysis of a social network. This type of analysis measures and examines the relationships and changes between entities with information flowing between them. As highlighted by Freeman (2004), SNA has the following four characteristics: (a) it is constituted by a structural insight based on the relationship between social actors; (b) it is based on systematic empirical data; (c) it largely relies on graphic visualizations; (d) it is based on the extensive use of mathematical or computational models.

SNA has come to be used in educational sciences later than in other social sciences. The tradition of experimental methods in educational sciences and the consideration of variables related to the individual, rather than the relationship, were previously reported to be the reason for the delay in the acceptance of social networks in educational sciences (Carolan, 2013). In the field of educational sciences, in recent years, interest in SNA studies has started to increase. The importance of out-of-class relationships along with in-class interactions in the teaching process has come to the forefront in much academic research. In addition, the opportunities that the new digital technologies create for information acquisition and sharing are another important point that can be examined within the scope of SNA. In addition to the individual characteristics of the student in educational environments, the behaviors of the student in the social context are also essential. Due to the structure of social network analysis, it offers the opportunity to examine and analyze individuals without separating them from their social environment (Barton, 1968). From this perspective, the social structure of learning and examining the student in its context can be seen as important advantages for using SNA in learning environments. In summary, education is a field with considerable interaction in terms of its structure. Accordingly, the use of social network approach in education can make significant contributions to education or learning in terms of the results to be obtained.

In this context, the ability of SNA to capture and analyze interactions across different learning environments further highlights its potential for educational research. SNA enables the analysis of the data collected from a large number of communication channels such as wikis, blogs, forums, all of which are components of online learning environments and used for interaction. This is a significant approach for the analysis of social interactions, both within technology-supported platforms and in face-to-face learning processes. Although SNA is a long-standing analysis method, the analysis of learning networks through SNA is still in their infancy (Palonen & Hakkarainen, 2014). Determining the situation in the studies on SNA approach, which is a relatively new field in the field of education, will shed light on future research. All scientific research is inevitably linked to the findings and results of previous research. Accordingly, it is essential to follow the trends by compiling scientific studies within measurable criteria at certain intervals to shed light on scientists who want to conduct research in any field. One of the widely used methods to systematically analyze and interpret these research trends is content analysis. Widely employed to reveal trends, content analysis is used to conduct scientific studies that provide an overview of information on a subject (Bozkurt *et al.*, 2015). This makes it a

useful approach to classifying and comparing data and reaching conceptual conclusions based on it (Cohen *et al.*, 2011).

SNA methods, approaches and modelling are increasingly being used to address research problems in the field of education (Froehlich et al., 2023). Examining how the social network approach is addressed in the educational context in higher education studies is important in terms of identifying the relationships in the context of learning at the higher education level, the structure of these relationships, and how these relationships are formed (Jan & Vlachopoulos, 2019). In addition, with such content analysis studies, it may be possible to determine which SNA measures and network characteristics are most frequently studied at the higher education level using SNA and which theoretical concepts, data collection methods, and tools are focused on. Furthermore, it may be useful in terms of identifying the deficiencies, as well as the prominent points in the studies. Besides, it may also contribute to the synthesis of the literature on SNA in an accurate and reliable way. However, while software tools, determination of interaction patterns, improvement of learning design and data collection method, data source, network type and connection type characteristics of the studies in the visualization group have been thoroughly examined in previous literature review studies on SNA (e.g., Cela et al., 2015; Sie et al., 2012), the present study examines the structural characteristics of metrics, application areas, software tools, data collection tools, data analysis methods, interaction tools in learning environments and learning environments.

1.1. Review of the Literature

To date, few studies have systematically compiled the recently increasing number of studies on social network analysis in the field of education. One of these studies was conducted by Cela et al. (2015) where the authors systematically analyzed the literature on SNA in the context of e-learning, as well as reviewed the contributions of SNA to the field of e-learning. The results revealed that these contributions could be categorized under three main topics: development of SNA software/tools, determination of interaction patterns, and improvement of learning design. In addition, Cela et al. (2015) also reviewed the years of publication, the number of citations, network characteristics, and SNA measures of the analyzed studies, finding that SNA is an effective tool for analyzing e-learning and could be used to determine the factors affecting the success or efficiency of the educational process. Another relevant study on SNA was conducted by Sie et al. (2012), who examined the application areas of SNA in the context of technologysupported learning, with the articles in SNA being applied in this particular context. The authors examined data collection methods, data sources, network types and connection type characteristics of the studies in the visualization group. General explanations were made about the studies in the simulation and intervention groups. The authors observed that these two systematic analysis studies dealt with the articles within the scope of e-learning and technologysupported learning and that none of the studies concerned the entire field of education. In addition, it was seen that the contributions of SNA to the field of e-learning, the year of the studies, the number of citations, network features, metrics used, software, network and connection types, and the principal application areas were analyzed in the examined studies. However, analyses on many features such as the main foci of the studies, mapped concepts, interaction intervals used, data collection tools, and so forth were not analyzed. By contrast, the present study encompasses all studies within the framework of educational sciences at the higher education level. Another important feature of the present study is that we undertake a comprehensive and detailed analysis of the studies in question from a range of perspectives.

1.2. Importance of the Study

The analysis of extant research using measurable criteria is important in terms of both determining the trends in the field and guiding future studies. The content analysis method, which can be used to this end, is suitable for conducting research with deductive and inductive approaches. In addition, content analysis method is not sufficiently understood and g, although

descriptive analyses are at the forefront in its application, previous studies lacked in systematicity and in-depth interpretation. To fill this gap in the literature, the present study will contribute to the literature in terms of addressing the stages of content analysis and an in-depth interpretation of the findings.

In recent years, the number of studies on SNA in many different fields has considerably increased (Sosa, 2022). In SNA, not only the characteristics of individuals, but also the connections between individuals and their characteristics are examined, which brings a new perspective to educational studies. Examining how the SNA approach, which is a relatively new field in the field of education, is addressed in educational studies at a higher education level will help to identify general trends in the studies and to reveal important points. Therefore, it will give an idea about which studies should be carried out in terms of which issues for higher education. (Cela *et al.*, 2015; Sie *et al.*, 2012) To date, very few studies have systematically compiled the recently increasing studies on SNA in the field of education. However, systematic analysis addresses the themes and basic ideas found in the research and is critical for quantification. In this respect, this review study is useful in terms of determining the issues in the focus of the studies on social network analysis and guiding the context and dimensions of the study areas.

Examining how SNA is conducted in educational studies at the higher education level will enable us to determine which research questions are addressed in this body of work, to reveal the relationships in the social networks examined and the structure of these relationships, to analyze the context where they are examined, to determine which SNA measures and network characteristics are most frequently studied and which approaches, analysis methods, and tools are focused on. In this framework, the present study can be useful in terms of revealing the issues that need to be researched at the higher education level and guiding the practices.

1.3. Aim of the Study

Due to its ability to examine interactions within learning environments, SNA has gained increasing attention in educational sciences. However, despite the growing number of studies in this field, there is a lack of a comprehensive literature review that would systematically analyze SNA research in educational contexts. To address this gap, this study aims to explore various aspects of SNA applications in education by addressing the following research questions:

- 1. What is the distribution by years?
- 2. What is the distribution of the application fields?
- 3. What software tools are used in the calculation of metrics?
- 4. What are the data analysis methods and data collection tools?
- 5. What are the structural characteristics of metrics?
- 6. What are the learning environments and interaction tools in the learning environment?

2. METHOD

This study employs a systematic literature review approach, using content analysis to examine the data. The following seven steps were followed (see Figure 1). In this study, we aimed to analyze the social network analysis studies conducted in the field of educational sciences at a higher education level. After determining the purpose of the research, the unit of analysis was defined as articles. In the sampling stage, a purposive sampling method was preferred. It was determined which databases would be included in the data collection process. After the database selection, search criteria were determined by an expert together with the present researcher.

For this study, we selected the studies in educational sciences published in the last 11 years (2010-2020) in the journals in the Web of Science database and conducted at the higher education level using social network analysis. After 2010, digital technologies and Big Data analysis have come to be more widely used in educational sciences. SNA has also been adopted

more in this context. The years 2010-2020 cover a period when SNA was increasingly used and methodologically developed in educational sciences. Due to the limited availability of previous studies in databases and the imcompleted of studies after 2020, publications between 2010 and 2020 provide a suitable time frame for the present investigation. The fact that previous studies examining the use of SNA in educational sciences generally cover this period makes the present study consistent with the literature. For this purpose, the keywords "used for the search of relevant publications were "higher education", "post-secondary education", "third-level", "tertiary education", "graduate", "undergraduate", "post-graduate", along with the terms "Social Network Analysis" and "SNA".

Figure 1. Flowchart of analysis process.



The query used when scanning with the keywords above was as follows:

("social network analysis" or SNA) and ("higher education" or "post-secondary education", or "third-level" or "tertiary education" or graduate or undergraduate or "post-graduate" or postgraduate)

This search returned a total of 141 articles. Next, the following selection criteria were applied to clean the dataset. First, conference proceedings, reports, and meeting abstracts were excluded in this selection step. Second, the inclusion and exclusion criteria were as follows:

Inclusion criteria

- •Published between 2010 and 2020
- •The keywords of the study should include Social Network Analysis, SNA, and concepts related to higher education
- •Publication in refereed journals
- •Written in English
- •Availability of full text
- •Pertaining to the field of educational sciences
- •Published in a journal in the Web of Science database
- •Realizing at the higher education level

Exclusion criteria

- •Articles that do not focus directly on the teaching process
- •Review studies

The present study conducted a systematic literature of existing literature using the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) criteria developed by Page et al (2021) (see Figure 2). The PRISMA process consisted of 3 successive classifications: identification, screening, and included. Since our aim was to examine the studies related to education within the scope of the study, the studies in the categories of "educational research" and "educational scientific" were filtered. In the first research, 47 of 141 articles were excluded from the sample because they were not related to the field of educational sciences. In the secondary review of 94 articles in line with these criteria, review studies or articles that did not focus directly on the teaching process (n = 19) were excluded. Accordingly, the final dataset amounted to 75 articles (see Appendix 1 for the full list).

Figure 2. Flowchart of the selection process.



Within the scope of this study, the coding scheme was created in the process within the framework of the research questions. An Excel table was created within the scope of the research questions, and codes were created in the context of the research questions. While some headings in the coding scheme were determined before the study, the scope of the coding scheme was expanded by adding different headings over time.

Next, descriptive content analysis and inductive content analysis were used together as data analysis methods. In descriptive content analysis, we aimed to create a general view based on frequencies and percentages depending on a research question (Thelwall, 2008). Inductive content analysis included the coding of methods, findings and interpretations of previous studies and presenting them within the framework of a theme (Zhang & Aslan, 2021; Braun & Clarke, 2006).

The obtained themes and codes, frequencies and percentages were reported in tables and graphs. During the analysis, our goal was to reveal similarities and differences in the data described in the categories or themes at interpretation levels. The analysis moved from data to a theoretical understanding—that is, from empirical findings to generalizations (Elo &Kyngäs, 2008). For this purpose, in addition to frequencies and percentages, detailed qualitative comments were included in the reporting part of the study.

2.1. Validity and Reliability

The 94 articles reached as a result of the first search were analyzed by three researchers. First, the abstracts of the studies were analyzed by two independent researchers and coded as (0-1) according to the inclusion and exclusion criteria. Cohen Kappa statistic was used to determine the agreement between the two researchers. The agreement between the two researchers was found to be .81. This agreement coefficient showed that the agreement between the two researchers was at a very good level (Lombard et al, 2002). The eight articles that were coded differently by the two researchers were analyzed by another person who is an expert in the field of CEIT and then discussed with the present researcher. The decision on each paper was reached through discussion and consensus. Based on these procedures, a total of 75 articles were retained in the final dataset.

The reliability of content analysis was ensured by a second coder included in the analysis. In the pilot study, eight articles were independently analyzed by a second researcher with a doctorate in Computer and Instructional Technology Education. The analyses of two coders were examined with the alpha coefficient defined by Krippendorff's alpha was calculated as .85. This value showed a very high rate (Krippendorff, 2004). Krippendorff's alpha was used because it reduces the chance effect and provides the opportunity to examine data other than all data types.

3. RESULTS

Within the scope of the research, the total frequency counts of some variables were equal to the total number of articles examined, while for others, they were either less or more numerous. For instance, in the distribution of authors' countries in the studies, a higher total than the number of articles was expected due to the possibility of multiple authors per article. Conversely, under the distribution of interaction tools in the learning environment, the total frequency was below the total number of articles, as not every article contained an interaction tool.

3.1. Years of Publication

Among the years examined, we found that the year with the highest number of publications was 2019 (f=12), while the year with the fewest published papers was 2011 (see Figure 3). The count of publications accessed in 2020 was 9, which was less than the previous year, which can be attributed to the fact that the articles were last scanned in May 2020.



Figure 3. Years of publication among the analyzed studies.

The results revealed that, despite several decreases between 2010 and 2020, there was generally an upward trend in the number of relevant publications. Similarly, Biancani and McFarland (2013) found a steady and significant increase in SNA studies in higher education from the early 2000s to 2012. The upward trend in publication numbers over the years can be attributed to several reasons. According to the *We are Social* (2020) report, while over 4.5 billion people worldwide use the internet, the number of social media users has exceeded 3.8 billion. The availability of large amounts of user data through social media applications and the effort to derive meaningful information through the analysis of these data are believed to have contributed to the increase in studies related to SNA. In addition, the development and support of more comprehensive and accessible statistical tools/software (Moolenaar, 2012) are seen as significant factors in the increase in the number of SNA studies. The increasing trend in publication numbers in the reviewed articles suggests a growing interest in SNA within the field of educational sciences. Finally, the reason for the relatively low number in 2020 is related to the deadline of the literature review article addition process.

3.2. Field of Application

Furthermore, the results revealed that most of the studies included in the dataset were conducted in the area of Educational Technology, accounting for 21% of studies (see Table 1), followed by administrative and management-related fields, which made up 16% of the dataset. The field of science was also prominent, with 10 studies.

Educational technology is broadly defined as the effort to facilitate learning and improve performance by creating, using, and managing technological processes and resources (Molenda & Januszewski, 2013). The relationships and networks that students form within the learning

environment have significant effects on student behaviors. In this context, SNA helps to understand the formation of student networks, the impact of these networks on students, and the interaction structures within networks (Grunspan, Wiggins & Goodreau, 2014). In educational research, SNA allows for the examination of nearly every type of social system in the context of students, classes, schools, or districts. In so doing, it can help reshape teaching and learning (Carolan, 2013). Studies on the use of technological platforms and applications such as Web 2.0 tools and online environments to improve and support education hold a significant place in the field of educational technologies. For instance, many online learning environments include Web 2.0 applications that facilitate collaborative content creation among students, the formation of social networks among students, and interactions between learners and teachers that positively affect the learning process (Cela et al., 2016). The need to examine the structure of interactions in these technology-supported platforms and the ability to obtain a large amount of interaction data through these platforms may have led to the extensive use of SNA in educational technologies. Today, SNA is the most commonly employed in educational technology, but it is also used in educational management and science. Owing to the large number of subjects examined, it can be assumed that interest in other fields is growing.

The reviewed studies were related to a total of 34 different fields where SNA is used. This finding suggests that SNA is used as an effective research method across a broad range of disciplines, particularly in educational sciences.

| Fields of Application | f | % |
|--|----|--------|
| Educational Technology | 16 | 21.33 |
| Administrative and Management Related Fields | 12 | 16.00 |
| Science | 10 | 13.33 |
| Information and Communication Technologies | 6 | 8.00 |
| Academic and Professional Development | 3 | 4.00 |
| Behavioral and Human Sciences | 3 | 4.00 |
| Engineering | 3 | 4.00 |
| Curriculum Development | 3 | 4.00 |
| Medical and Health Education | 3 | 4.00 |
| Mathematics | 2 | 2.67 |
| Psychology | 2 | 2.67 |
| Higher Education Programs | 2 | 2.67 |
| Sociology | 1 | 1.33 |
| Research Methods | 1 | 1.33 |
| Fine Arts | 1 | 1.33 |
| Education of Language | 1 | 1.33 |
| Learning Sciences | 1 | 1.33 |
| Undefined | 5 | 6.67 |
| Total | 75 | 100.00 |

Table 1. Fields of application of SNA in the dataset.

3.3. Software Used to Calculate Metrics

With regard to the software used to calculate metrics, we found that he most preferred software for calculating metrics was Ucinet (f=36, 37.5%), followed by Netdraw (f=16) and the R programming language (f=8) (see Table 2). Ucinet, the most frequently used software, was originally developed Borgatti *et al.* (2002), and can analyze both one-mode and two-mode data. Ucinet includes a diverse set of network analysis tools such as centrality measures, subgroup identification, role analysis, basic graph theory, and probability-based statistical analysis (Apostolato, 2013).

| Software | f | % |
|---------------------------------------|----|--------|
| Ucinet | 36 | 37.50 |
| Netdraw | 16 | 16.67 |
| R Programming language and plugins | 8 | 8.33 |
| Gephi | 6 | 6.25 |
| Netminer | 5 | 5.21 |
| NodeXL | 4 | 4.17 |
| Social Network Visualizer | 2 | 2.08 |
| NetworkX | 2 | 2.08 |
| Python | 2 | 2.08 |
| yED graph tool | 2 | 2.08 |
| Calculation tool integrated on Canvas | 1 | 1.04 |
| Greasemonkey script | 1 | 1.04 |
| Undefined | 11 | 11.46 |
| Total | 96 | 100.00 |

Table 2. Software used to calculate metrics.

Its comprehensive set of features and functions may account for Ucinet's popularity among scholars. Ucinet is a useful tool in social network analysis studies since it combines network analysis and visualization skills. As to Netdraw, an important aspect contributing to its popularity is its availability as an add-on for visualizing whole network structures. Finally, regarding R, in recent years, R has become increasingly popular in investigations completed in 2018 and after (f=7). R is thought to provide more convenient data entry and more accurate visualizations (Hopkins, 2017). Besides modeling network relationships using larger datasets, R also facilitates faster analysis (Hopkins, 2017). The SNA Llibraries and packages like igraph, ggraph, and tidygraph in R enable users to calculate and visualize metrics found in Ucinet and more. For these reasons, R program is a popular software used in many SNA studies.

3.4. Data Analysis Methods

With regard to the data analysis methods, it SNA was found to be used in conjunction with quantitative analysis (f=27), qualitative analysis (f=20), both quantitative and qualitative analyses (f=14), and solely SNA (f=14), respectively (see Table 3). Studies employing both social network analysis and quantitative analysis were structured in two different ways. On the one hand, SNA and quantitative analysis were conducted independently (f=16). On the other hand, SNA analysis was conducted first, and the metrics obtained from this analysis were subsequently examined through quantitative analyses (f=11).

| Data Analysis Methods | f | % |
|--|----|--------|
| SNA + Quantitative analysis | 27 | 36.00 |
| Independent SNA and quantitative analysis | 16 | 21.33 |
| Quantitative analysis using SNA results | 11 | 14.67 |
| SNA + Qualitative analysis | 20 | 26.67 |
| Independent SNA and Qualitative analysis analysis | 16 | 21.33 |
| Qualitative analysis using SNA results | 4 | 5.33 |
| SNA + Quantitative analysis + Qualitative analysis | 14 | 18.67 |
| Only SNA | 14 | 18.67 |
| Total | 75 | 100.00 |

Table 3. Data analysis methods used in the analyzed studies.

Similarly, studies using both SNA and qualitative analysis were conducted in two different ways, mirroring the quantitative approach. First, SNA and qualitative analysis were conducted independently (f=16). Second, qualitative analysis was initially conducted, and the data obtained from this analysis were then examined using SNA (f=4). In studies using both SNA and quantitative analysis, statistical methods such as correlation and regression analyses were used alongside SNA to compare and predict relationships between metrics derived from interaction data and other variables. For example, *Cela et al.* (2016) conducted correlation analyses to determine whether various SNA metrics such as centrality, closeness, betweenness, and density, calculated using the data from an online learning environment's discussion forum, were related to students' learning styles. The authors found a low but significant correlation between active learning style and all the SNA metrics of centrality, closeness, betweenness, and density.

In studies using both SNA and qualitative analysis, content analysis was particularly frequently used, followed by focus group discussions. These types of studies were arranged in two ways. First SNA and qualitative analysis were carried out independently. For instance, in one study, Kuznetcova *et al.* (2019) used SNA to examine changes in student interactions over time, while interviews and content analysis were used to determine changes in student perceptions of using the virtual environment (Second Life) as part of the course. In Second, qualitative analysis was performed first, followed by SNA using the data gained from this analysis. For instance, Vázquez-Cano *et al.* (2016) aimed to figure out educational functionality of personal learning environments (PLEs) and open educational resources (OER). To this end, the authors first identified the most frequently used concepts related to the advantages and disadvantages of personal learning environments and open educational resources through content analysis of survey data answered by participants. Then, the relationships between these identified concepts were examined using SNA.

Furthermore, in the studies included in our sample, data analysis methods combining qualitative, quantitative, and social network analysis were also observed. For instance, Msonde and Aalts (2017) aimed to determine how differently designed learning environments affected student interaction, participation, and higher-order thinking. To this end, the data were collected from interviews, achievement tests, and the content of online discussion forums. Repeated measures ANOVA was then used to analyze the test scores of the students. Social network analysis was used to analyze online discussion forum logs, network densities, and interaction cliques. To analyze changes in students' thoughts, posts from online discussion forums were examined using content analysis.

3.5. Data Collection Tools

Concerning the data collection tools were examined, we found that relevant approaches included analyzing the records obtained from electronic systems/tools, surveys, sociometric questionnaires, academic achievement scores, interview forms, observation forms, scales, workshop and annual meeting reports, learning journals, reflection reports, and university registration office data (see Table 4). Electronic systems/tools were found to be the most frequently used data collection tools (f=56, 45.9%). Within electronic systems/tools, discussion posts (f=21) were the most used, followed by records obtained from learning management systems and online learning systems (f=18). After electronic systems/tools, surveys were determined to be the second most frequently used data collection tool (f=26, 21%). The data collected through sociometric surveys were the third most used data collection tools (f=14).

In recent years, various learning management systems (LMS) like Moodle, ATutor, Dokeos, Docebo, eStudy, Drupal, DotLRN, eFront, Sakai, Blackboard, Canvas, both open-source and commercial, have come to be used for educational purposes. Moreover, various electronic systems, including social network-based online learning environments, virtual classrooms, and social media applications like Facebook and Twitter, were also found to be widely employed

in education. The ability of these systems to store diverse and substantial amounts of interaction data has facilitated the collection of data about actors and relationships forming social networks in the reviewed studies, leading to the frequent use of various electronic systems and tools as learning environments, thereby highlighting electronic systems/tools as prominent data collection tools.

| Data Collection Tools | f | % |
|-------------------------------------|-----|--------|
| Electronic systems/tools | 56 | 45.90 |
| Discussion Forums | 21 | 17.21 |
| LMS/Online learning system records | 18 | 14.75 |
| Blog comments | 5 | 4.10 |
| E mail data | 2 | 1.64 |
| Social messaging app records | 2 | 1.64 |
| Facebook data | 2 | 1.64 |
| Wiki records | 1 | 0.82 |
| Bulletin boards | 1 | 0.82 |
| Social networking media content | 1 | 0.82 |
| Personal Digital Asisstant (PDA) | 1 | 0.82 |
| Cohort evaluation tool | 1 | 0.82 |
| Evaluation tool with Phyton | 1 | 0.82 |
| Survey | 26 | 21.31 |
| Sociometric survey | 14 | 11.48 |
| Academic Achievement test | 8 | 6.56 |
| Interview forms | 7 | 5.74 |
| Observation forms/records | 5 | 4.10 |
| Scale | 2 | 1.64 |
| Workshop and annual meeting reports | 1 | 0.82 |
| Learning Journals | 1 | 0.82 |
| Reflection Reports | 1 | 0.82 |
| Registrar's office forms | 1 | 0.82 |
| Total | 122 | 100.00 |

Table 4. Data collection tools in studies.

Under the theme of electronic systems/tools, data collection included discussion forums, LMS/online learning records, blog comments, email data, social messaging app records, Facebook data, wiki logs, digital bulletin boards, social network environment contents, system usage logs, digital personal assistant records, cohort assessment tool records, and data from assessment tools prepared with Python. We found that the most frequently used data collection tool in the electronic system/tools theme was discussion forums. Recently, the development of online technologies has transformed communication and interaction methods among students and between students and instructors. Specifically, due to the easy access to electronic systems and tools, where students and teachers continue discussions on course-related topics, the usage of online forums has become particularly widespread (Parks-Stamm et al., 2017). Discussion forums are online platforms where participants engage in asynchronous debates by posting responses to each other. On these platforms, users can interact with others by exchanging messages called posts, discussing specific topics (Grützmann et al., 2016). Of note, asynchronous discussion forums provide data for both instructors and researchers to observe the quality of interaction and the collaborative process of knowledge creation (Martono & Salam, 2017).

The second most frequently used data collection tool in the analyzed papers was surveys. Although participants' behaviors can be collected through records obtained from electronic systems/tools, surveys are needed when opinions have to be gathered. In addition, some studies were conducted in face-to-face learning environments, necessitating the direct collection of data from participants through surveys. Furthermore, surveys were required to evaluate the environment and processes used in the study. For instance, to determine whether an LMS (Moodle) or an instant messaging app (Wechat) were more useful for collaborative learning, the data were collected via surveys. In the analyzed studies, some collected the data through surveys to identify the individual characteristics of the people forming the social network. Approximately 80% of the reviewed studies used SNA along with quantitative and qualitative analyses. In these studies, the fact that some data collected from students through surveys supports this result.

The third most frequently used approach to data collection was sociometric surveys, which typically consisted of questions aimed at determining, for instance, who individuals work with more, get along with better, or turn to most for learning support within a group. In the reviewed face-to-face studies, sociometric surveys were used as a quick and effective data collection tool to gather interaction data. The foundations of SNA are based on Moreno's sociometry method. The purpose of sociometry is to reveal the social relations within a group and to numerically determine who accepts or rejects whom within the group (Özdemir & Keser, 2019). Over time, combining the sociometry technique and graph theory emerging in mathematics, the concept of SNA has taken its current form (Somyürek & Güyer, 2020). Said differently, it is expected that sociometric surveys, which are the primary data collection tool in implementing sociometry techniques as a significant originator of social network analysis, will be used in social network analysis studies.

3.6. Structural Characteristics of Metrics

Metrics refers to examining the specific attributes or properties (e.g., centrality, density, betweenness, etc.) used to analyze data in research studies. It involves looking into how these metrics are defined, calculated, and interpreted within the context of the research, as well as understanding their implications for the study's findings and conclusions (Hansen *et al.*, 2020). The metrics used in the reviewed studies were examined and categorized into themes of centrality, group characteristics, group/actor power, group interconnectedness, group internal hierarchy, and subgroup properties (see Table 5). The results showed that, in the sample, centrality measures (f=77) were the most frequently used, followed by group characteristics (f=58), and then group interconnectedness (f=28) metrics. The themes related to metrics in the reviewed studies were based on the classifications of metrics by Liebowitz (2006) and Shu and Gu (2018). In addition, some themes were introduced by the researchers.

Centrality measures were criteria that provide information about an individual's position within the overall network. The centrality metric is crucial to identify the status of relationships in a social network and determine individuals who engage in more interactions during collaborative processes, as well as understand the overall interaction structure within the network. The centrality measures theme included degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, hub and authority centrality, and PageRank centrality metrics. Degree centrality facilitates the identification of the importance of individuals in a network and aids in pinpointing the most active or passive students within the network (Wasserman & Faust, 1994). In the present study, the concept of degree centrality in this study corresponded to the local degree centrality in the literature, which captures the extent to which the social network revolves around a single actor (Somyürek & Güyer, 2020).

| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$ |
|---|
| |
| Bub Floar 17 55.00 Density 32 14.55 Node 8 3.64 Average degree 7 3.18 Edges 5 2.27 Size 2 0.91 Diameter 1 0.45 Tolerance 1 0.45 Breadth 1 0.45 Breadth 1 0.45 Sub-Total 58 26.36 Connections 9 1.82 Transitivity 7 3.18 Reciprocity 6 2.73 Connectivity 3 1.36 Efficiency 2 0.91 Connectivity Density 1 0.45 Sub-Total 28 12.72 Centralization /Power/ Freeman Centralization /Global Centralization 17 5.00 Network Centralization Index 5 2.27 |
| |
| |
| |
| |
| $ \begin{array}{c cccc} Group characteristics & \hline Diameter & 1 & 0.45 \\ \hline Diameter & 1 & 0.45 \\ \hline Tolerance & 1 & 0.45 \\ \hline Frequency & 1 & 0.45 \\ \hline Breadth & 1 & 0.45 \\ \hline Sub-Total & 58 & 26.36 \\ \hline Connections & 9 & 1.82 \\ \hline Transitivity & 7 & 3.18 \\ \hline Reciprocity & 6 & 2.73 \\ \hline Connectivity & 6 & 2.73 \\ \hline Connectivity & 3 & 1.36 \\ \hline Efficiency & 2 & 0.91 \\ \hline Connectivity Density & 1 & 0.45 \\ \hline Sub-Total & 28 & 12.72 \\ \hline Centralization / Power/ Freeman \\ \hline Centralization / Global Centralization \\ \hline Network Centralization Index & 5 & 2.27 \\ \hline \end{array} $ |
| $ \begin{array}{c c c c c c c c c c c c c c c c c c c $ |
| Frequency10.45Frequency10.45Breadth10.45Sub-Total5826.36Connections91.82Transitivity73.18Reciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Breadth10.45Breadth10.45Sub-Total5826.36Connections91.82Transitivity73.18Reciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Breadmin10.45Sub-Total5826.36Connections91.82Transitivity73.18Reciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Sub-Fotal5.820.30Sub-Fotal91.82Transitivity73.18Reciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Group interconnectedness71.62Transitivity73.18Reciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Group interconnectednessReciprocity62.73Connectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Group interconnectednessConnectivity31.36Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Connectivity51.30Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Efficiency20.91Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Connectivity Density10.45Sub-Total2812.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Sub-Fotal2312.72Centralization /Power/ Freeman Centralization/ Global Centralization175.00Network Centralization Index52.27 |
| Centralization / Global Centralization175.00Network Centralization Index52.27 |
| Network Centralization Index52.27 |
| |
| Group/Actor power Interaction power 2 0.91 |
| Mean tie strength 2 0.91 |
| Network modularity 1 0.45 |
| $\frac{1}{27} = \frac{1}{27}$ |
| Cohesion index 6 2.73 |
| $\frac{182}{\text{Clustering Coefficient}}$ |
| Mean distance 1 0.45 |
| Group internal hierarchy Mean weighted degree 1 0.45 |
| Hierarchy coefficient 1 0.45 |
| Cohesion index 6 2.73 |
| $\frac{13}{545}$ |
| $\frac{15}{15}$ |
| Subgroup characteristics K play 1 0.45 |
| Subgroup enalacteristics $\frac{K ple x}{Sub Total}$ $\frac{0.45}{2.24}$ |
| Sub-10tal 0 5.04 F Lindex 2 1.26 |
| $\begin{array}{c} -1 & \text{Index} & 5 & 1.30 \\ \hline \\ \hline \\ \text{Other} & 6 & 2.72 \\ \hline \end{array}$ |
| One 0 2.12 Total 220 100.00 |

Table 5. Structural characteristics of metrics.

In the theme of group characteristics, the metrics included were density, nodes, average degree, edges, volume, diameter, tolerance, frequency, and breadth. Density was the most frequently used metric in the dataset, providing general information about the group and defining its overall framework. Network density measurement gives an idea of how many individuals within a network interact with each other and the frequency of these interactions, revealing the degree of relationships such as collaboration and friendship among group members (Martinez *et al.*, 2003). In one relevant study, density was used to show the frequency of information delivery between individuals (Ergün &Usluel, 2016). It was also used in online learning environments by Msonde and Aalst (2017) to determine the density of connected messages and the entire network, identifying patterns of interaction among students. Furthermore, Lee and Bonk (2016) examined the weekly change in peer relations through network density, while Lorenzo, Sicilia, and Sánchez (2012) used the density metric to display and compare the overall connection among participants in two different learning environments (LMS/MMOL).

The third prominent theme related to the structural characteristics of metrics was group interconnectedness. Connections, connectedness, reciprocity, connectivity, efficiency, and connectedness density are all categories included in the theme of group interconnectedness. Group interconnectedness refers to whether group members make selections among each other and communicate with each other. It is frequently used to determine the level of harmony within the group (Hu & Racherla, 2008). Connectedness indicates whether a network is structured as a single cluster or several smaller clusters. It can also be used to identify communication, information, and emotional exchange among members (Shu & Gu, 2018). For instance, high connectedness means that members within an application community can easily access each other.

Two significant metrics that reveal the entire structure of a network are centrality and density (Scott, 2000). Of note, centralization and density are two concepts that do not complement each other. While density is a measure showing the overall integration of a network, centralization focuses on how much this integration occurs at certain points (Ağcasulu, 2018). Therefore, centrality and density metrics are thought to be preferred for providing insight into the entire structure of the network and indicating around which center the network is concentrated.

3.7. Learning Environments

The learning environments in the reviewed studies were examined and categorized into the following five themes: Learning Management System (LMS), online learning environment, face-to-face learning environment, communication tools/environments, and virtual realitybased learning environments (see Table 6). The results revealed that the most frequently used learning environment was the LMS (f=24, 32%). Within learning management systems, Moodle was the most used (f=15), followed by Blackboard (f=3), Canvas (f=1), Angel (f=1), Bespoke (f=1), Yellowdig (f=1), and Yammer (f=1). After learning management systems, the second most used learning environment was face-to-face learning environments (f=20, 27%), including classroom settings (f=13), workshops/seminars (f=4), laboratories (f=2), and internship settings (f=1). The third most frequently used learning environment was online learning environments (f=12, 16%) that encompassed ELGG online social learning environment, Massive Open Online Courses (MOOCs), OPAL online peer support learning environment, WASP collaborative social sharing and learning environment, Virtual math teams for mathematics teaching, Ning online social learning environment, UABC virtual classroom, the university's own online learning environment, Wordpress based multi-blog environment, and, finally, Piazza online discussion environment.

| Theme | Learning Environments | f | % |
|--|---|----|--------|
| | Moodle | 15 | 20.00 |
| | Blackboard | 3 | 4.00 |
| | Canvas | 1 | 1.33 |
| | Bespoke | 1 | 1.33 |
| Learning Management | Baidu | 1 | 1.33 |
| by stem | Angel | 1 | 1.33 |
| | Yellowdig | 1 | 1.33 |
| | Yammer | 1 | 1.33 |
| | Total | 24 | 32.00 |
| | Classroom | 13 | 18.67 |
| | Workshops and Seminar | 4 | 5.33 |
| Face to Face Learning Environment | Laboratory | 2 | 2.67 |
| | Internship environment | 1 | 1.33 |
| | Total | 20 | 26.67 |
| | ELGG (Online social network learning environment) | 3 | 4.00 |
| | MOOC | 1 | 1.33 |
| | OPAL (Online peer support learning environment) | 1 | 1.33 |
| | WASP (Collaborative social sharing and learning environment) | 1 | 1.33 |
| Online Learning | Virtual math teams (Collaborative online study environment developed for Math) | 1 | 1.33 |
| Environment | NING (Online social network learning environment) | 1 | 1.33 |
| | UABC (Virtual classroom) | 1 | 1.33 |
| | University-owned online learning environment | 1 | 1.33 |
| | Piazza (Online discussion environment) | 1 | 1.33 |
| | Wordpress based on a multi-blog environment | 1 | 1.33 |
| | Total | 12 | 16.00 |
| | WeChat messaging tool | 2 | 2.67% |
| Environments | Facebook | 2 | 2.67% |
| | Total | 4 | 5.34 |
| Virtual Reality Based Learning Environment (MMOL- Second Life) | | 3 | 4.00 |
| Undefined | | 12 | 14.67 |
| Total | | 75 | 100.00 |

Table 6. Learning environments in reviewed studies.

The most frequently used learning environment in the reviewed studies was the Learning Management System (LMS), a web-based application encompassing learning content, student interaction, assessment tools, learning progression processes, and student activities (Kasim & Kalid, 2016; Srichanyachon, 2014). One of the fundamental functions of these systems is to facilitate interaction between students and instructors, as well as among peers, through

computer-mediated communication (CMC) resources such as discussion forums and real-time chats. A total of eight different learning management systems were preferred in 24 studies as a learning environment. We also found that Moodle was the most preferred among LMSs. Among the factors contributing to Moodle's preference were its open-source and free nature, compatibility with Windows, Linux, Mac OS operating systems, scalability to support many users, and multilingual support.

Although SNA frequently recalls online systems, face-to-face environments ranked second in usage. The reviewed SNA studies were also conducted in face-to-face settings. In addition to classroom environments, the data were collected from seminars, workshops, and laboratory settings. Interactions in real classroom environments can be collected directly or indirectly from students, and various variables can be predicted with these relationships. Understanding whether students are more actively engaged in virtual or real classroom environments will enhance our comprehension of the significance of these studies. Comparative insights from both environments can provide a more nuanced understanding of student engagement and learning dynamics in different educational contexts.

In the examined studies, online learning environments were the third most frequently used as a learning environment. In general, online learning is a method used in distance education, allowing the synchronous and asynchronous exchange of resources over a communication network. An online learning environment is also a system that technically and socially surrounds the learner and the teacher (Khan, 1998).

The use of online learning environments for educational purposes is growing due to their potential to support interaction (Moore *et al.*, 2011), as these environments provide robust communication structures and facilitate collaborative knowledge construction processes (Bardakçı *et al.*, 2014). Within this theme, the most frequently used online learning environment was ELGG, an open-source social networking tool developed for educational institutions or those wanting to create collaborative social platforms. ELGG encompasses tools like messages, files, profiles, wikis, blogs, and presentations in its portfolio module, while social bookmarking, multimedia sharing platforms are in its social media module. In addition, the ability to create three different social network structures in ELGG environments – friends, groups, and classes – is one of its significant and notable features. ELGG's advanced portfolio feature may be considered a distinguishing aspect from other online environments. Its use of open-source code and the provision of a collaborative social networking framework are the reasons underlying its frequent use in the examined studies.

3.8. Interaction Tools in the Learning Environment

The interaction tools present in the learning environment analyzed in the reviewed studies were examined and categorized into the following seven themes: discussion forums/boards, blogs, wikis, messaging applications, email, interactive portfolios, and online reflection questions (Table 7). The results showed the most used interaction tool was the discussion forum (f=32, 58.18%), followed by blogs (f=11, 20%), wikis (f=4, 7.27%), and messaging applications (f=4, 7.27%).

Previous studies also found the discussion forum to be the most frequently used interaction tool in learning environments. Discussion is employed as a teaching strategy for knowledge building in collaborative environments (Holmes, 2005). Online discussion environments are both learning spaces and assessment tools encouraging in-depth thinking and providing the necessary time for the ideas to mature. In these environments, students build and share new information by adding responses previously given by teachers and other students. Discussion forums offer students the opportunity to review and reevaluate their own responses and gain insights into the thoughts of other participants. This process of reconsideration and assessment can enhance students' higher-order thinking skills. Designing discussion forums with students is an effective practice based on cognitive learning theories (Markel & Eci, 2001). The

contributions of discussion forums to the learning process, their status as a significant component of frequently preferred learning environments like LMS and online platforms, and their widespread use in collaborative learning-based studies suggest that many studies would employ these tools.

| Interaction Tools | | f | % |
|-----------------------------|---|----|-------|
| Discussion forum/board | | 32 | 58.18 |
| Blog | | 11 | 20.00 |
| Wiki | | 4 | 7.27 |
| | Wechat (Instant messaging app) (f=2) | | |
| Messaging Applications | Virtual Math Team (Messaging application in a collaborative social learning environment) (f=1) WASP (Messaging application in a collaborative social networking and learning environment) (f=1) | 4 | 7.27 |
| E-mail | | 2 | 3.64 |
| Interactive portfolio | | 1 | 1.82 |
| Online reflection questions | | 1 | 1.82 |
| Total | | 55 | 100 |

Table 7. Interaction tools in the learning environment.

Blogs and wikis were also found to be important tools for students to engage in project work and to reflect and think during the evaluation process. Such Web 2.0 tools enable users not only to create a wide variety of materials but also to receive comments from others and provide feedback (Gray *et al.*, 2010). In social network analysis, the assessment of student interactions through reflections created by students and peer evaluations may have made blogs and wikis preferred tools. These platforms allow for a rich tapestry of student engagement and interaction, thereby enabling a more nuanced and detailed SNA.

4. DISCUSSION and CONCLUSION

Analyzing scientific studies provides an in-depth examination of the subject and offers a general view of the related field (Al, 2008). In the present study, we aimed to identify the trends in SNA analysis studies in the field of educational sciences in higher education, as well as to show the gaps in literature and formulated recommendations for further research. To this end, we performed a content analysis of a total of 75 SNA studies concerned with the teaching process in the field of educational sciences at the higher education level. Relevant publications were collected from the Web of Science database, with publications dates between 2010 and 2020. The findings provide a holistic view of the growing body of the research literature on SNA and provide a preliminary basis for the overall context.

Our study emphasizes the strong potential of SNA practices in the learning process. The research offers an insight into SNA practices at the higher education level in terms of determining interaction and engagement in the learning process and ultimately maximizing learning. The potential benefits of SNA in educational sciences appear to make it a valuable tool for educational processes along with the advancement of technology. However, further research is needed to build a deeper understanding of the benefits as well as the challenges and problems of SNA such as inaccurate interpretation of student interactions and the impact of social dynamics. Different research methods, different application areas, and studies with a larger pool of participants will reveal the effectiveness of SNA. Taken together, the findings of this study contribute to expanding our knowledge about the relationships between SNA domains and provide suggestions on how to use SNA in different studies.

As the use of SNA in education continues to expand, future research should focus on integrating SNA with emerging technologies and advanced data analysis techniques, such as artificial intelligence and machine learning, to enhance its applicability in diverse learning environments. Furthermore, while the present study highlights the role of SNA in identifying interaction patterns and engagement levels, future studies should also explore its potential in personalized learning, adaptive educational systems, and digital learning analytics. Moreover, interdisciplinary collaborations incorporating cognitive science, psychology, and education technology can provide a more comprehensive understanding of how social interactions affect learning outcomes. Expanding SNA research beyond student interactions to include educator and institutional networks can provide valuable insights into the broader dynamics of the educational system. Finally, longitudinal studies investigating the long-term impact of SNA-based interventions will be crucial in shaping future educational policies and pedagogical strategies, ensuring that SNA continues to meaningfully contribute to the advancement of higher education.

5. SUGGESTIONS

5.1. Suggestions for Further Research

The most frequently examined SNA metrics in the reviewed studies were centrality, density and centralization. However, in the study of social learning and collaboration, analyzing interactions in social networks and network structures from different perspectives is important to answer different research questions. In the reviewed studies, we observed that the cohesion index, which shows the cohesion level of the groups, was examined in five studies, while the external-internal index, which reveals the difference between the interactions of the students in certain groups outside the group and the interactions within the group, was examined in only three studies. Similarly, some of the metrics such as average distance, average, weighted degree, K-plex, efficiency, and so forth were used in only one study. In future research, instead of analyzing the most well-known metrics, it would be useful to use appropriate and less examined metrics to answer different research questions such as determining the study groups or examining their effectiveness.

Furthermore, the results revealed that most of the reviewed studies are conducted using SNA and quantitative methods to analyze learner interactions, while the number of studies using SNA and qualitative methods together has been increasing in recent years. In SNA analysis studies, where mathematical and statistical techniques are at the forefront, supportive qualitative analyses would be needed to determine the quality of the interaction. The studies using qualitative analyses and SNA methods were structured in the following two different ways. On the one hand, SNA and qualitative analysis were carried out independently of each other. On the other hand qualitative analysis was performed first, while SNA was applied by using the data obtained as a result of this analysis. In the analyzed studies, we observed that the studies of the second type were particularly rare. Accordingly, it is important to increase the number of such studies due to their potential to both make sense of the content of the same data and to identify new patterns in the data.

Only two of the actors in the studies were non-personal entities. Although SNA mainly aims to study social interactions, interactions between non-personal entities such as events, objects, countries and organizations can also be studied with SNA. Accordingly, to reveal the relationship between learning environments, learning objects, concepts, theories, ideas, and so forth, in future research, non-personal entities should be considered as actors.

Overall, about 20% of the features examined by visualization in the analyzed studies are used to examine the change in the network structure in the process. Graphs showing the change in the process can be used to present the change in the network structure before and after the application, or they can be used to show weekly or periodic changes. In the analyzed studies, such changes were identified; however, the reasons for this change were not analyzed in periods

when there were significant and clear changes. Therefore, analyzing the reasons for change would be an important research direction in future studies.

In the present study, we focused on SNA studies in the field of education carried out at the higher education level in a 10-year period. In future studies, longitudinal network analyses would need to be conducted over certain intervals, potentially showing the change and importance of the findings in these intervals. Thus, 5-year or 10-year changes can be analyzed and the reasons such as methods, techniques, concepts, and technologies for these changes can be determined.

5.2. Suggestions for the Practitioners

In various studies among the reviewed articles, communities of practice, communities of inquiry/research and learning communities were addressed and the relationships of various conditions such as students' effectiveness in the community, social, cognitive and learning agency with some metrics calculated by social network analysis were determined. By calculating and reporting the metrics reported in these studies in online learning environments, measures can be taken to create and increase effectiveness of the learning communities.

The reviewed studies showed that SNA is widely used to analyze interactions between students in collaborative work environments. Examining the results obtained from these studies would be useful to design and organize collaborative learning environments.

Acknowledgments

This research is part of thesis "Investigation of Social Network Analysis Studies Conducted at Higher Education Level in Educational Sciences".

Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the authors.

Contribution of Authors

Akça Okan Yüksel: Investigation, Resources, Visualization, Software, Formal Analysis, and Writing-original draft. Sibel Somyürek: Methodology, Supervision, Critical Review, and Validation.

Orcid

Akça Okan Yüksel b https://orcid.org/0000-0002-5430-0821 Sibel Somyürek b https://orcid.org/0000-0001-7803-1438

REFERENCES

- Agcasulu, H. (2018). A method for assessing relations in social sciences: Social Network Analysis. *Journal of Graduate School of Social Sciences*, 22(Special Issue 2), 1915-1933.
- Al, U. (2008). Scientific Publication Policy of Turkey: A Bibliometric Approach Based on Citation Indexes (Unpublished Doctoral Dissertation), Hacettepe University, Ankara.
- Apostolato, I.A. (2013). An overview of software applications for social network analysis. *International Review of Social Research*, *3*(3), 71-77. https://doi.10.1515/irsr-2013-0023
- Bandyopadhyay, S., Rao, A.R., &Sinha, B.K. (2011). One introduction to social network analysis, Sage.
- Bardakçı, S., Alakurt, T., & Keser, H. (2014). Student roles and behaviors in online learning environments. *Hacettepe University Journal of Education*, 29(1), 47-60.
- Barton, A. (1968). Bringing society back in survey research and macro-methodology. *American Behavioral Scientist*, 12(2), 1–9.

- Biancani, S., & McFarland, D.A. (2013). Social networks research in higher education. W.P. Laura (Ed). In *Higher education: Handbook of theory and research* (pp. 151-215). Springer, Dordrecht. https://doi.org/10.1007/978-94-007-5836-0_4
- Borgatti, S.P., Everett, M.G. & Freeman, L.C. (2002). Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies.
- Borgatti, S.P., Everett, M.G., & Johnson, J.C. (2013). Analyzing social networks, Sage.
- Bozkurt, A., Akgun-Ozbek, E., Yilmazel, S., Erdogdu, E., Ucar, H., Guler, E., ..., Aydin, C. H. (2015). Trends in distance education research: A content analysis of journals 2009-2013. *International Review of Research in Open and Distributed Learning*, *16*(1), 330-363.
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa
- Carolan, B.V. (2013). Social network analysis and education: Theory, methods & applications. Sage.
- Cela, K.L., Sicilia, M.Á., &Sánchez, S. (2015). Social network analysis in e-learning environments: A preliminary systemati creview. *Educational Psychology Review*, 27(1), 219-246. https://doi.org/10.1007/s10648-014-9276-0
- Cela, K., Sicilia, M.Á., & Sánchez-Alonso, S. (2016). Influence of learning styles on social structures in online learning environments. *British Journal of Educational Technology*, 47(6), 1065-1082. https://doi.org/10.1111/bjet.12267
- Chen, B., & Huang, T. (2019). It is about timing: Network prestige in asynchronous online discussions. *Journal of Computer Assisted Learning*, 35(4), 503-515. https://doi.org/10.111 1/jcal.12355
- Cohen, L.M., Manion, L., & Morrison, K. (2011). Research methods in education. Routledge.
- Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing*, 62(1), 107-115. https://doi.org/10.1111/j.1365-2648.2007.04569.x
- Ergün, E., &Usluel, Y.K. (2016). An analysis of density and degree-centrality according to the social networking structure formed in an online learning environment. *Journal of Educational Technology & Society*, *19*(4), 34-46. https://www.jstor.org/stable/jeductechsoc i.19.4.34
- Freeman, L.C. (2004). *The development of social network analysis: A study in the sociology of science*. ΣP EmpiricalPress.
- Froehlich, D.E., Van Waes, S., & Schäfer, H. (2020). Linking quantitative and qualitative network approaches: A review of mixed methods social network analysis in education research. *Review of research in education*, 44(1), 244-268. https://doi.org/10.3102/009173 2X20903311
- Gray, K., Thompson, C., Sheard, J., Clerehan, R., & Hamilton, M. (2010). Students as Web 2.0 authors: Implications for assessment design and conduct. *Australasian Journal of Educational Technology*, 26(1), 105-122. https://doi.org/10.14742/ajet.1105
- Grunspan, D.Z., Wiggins, B.L., & Goodreau, S.M. (2014). Understanding classrooms through social network analysis: A primer for social network analysis in education research. *CBE-Life Sciences Education*, 13(2), 167-178. https://doi.org/10.1187/cbe.13-08-0162
- Grützmann, A., Zambalde, A.L., & De SouzaBermejo, P.H. (2016). Internet Technologies and Innovation: A Framework Based on the Study of Brazilian Companies. In *Handbook of Research on Information Architecture and Management in Modern Organizations* (pp. 256-273). IGI Global. https://doi.10.4018/978-1-4666-8637-3.ch012
- Hansen, D.L., Shneiderman, B., Smith, M.A., & Himelboim, I. (2020). Analyzing Social Media Networks With Node XL Insights from a Connected World (Second Edition). Elsevier. https://doi.org/10.1016/C2018-0-01348-1
- Haythornthwaite, C. (2008). Learning relations and networks in web-based communities. *International Journal of Web Based Communities*, 4(2), 140-158. https://doi.org/10.1504/IJ WBC.2008.017669

- Holmes, K. (2005). Analysis of asynchronous online discussion using the SOLO Taxonomy. *Australian Journal of Educational & Developmental Psychology*, 5, 117-127.
- Hopkins, M. (2017). A Review of social network analysis and education: Theory, methods, and applications. *Journal of Educational and Behavioral Statistics*, *42*(5), 639-646. https://doi.org/10.3102/107699861769811
- Hu, C., &Racherla, P. (2008). Visual representation of knowledge networks: A social network analysis of hospitality research domain. *International Journal of Hospitality Management*, 27(2), 302-312. https://doi.org/10.1016/j.ijhm.2007.01.002
- Jan, S.K., & Vlachopoulos, P. (2019). Social network analysis: A framework for identifying communities in higher education online learning. *Technology, Knowledge and Learning*, 24(4), 621-639. https://doi.org/10.1007/s10758-018-9375-y
- Kasim, N.N.M., & Khalid, F. (2016). Choosing the right learning management system (LMS) for the higher education institution context: A systematic review. *International Journal of Emerging Technologies in Learning*, 11(6), 55-61. https://doi.org/10.3991/ijet.v11i06.5644
- Khan, B.H. (1998). Web-based instruction (WBI): An introduction. *Educational Media International*, 35(2), 63-71. https://doi.org/10.1080/0952398980350202
- Krippendorff, K. (2004). *Content analysis: An introduction to its methodology*. Thousand Oaks. Sage.
- Kuznetcova, I., Glassman, M., & Lin, T.J. (2019). Multi-user virtual environments as a pathway to distributed social networks in the classroom. *Computers & Education*, 130, 26-39. https://doi.org/10.1016/j.compedu.2018.11.004
- Lee, J., & Bonk, C.J. (2016). Social network analysis of peer relationships and online interactions in a blended class using blogs. *The Internet and Higher Education*, 28, 35-44. https://doi.org/10.1016/j.iheduc.2015.09.001
- Liebowitz, J. (2006). Keynotepaper: Developing knowledge and learning strategies in mobile organisations. *International Journal of Mobile Learning and Organisation*, 1(1), 5–14. https://doi.org/10.1504/IJMLO.2007.011186
- Lombard, M., Snyder-Duch, J., & Bracken, C.C. (2002). Content analysis in mass communication: Assessment and reporting of intercoder reliability. *Human communication research*, 28(4), 587-604.
- Lorenzo, C.M., Sicilia, M.Á., &Sánchez, S. (2012). Studying the effectiveness of multi-user immersive environments for collaborative evaluation tasks. *Computers & Education*, 59(4), 1361-1376. https://doi.org/10.1016/j.compedu.2012.06.002
- Markel, S.L., & Eci, E.E. (2001). Technology and education online discussion forums. Online Journal of Distance Learning Administration, 4. https://www.westga.edu/~distance/ojdla/s ummer42/markel42.pdf
- Martinez, A., Dimitriadis, Y., Rubia, B., Gómez, E., & De La Fuente, P. (2003). Combining qualitative evaluation and social network analysis for the study of classroom social interactions. *Computers & Education*, 41(4), 353-368. https://doi.org/10.1016/j.compedu.20 03.06.001
- Martono, F., & Salam, U. (2017). Students' learning in asynchronous discussion forums: A meta-analysis. *International Journal of Information and Communication Technology Education (IJICTE)*, 13(1), 48-60. https://doi.org/10.4018/IJICTE.2017010105
- Molenda, M., &Januszewski, A. (2013). Educational technology: A definition with commentary. Routledge.
- Moolenaar, N.M. (2012). A social network perspective on teacher collaboration in schools: Theory, methodology and applications. *American Journal of Education*, 119, 7-39. https://doi.org/10.1086/667715
- Moore, J.L., Dickson-Deane, C., &Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same?. *The Internet and Higher Education*, 14(2), 129-135. https://doi.10.1016/j.iheduc.2010.10.001

- Msonde, S.E., & Van Aalst, J. (2017). Designing for interaction, thinking and Academic achievement in a Tanzanian undergraduate chemistry course. *Educational Technology Research and Development*, 65, 1389-1413. https://doi.10.1007/s11423-017-9531-4
- Norman, H., Nordin, N., Yunus, M.M., &Ally, M. (2018). Instructional design of blended learning with MOOCs and social network analysis. *Advanced Science Letters*, 24(11), 7952-7955. https://doi.org/10.1166/asl.2018.12464
- Özdemir, O. & Keser, N. (2019). A network analysis of the comparison of social networking role of students in learning environments. *Turkish Journal of Educational Studies*, 6(2), 1-30. https://doi.org/10.33907/turkjes.559160
- Page, M.J., Moher, D., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., ..., McKenzie, J.E. (2021). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *BMJ 2021*, 372. https://doi.org/10.1136/bmj.n 160
- Palonen, T., & Hakkarainen, K. (2014). Social network analyses of learning at workplaces. In Discourses on professional learning: On the boundary between learning and working (pp. 293-315). Springer.
- Parks-Stamm, E.J., Zafonte, M., &Palenque, S.M. (2017). The effects of instructor participation and class size on student participation in an online class discussion forum. *British Journal* of Educational Technology, 48(6), 1250-1259. https://doi.org/10.1111/bjet.12512
- Scott, J. (2000). Social Network Analysis: A handbook. Sage.
- Shu, H., &Gu, X. (2018). Determining the differences between online and face-to-face student– group interactions in a blended learning course. *The Internet and Higher Education*, 39, 13-21. https://doi.org/10.1016/j.iheduc.2018.05.003
- Sie, R.L., Ullmann, T.D., Rajagopal, K., Cela, K., Bitter–Rijpkema, M., & Sloep, P.B. (2012). Social network analysis for technology-enhanced learning: Review and future directions. *International Journal of Technology Enhanced Learning*, 4(3), 172-190. https://doi.org/10. 1504/IJTEL.2012.051582
- Somyürek & Güyer (2020). Social Network Analysis. G. Tüyer, Y. Halil, Yıldırım, S. (Ed.). *In Educational data mining and learning analytics* (pp. 329-375). Anı Publishing.
- Sosa, S. (2022). Social network analysis. J. Vonk & T.K. Shackelford (Eds). *In Encyclopedia of animal cognition and behavior* (pp. 6527-6544). Springer International Publishing.
- Srichanyachon, N. (2014). EFL learners' perceptions of using LMS. *Turkish Online Journal of Educational Technology-TOJET*, 13(4), 30-35.
- Thelwall, M. (2008). Bibliometrics to webometrics. *Journal of Information Science*, 34(4), 605-621. https://doi.org/10.1177/0165551507087238
- Vázquez-Cano, E., Martín-Monje, E., &Castrillo de Larreta-Azelain, M.D. (2016). Analysis of PLEs' Implementatio nunder OER Design as a Productive Teaching-Learning Strategy in Higher Education. *Digital Education Review*, 29, 62-85.
- Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. Cambridge, Cambridge University.
- We are Social (2020). *Digital in 2020*. https://wearesocial.com/blog/2020/01/digital-2020-3-8-billion-people-use-social-media
- Zhang, K., & Aslan, A.B. (2021). AI Technologies for education: Recent research & future directions. Computers and Education: *Artificial Intelligence*, *2*, 100025. https://doi.org/10.1 016/j.caeai.2021.100025

APPENDIX

| No | Name of Study | Name of Author(s) | Name of the Journal | Year |
|-----|--|-------------------------------------|-----------------------|------|
| 1 | 'Seeing' the learning community: An | Dawson | British Journal of | 2010 |
| | exploration of the development of a resource | | Educational | |
| 2 | for monitoring online student networking | | Technology | 2010 |
| 2 | Exploratory study on the patterns of online | Heo, Lim & Kim | Computers & | 2010 |
| | project-based learning | | Education | |
| 3 | Patterns of interaction during rounds: | Walton & Steinert | Medical Education | 2010 |
| - | implications for work-based learning | | | |
| 4 | Measuring creative potential: Using social | Dawson, Tan & | Australasian Journal | 2011 |
| | network analysis to monitor a learners' | McWilliam | of Educational | |
| 5 | creative capacity | U | Technology | 2012 |
| 3 | Multidimensional Analysis of Math and | Hora & Ferrare | Journal of the | 2012 |
| | Science Undergraduate Course Planning and | | Learning Sciences | |
| | Classroom Teaching | | | |
| 6 | Studying the effectiveness of multi-user | Lorenzo, Sicilia & | Computers & | 2012 |
| | immersive environments for collaborative | Sanchez | Education | |
| 7 | evaluation tasks | Diantias Hamándaz | Journal of Studios in | 2012 |
| / | Divisions in Developing Social Learning | Nanclares Jindal- | International | 2012 |
| | Relations in the Classroom | Snape & Alcott | Education | |
| 8 | Expanded Markers of Success in | Goertzen, Brewe & | International Journal | 2013 |
| | Introductory University Physics | Kramer | of Science Education | |
| 9 | Online Learner Self-Regulation: Learning | Shea, Hayes, Uzuner | The International | 2013 |
| | Presence Viewed through Quantitative | Smith, Vickers, | Review of Research in | |
| | Content- and Social Network Analysis | Bidjerano, Gozza- | Open and Distributed | |
| | | Wilde & Tseng | Leanning | |
| 10 | Peer tutoring with the aid of the Internet | Evans & Moore | British Journal of | 2013 |
| | 0 | | Educational | |
| | | | Technology | |
| 11 | Understanding social learning relations of | Rienties, Heliot & | Higher Education | 2013 |
| | international students in a large classroom | Jindal-Snape | | |
| 12 | Collaboration and Social Networking in | Gewerc, Montero & | Media Education | 2014 |
| | Higher Education | Compostela | Research Journal | 2011 |
| 13 | Communication patterns in massively open | Gillani & Eynon | Internet and Higher | 2014 |
| | online courses | 2 | Education | |
| 14 | How media choice affects learner interactions | Thoms & Eryılmaz | Computers & | 2014 |
| | in distance learning classes | | Education | |
| 15 | Investigating value creation in a community | Cowan & Menchaca | Distance Education | 2014 |
| | of practice with social network analysis in a | | | |
| 1.6 | hybrid online graduate education program | | | 0014 |
| 16 | Personal learning environments, higher | Casquero, Ovelar, | Culture and Education | 2014 |
| | the effects of service multiplexity on | Romo & Demo | | |
| | undergraduate students' personal networks | | | |
| 17 | The effect of social interaction on learning | Lu & Churchill | Interactive Learning | 2014 |
| | engagement in a social networking | | Environments | |
| 10 | environment | D' | | 2014 |
| 18 | 10 Let Students Self-Select or Not: That Is the Question for Teachers of Culturally | Kienties, Alcott, & Jindal-Snape | JOUTHAL OF STUDIES IN | 2014 |
| | Diverse Groups | Jinuar-Shape | Education | |
| 19 | Understanding (in)formal learning in an | Rienties & Kinchin | Teaching and Teacher | 2014 |
| | academic development programme: A social | | Education | |
| | network perspective | | | |

| 20 | Understanding Classrooms through Social Network Analysis: A Primer for Social Network Analysis in Education Research | Grunspan, Wiggins & Goodreau | Life Sciences Education | 2014 |
|----|--|--|--|------|
| 21 | Using social networking environments to support collaborative learning in a Chinese university class: Interaction pattern and influencing factors | Lu & Churchill | Australasian Journal of Educational Technology | 2014 |
| 22 | Analysis of Social Worker and Educator's Areas of Intervention Through Multimedia Concept Maps And Online Discussion Forums In Higher Education | Vázquez-Cano, López Meneses & Sánchez-Serrano | Electronic Journal of e-Learning | 2015 |
| 23 | Exploring the nature of teacher-student interaction in small-group discussions in a Chinese university setting | Li, Zheng, Tang & Sang | Journal of Computers in Education | 2015 |
| 24 | Exploring the Roles of Social Participation in Mobile Social Media Learning: A Social Network Analysis | Norman, Nordin, Din, Ally & Doğan | International Review of Research in Open and Distributed Learning | 2015 |
| 25 | Study of the influence of social relationships among students on knowledge building using a moderately constructivist learning model | Alonso, Manrique, Martinez & Vines | Journal of Educational Computing Research | 2015 |
| 26 | The influence of relationship networks on academic performance in higher education: a comparative study between students of a creative and a non-creative discipline | Toma´s-Miquel, Exposito-Langa & Nicolau-Julia | Higher Education | 2015 |
| 27 | Unpacking (in)formal learning in an academic development programme: a mixed- method social network perspective | Rienties, Bart, Hosein & Anesa | International Journal for Academic Development | 2015 |
| 28 | An Analysis of Density and Degree- Centrality According to the Social Networking Structure Formed in an Online | Ergun & Koçak Usluel | Educational Technology & Society | 2016 |
| 29 | Analysis of Discussion Board Interaction in an Online PeerMentoring Site | Ruane & Lee | Online Learning | 2016 |
| 30 | Analysis of PLEs' implementation under OER design as a productive teaching- learning strategy in Higher Education. A case study at Universidad Nacional de Educacion a Distancia | Vázquez-Cano, Martín-Monje & Larreta-Azelain | Digital Education Review | 2016 |
| 31 | Collaboration Levels in Asynchronous Discussion Forums: a Social Network | Luhrs & McAnally- Salas | Journal of Interactive Online Learning | 2016 |
| 32 | Influence of learning styles on social structures in online learning environments | Cela, Scilia & Sánchez-Alonso | British Journal of Educational Technology (BIET) | 2016 |
| 33 | Predicting Peer Nominations Among Medical Students: A Social Network Approach | Michalec, Grbic, Veloski, Cuddy & Hafferty | Academic Medicine | 2016 |
| 34 | Social network analysis of peer relationships and online interactions in a blended class using blogs | Lee & Bonk | Internet and Higher Education | 2016 |
| 35 | Toward evidence-based learning analytics: Using proxy variables to improve asynchronous online discussion | Kim, Park, Yoon & Jo | Internet and Higher Education | 2016 |
| 36 | Beyond students' perceptions: investigating learning presence in an educational blogging | Jimoyiannis & Tsiotakis | Journal of Applied Research in Higher Education | 2017 |
| 37 | Building a Sustainable Quality MattersTM Community of Practice Through Social Network Analysis | Cowan, Richter, Miller, Rhode, Click & Underwood | American Journal of Distance Education | 2017 |
| | | | | |

| 38 | Designing for interaction, thinking and academic achievement in a Tanzanian undergraduate chemistry course | Msonde & Van Aalst | Educational Technology Research and Development | 2017 |
|----|--|--|---|------|
| 39 | Exploring collaborative learning effect in blended learning environments | Sun, Liu, Luo, Wu & Shi | Journal of Computer Assisted Learning | 2017 |
| 40 | Making the most of "external" group members in blended and online environments | Hernández- Nanclares, García- Muñiz & Rienties | Interactive Learning Environments | 2017 |
| 41 | Moving Beyond Smile Sheets: A Case Study on the Evaluation and Iterative Improvement of an Online Faculty Development Program | Chen, Lowenthal, Bauer, Heaps & Nielsen | Online Learning | 2017 |
| 42 | The influences of an experienced instructor's discussion design and facilitation on an online learning community development: A social network analysis study | Ouyang & Scharber | Internet and Higher Education | 2017 |
| 43 | Three interaction patterns on asynchronous online discussion behaviours: A methodological comparison | Park & Lee | Journal of Computer Assisted Learning | 2017 |
| 44 | A tale of two communication tools: Discussion-forum and mobile instant- | Sun, Lin, Wu, Zhou & Luo | British Journal of Educational | 2018 |
| 45 | Building a Community of Transformation and a Social Network Analysis of the POGIL | Shadle, Liu, Lewis & Minderhout | Innovative Higher Education | 2018 |
| 46 | Determining the differences between online and face-to-face student–group interactions | Shu & Gu | The Internet and Higher Education | 2018 |
| 47 | Enhancing (in)formal learning ties in interdisciplinary management courses: a | Rienties & Héliot | Studies in Higher Education | 2018 |
| 48 | Facilitating critical thinking in asynchronous online discussion: comparison between peer- | Oh, Huang, Mehdiabadi & Ju | Journal of Computing in Higher Education | 2018 |
| 49 | Fostering student engagement in online discussion through social learning analytics | Chena, Changa, Ouyanga, & Zhou | The Internet and Higher Education | 2018 |
| 50 | Identifying online communities of inquiry in higher education using social network analysis | Jan | Research in Learning Technology | 2018 |
| 51 | Just plain peers across social networks: Peer- feedback networks nested in personal and academic networks in higher education | Dingyloudi & Strijbos | Learning, Culture and Social Interaction | 2018 |
| 52 | Turning Groups Inside Out: A Social Network Perspective | Rienties & Tempelaar | Journal of the Learning Sciences | 2018 |
| 53 | Understanding the development of interest and self-efficacy in active-learning | Dou, Brewe, Potvin, Zwolak & Hazari | International Journal of Science Education | 2018 |
| 54 | What learning analytics tells us: group behavior analysis and individual learning diagnosis based on long-term and large-scale data | Zhang, Zhang, Zou & Huang | Educational Technology & Society | 2018 |
| 55 | A sociocultural approach to using social networking sites as learning tools | Borge, Ong & Goggins | Education Technology Research and Development | 2019 |
| 56 | Detecting Topics Of Chat Discussions In A Computer Supported Collaborative Learning (CSCL) Environment | Afacan Adanır | Turkish Online Journal of Distance Education | 2019 |
| 57 | Developing learning relationships in intercultural and multidisciplinary environments: a mixed method investigation of management students' experiences | Héliot, Mittelmeier & Rienties | Studies in Higher Education | 2019 |

| 58 | Examining undergraduate student retention in mathematics using network analysis and relative risk | Woolcott, Chamberlain, Whannell & Gallig |
|----|--|--|
| 59 | How Widely Can Prediction Models Be Generalized? Performance Prediction in Blended Courses | Gitinabard, Xu, Heckman, Barnes Lynch |
| 61 | and peer influence relate to knowledge and use of evidence-based teaching practices It is about timing: Network prestige in | Chen & Huang |
| 01 | asynchronous online discussions | enen er mung |
| 62 | Multi-user virtual environments as a pathway to distributed social networks in the classroom | Kuznetcova, Glassman & Lin |
| 63 | Social Network Analysis: A Framework for Identifying Communities in Higher | Jan & Vlachopoul |
| 64 | Studying STEM Faculty Communities of Practice through Social Network Analysis | Ma, Herman, Wes Tomkind & Mestre |
| 65 | The peer interaction process on Facebook: a social network analysis of learners' online conversations | Peeters |
| 66 | When Does Collaboration Lead to Deeper Learning? Renewed Definitions of | Ellis, Han & Pardo |
| 67 | Campus Connections: Student and Course Networks in Higher Education | Israel, Koester & McKay |
| 68 | Exploring Social Network Structure Patterns Suitable to the Community of Inquiry Model Moderated by the Task | Tirado-Morueta, Lopez, Rodriguez |
| 69 | How do students conceptualise the college internship experience? Towards a student centred approach to designing and implementing internships | Hora, Parrott & He |
| 70 | Learner participation regulation supported by long-term peer moderation and participation feedback during asynchronous discussions | Gaul & Kim |
| 71 | Social Capital in Higher Education Partnerships: A Case Study of the Canada– | Larsen & Tascon |
| 72 | Study Habits and Attainment in Undergraduate Mathematics: A Social | Alcock, Martinez, Patel & Sirl |
| 73 | Teacher Presence in a Different Light: Authority Shift in Multi-user Virtual | Kuznetcova, Lin & Glassman |
| 74 | The role of social annotation in facilitating collaborative inquiry-based learning | Chan & Pow |
| 75 | To design or to integrate? Instructional design versus technology integration in developing learning interventions | Kale, Roy & Yuan |

| Woolcott, Chamberlain, Whannell & Galligan | International Journal of Mathematical Education in Science | 2019 |
|--|--|------|
| Gitinabard, Xu, Heckman, Barnes & Lynch | IEEE Transactions On Learning Technologies | 2019 |
| Lane vd. | International Journal of STEM Education | 2019 |
| Chen & Huang | Journal of Computer Assisted Learning | 2019 |
| Kuznetcova, Glassman & Lin | Computers & Education | 2019 |
| Jan & Vlachopoulos | Technology, Knowledge and | 2019 |
| Ma, Herman, West, Tomkind & Mestre | The Journal of Higher Education | 2019 |
| Peeters | Education and Information | 2019 |
| Ellis, Han & Pardo | IEEE Transactions On Learning | 2019 |
| Israel, Koester & McKay | Innovative Higher Education | 2020 |
| Tirado-Morueta, Lopez, Rodriguez & Gomez | Journal of Educational Computing Research | 2020 |
| Hora, Parrott & Her | Journal of Education and Work | 2020 |
| Gaul & Kim | Journal of Computers in Education | 2020 |
| Larsen & Tascon | Higher Education Policy | 2020 |
| Alcock, Martinez, Patel & Sirl | Journal for Research in Mathematics | 2020 |
| Kuznetcova, Lin & Glassman | Technology, Knowledge and | 2020 |
| Chan & Pow | Learning Computers & Education | 2020 |
| Kale, Roy & Yuan | Educational Technology Research and Development | 2020 |