The Latest Research Trends of Teaching & Learning in Higher Education by Leveraging Advanced technology and Big data

Young-Eun Park (ypark@psu.edu.sa)
Prince Sultan University

Research

Keywords: Teaching/Learning Strategies, Trends, Higher Education, Big Data, Semantic network analysis

DOI: https://doi.org/10.21203/rs.3.rs-41427/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.  Read Full License
Abstract

Digital transformation in higher education has had a transformative effect on modern education. It means transforming an institutional core value of education to better meet students’ needs by leveraging digital technology and big data. Accordingly, this study aims to catch the principal directions, trends, or new paradigms as predictors with a linkage of each topic by identifying the latest research agendas of teaching and learning in higher education through semantic network analysis. For this, 285 research articles from four international ‘top-tier’ journals ranked as ISI/SCOPUS Q1 were gathered in the area of teaching and learning in higher education for two years in 2018 ~ 2019, and then it was analyzed using a text mining technique that processes natural language. Consequently, the study of researches on teaching and learning shows a relatively high connection with ‘student’ or ‘student-centered/led’ rather than ‘teacher-led’. Moreover, it is observed that the practice and assessment of learning can be achieved through various activities including community activities. Besides that, experience-based classes, research in academic contexts, the effect of group activities, how students’ perceptions or feelings and relationships affect learning outcomes were mentioned as the main topics through topic modeling of LDA, a machine learning algorithm. This study proposes that educators, researchers, and academic leaders can exert the remarkable power to reshape the educational programs for future quality education properly and a timely fashion based on recognizable trends or topics in teaching and learning of higher education.

1. Introduction

Digital transformation in higher education covers many things from using digital tools such as LMS (Learning Management System), Interactive whiteboard, etc. in university classrooms to digitizing university documents, and so on. However, it does not just involve in utilizing tools. The change can be more profound and deep, incorporating whole aspects of education, although there is an initial resistance to new technologies, mainly because some are continually changing (u-planner, 2020). Besides, we need to consider that no matter what has happened to us in the past or what is going on in our lives; there is no power to keep us from having an unknown future with high uncertainty. This is why we should be aware of the latest trends or changing circumstances around us or within our campus environments. Accordingly, efforts to look at trends or predict a new paradigm based on historical data in teaching and learning has been around for a long time in the various educational sectors of higher education (Ausubel, 1968; Elton & Laurillard, 1979; Entwistle, 1973; Evans, 1968). In particular, main issues, which have traditionally started from finding trends about students’ learning (Entwistle, 1973; Guri-Rozenblit, 1991) are expanding into teaching and learning broadly (Fryer & Bovee, 2020; Henderson, Selwyn & Aston, 2015; Tierney, 2019), furthermore, now into research and development (Barrie, & Prosser, 2002; Choi, 2017; Elton & Laurillard, 1979; Executive Core, 2015; Foster, 2019; Kim, 2015; Maxwell, 2019; Nikitina & Lapina, 2017; Nomuoja, 2010; OECD 2010; 2019). Moreover, previous studies favored measuring the achievement or improvement of curriculum in higher education and measuring the outcomes to fulfill the highest standards (Angelo, 1996; Angelo and Cross, 1993; Banta, Land, Black and Olander, 1996; Bragg, 1995). Besides that, past research trends that studied various factors affecting students’ learning attitudes and learning outcomes have been extended to various areas of research. Those comprehensively connect diverse educational issues and teaching and learning methods, for example, new techniques such as flipped learning, blended learning, and any interactive ways to maximize the effectiveness of education. (Biggs, 2001; Churchill, 1982; Park, 2009; Pitan & Muller, 2019; Price & Kirkwood, 2014; Shen & Ho 2020; Yilmaz & Keser, 2016; Zainuddin & Halli, 2016). Furthermore, there is an ever-increasing range of connections with various stakeholders around education, management and administration of higher education, policy and leadership (Bauer & Henkel, 1997; Bok, 2003; Marginson & Considine, 2000; OECD, 2007; World Bank, 2002).
Thus, recognizing the latest issues or trends of how teaching and learning in higher education have conducted in research has a remarkable meaning to reflect the present and previous studies and seek desirable directions in the development of future education (Barrie, & Prosser, 2002; Choi, 2017; Executive Core, 2015; Foster, 2019; Kim, 2015; Maxwell, 2019; Nikitina & Lapina, 2017; Nomuoja, 2010). Consequently, various researchers in diverse educational sectors have shown many distinguished studies related to this topic with different perspectives to keep up with the most popular and the latest educational trends. However, the most studies are independent studies based on a specific situation or context rather than grasping the overall educational flow. And most of them were investigated with qualitative and subjective methods through surveys and interviews (such as focus group interview) or reviews of scientific publications (such as articles or books, courses syllabus, etc.) to gather non-numerical data manually. Although this qualitative research approach provides obvious implications and contributions comprehensively for understanding and exploring the totality of an educational situation or a phenomenon in higher education, it is a study confined to individual conditions or specific circumstances independently. Moreover, there is a potential to create subjective judgments or arguments when applying for different occasions or environments (Nikitina & Lapina, 2017; Nomuoja, 2010). Therefore, this study aims to supplement the limitations of those existing studies and pays attention to grasping the recent general flow of teaching and learning through big data. By identifying the latest teaching and learning trends in higher education through semantic network analysis, a text mining technique using big data of unstructured texts, this study catches the key directions and main topics including the linkage of each topic. Finally, this research can provide a wealth of insights to guide educators, researchers, and academic leaders in higher education in terms of quality education in the face of rapidly changing educational trends, dynamic environments, and the different needs or pressures of diverse stakeholders around higher education.

2. Literature Review

2.1. Researches on teaching and learning in Higher Education

Past or present, critical issue to higher education lies in teaching and learning. Based on this, different agendas from a wide variety of perspectives (e.g., educational administration or management) are gradually evolving. However, we need to go back to the fundamentals and focus on the central subject of teaching and learning (Biggs, 2001; Churchill, 1982; Jarvenoja, Lalley, Houston, & Gasteen, 2018; Naykki, & Tormanen, 2019; Park, 2009; Pitan & Muller, 2019; Price & Kirkwood, 2014; Shen & Ho 2020; Yilmaz & Keser, 2016; Wood, Galloway, Sinclair, & Hardy, 2018; Zainuddin & Halili, 2016). Traditionally, education has focused on finding the various matters surrounding the students and the role of teachers to examine the effects of learning and the factors that influence it, that is, to find cause and effect in teaching and learning (Elton, 1977; Elton & Laurillard, 1979; Entwistle, 1973). This has progressed into an in-depth discussion of how psychological factors, such as students’ perceptions, feelings, or relationships with teachers, influence learning outcomes (Jarvenoja, Naykki, & Tormanen, 2019; Martin, Wang, & Sadaf, 2018; Xing, Tang, & Pei, 2019). What is more, many studies examined how various demographical factors such as gender, race, and income level of families affect students’ learning or its outcomes (Chevalier, 2011; Lalley, Houston, & Gasteen, 2018; Kelly, O’Connell, & Smyth, 2010; Strauss & De La Maisonneuve, 2009). In addition to this approach, attention was paid to the teachers’ point of view to find out more effective ways for teaching, and what new teaching methods were being developed and used, and how those methods worked. Flipped learning, blended learning, online learning, or interactive learning using various technology tools or simulation game: these are the most recently adopted teaching methods (Foster, 2019; Heilstra, & Siguroardottir, 2017; Hilliard, & Stewart, 2019; Iniguez, 2015; Lomer & Anthony-Okeke, 2019; Wood, Galloway, Sinclair, & Hardy, 2018).
Other endeavors have been made to find general trends in teaching and learning with a holistic perspective (Deng, Benckendorff, & Gannaway, 2019; Elton & Laurillard, 1979; Foster, 2019; Guri-Rozenblit, 1991; Henderson, Selwyn & Aston, 2015; Kim, 2015; Maxwell, 2019; Nikitina & Lapina, 2017; Nomuoja, 2010). Deng, Benckendorff, & Gannaway (2019) focused on identifying trends and categorizing the study on Massive Open Online Courses in teaching and learning. Elton & Laurillard (1979) sought to find research trends in students’ learning and discover new research paradigms. They analyzed the trends to uncover the determinants of how humans learn, the differences among individuals in human learning, how content elements affect learning, and how contextual factors affect learning. Guri-Rozenblit (1991) reviewed and analyzed four books that can use to examine trends in learning. Based on this, he defined the definitions of distance education and open education. He covered a wide range of free public / distance systems, course design, advanced technology, and delivery systems, student support and survival issues, and lastly, inter-university and inter-institutional collaboration issues. Henderson, Selwyn & Aston (2015) studied students’ perceptions of useful digital technologies in teaching and learning in the university, which has an online education or interactive education through an online system. It is attracting attention as research that captures the transforming the nature of university education. Nikitina & Lapina (2017) proposed that recent business education trends were organized into three categories: a curriculum that meets the desire of society and business, partnership & networking, and a modern and flexible teaching method in their research. Besides, new forms of teaching and learning, including blended learning, interactive learning, and flipped learning, have addressed by many scholars (Heilstra, & Siguroardottir, 2017; Hilliard, & Stewart, 2019; Lomer & Anthony-Okeke, 2019; Wood, Galloway, Sinclair, & Hardy, 2018). Besides that, a large number of studies have mainly concentrated on the numerous factors or trends affecting educational development and management (Foster, 2019; Kim, 2015; Maxwell, 2019; Nikitina & Lapina, 2017; Nomuoja, 2010). For instance, Nomuoja (2010) studied the current trends emerging in business schools of higher education. Consequently, career awareness, risk management, people-oriented strategy and its management, and skills-based curriculum were mainly discussed. Moreover, there are interviews results from global top MBA schools to discover major MBA trends such as ‘growing trend of double degrees’, ‘growth acceleration of online or technology-based education and blended learning in business education (Iniguez, 2015; Foster, 2019; Maxwell, 2019).

However, despite the fact that a substantial amount of research work has been done with the broad and varied perspectives on teaching and learning, most of them were independent studies, which are investigated based on a specific situation or context rather than grasping the overall educational flow or trends. Moreover, there is still a lack of research that looks at the global direction of such research more objectively and quantitatively using big data. Thus, this study began to fill in the gap of these existing studies.

2.2. Semantic Network Analysis using big data of the unstructured text

We live in an age where everything is uncertain and rapidly changing (Levine, 2019; Kim & SNU Consumer Trend Analysis Center, 2019; Park, 2019). The best way to cope with this uncertain and unknown future is to predict and prepare for the future based on a variety of historical big data by reducing this prediction error. In this regard, people focus on using big data to read trends and prepare for the unknown future. This substantial phenomenon is well represented in diverse and separate research fields as well. Many scholars in a very different area are working actively to discover insights into big data using various data mining techniques (Doerfel, 1998; Kharlamov, Gradoselskaya, & Dokuka, 2018; Shneiderman & Aris, 2006; Steyvers & Tenenbaum, 2005; Park & Alenezi, 2018; Park, 2019; Yoon & Park, 2007; Yun & Park, 2018). Due to the breakthrough technology, we can deal with big data or data sets, which are too complex or large to be dealt with by traditional data-processing approaches. In particular, it
became possible to analyze a large amount of unstructured text data through text mining, one of the data mining techniques, as linguistic techniques have developed and applied to diverse areas (Wright, 2018).

A morphological or semantic network analysis deals with dividing a sentence into the smallest meaningful unit of language, namely, morphemes by importing unstructured text data such as speeches, comments, or posting in social media like Twitter, Instagram, or any bibliographic information (for example, books, scholarly articles, records, interviews, etc.) (Doerfel, 1998; Drieger, 2013; Kharlamov, Gradoselskaya, & Dokuka, 2018; Nulty, 2017, Park, 2019; Yun & Park, 2018). It automatically extracts words in sentences, paragraphs, and documents to make it simple to construct a word-to-word network according to the degree of nearness or adjacency between words (Atteveldt, 2008; Kharlamov, Gradoselskaya, & Dokuka, 2018). Based on that, network structures provide intuitive and beneficial illustrations for modeling semantic inference and knowledge (Steyvers & Tenenbaum, 2005). Through this, we can comprehend the relationship among words or understand their association by combining topics through proper interpretations in a given text (Rice & Danowski, 1991; Cyram NetMiner, 2019; Steyvers & Tenenbaum, 2005). The more commended, the larger the size of the morpheme or word. Then, it can be seen at first sight, as it were, to visually stress major issues or agendas such as keywords in unstructured documents to extract key attributes, mainly in big data that manages a large amount of information (Lambert, 2017). Nodes in a semantic network mean words, and links are word-to-word adjacency relationships (Nulty, 2017). Until recently, network analysis required data structured by nodes and ties ahead of time, and the subsequent processes were performed by individual programs, which required plenty of human efforts and time. However, for now, with the development of state-of-the-art technology, natural language processing is built into data mining programs, which can directly enter unstructured text data and extract words (nodes) in morphological units and create network data encompassing words. This broadens the horizon of network analysis with massive unstructured text data (Cyram NetMiner, 2019; Kim, Choi, & Youm, 2017). Accordingly, a large number of scholars has ripened into a semantic network analysis as a powerful tool of text mining in numerous ways since Rice & Danowski (1991) built a basic framework for network analysis (Doerfel, 1998; Monge & Eisenberg, 1987; Rice & Danowski, 1991; Stohl, 1993).

The purpose of analyzing text using text mining is very diverse. It is possible to read between the lines in which the document intends to deliver by reassembling the text. Also, by visually grasping the relationship between the main concepts and other keywords in the text, it is possible to understand various types of networks. Through this, it is achievable to analyze the roles of words and their relationships by recognizing the word associations. One of the biggest advantages of text mining is to analyze the words both qualitatively and quantitatively.

Additionally, it uses to visualize or illustrate the relationship between objects or people in text and topic modeling as well (Kharlamov, Gradoselskaya, & Dokuka, 2018; Nulty, 2017). For this, a large amount of information can efficiently and effectively utilize to generate more comprehensive and extended knowledge, analytical reasoning, and even explorative analysis, which is the final goal of text analysis (Cyram NetMiner, 2019; Drieger, 2013). With those benefits of this approach, many scholars have discussed various topics with different perspectives using big data. Many scholars and observers have found huge opportunities and tremendous potentials of semantic network analysis with recognizing centrality indicators between words and sub-network structures of words (Lee, Choi, & Kim, 2010; Rice, 2005; Wasserman & Faust, 1994). Many of those studies exhibit the possibility of the ongoing development of the semantic networks as a powerful research tool emerging with the advent of the big data era. In particular, semantic network analysis is used in research to study teaching and learning in higher education. Shen & Ho (2020) showed the importance of technology-enhanced learning (TEL) through a semantic approach as an inspired way to improve the outcomes of teaching and learning in high education. Kim (2015) determined the study trends of music education using the semantic network analysis, and Lee (2016) analyzed the research trends in the
area of journalism, pursuing the key words of the abstract of research articles published in 2005-2015 through semantic network analysis, then, finally established knowledge system as a result. Besides that, Kim, Choi, & Youm (2017) applied semantic network analysis to draw significant agenda of the opinions on nursing care service by extracting data from online news and social media data. Recently, Park (2019) took the data of news media and social media to compare the trends from the two different kinds of big data sources to predict the sustainability of leading Korean companies.

Based on those previous studies, this research aims to investigate the most recent research issues and trends of teaching and learning in higher education through semantic network analysis. Using a large amount of unstructured text data, we can effectively and efficiently discover trendy insights and directions of future education in teaching and learning and, furthermore, in research (Doerfel, 1998; Shneiderman & Aris, 2006; Steyvers & Tenenbaum, 2005). Accordingly, it expects to generate subsequent development of knowledge and intuition to comprehend a new paradigm of future education in general, which is just around the corner. It would be very constructive and beneficial to educators, researchers, and even academic leaders and administrative leaders in higher education.

2.3. Proposed research framework

In order to pinpoint major agendas and trends in teaching and learning of higher education, semantic network analysis, which is a data mining technique, was used in this study. Accordingly, there is no theoretical framework with hypotheses in this study as the data-driven approach is used in this paper. This data-driven methodology became an extraordinarily capable and promising area. A huge amount of information reserved in electronic and digital records on the internet brings tremendous opportunities and impacts remarkably for knowledge discovery, information extraction, and analytical reasoning in education fields (Doerfel, 1998; Monge & Eisenberg, 1987; Wright, 2018). Thus, this empowers one to extract important algorithmic properties that give powerful intuitions and insights into the structure of networks and graphs (Steyvers & Tenenbaum, 2005; Zaki & Meira, 2014). As previous literature shows, a researcher can collect big data from various sources such as news channels and social media, search engines, other financial reports, etc. (Park, 2019). In this study, the data gathered for analysis through search engines. Figure 1 shows the proposed framework of this study with a holistic approach.

This study attempts to determine the most recent research agendas or trends of the leading higher education journals about teaching and learning in 2018 and 2019 through semantic network analysis. As the global trend is changing very fast, this study emphasizes teaching and learning in the last two years. For this purpose, the following research questions were established.

(1) What are the main trends or agendas of teaching and learning in higher education in the last two years?

(2) What are the key attributes of teaching and learning in higher education, and what are the implications of this?

(3) How are the specific sub-domains (topic modeling) of teaching and learning in higher education categorized as future education strategies?

3. Data Collection And Method
This study aims to identify the most recent educational trends, and predict future directions or shifts by recognizing the main issues of teaching and learning in Higher education. For that, the data collected from 285 research articles of four international ‘top-tier’ journals ranked as ISI/SCOPUS Q1 in this field for two years (2018~2019) with some selection criteria: ISI/SCOPUS reputed publishers / open-access journals, and international peer-reviewed journals. Then, semantic network analysis, a powerful and compelling technique in a significant data era, used to extract patterns or directions with uncovering data-empowered insights. Consequently, 587 unique keywords, 1743 sentences, and 285 paragraphs and documents were identified in 285 abstracts of research articles through the program of NetMiner4’s semantic network analysis.

### Table 1
The list of journals selected along with selection criteria fulfillment

| No | Journal Name                      | Journal Quartile | Publisher (Annual Issues) | ISI/SCOPUS | Reputed publishers / Open-access journals | International Peer-reviewed |
|----|-----------------------------------|------------------|---------------------------|------------|------------------------------------------|----------------------------|
| 1  | Active Learning in Higher Education | Q1               | Sage Publications         | ✓          | ✓                                       | ✓                          |
| 2  | Studies in Higher Education       | Q1               | Taylor & Francis          | ✓          | ✓                                       | ✓                          |
| 3  | Teaching in Higher Education      | Q1               | Taylor & Francis          | ✓          | ✓                                       | ✓                          |
| 4  | Internet and Higher Education     | Q1               | Elsevier BV               | ✓          | ✓                                       | ✓                          |

Source: Scimago ([www.scimagijr.com](http://www.scimagijr.com)) and each journal website below

1) Active Learning in Higher Education ([https://journals.sagepub.com/loi/alha](https://journals.sagepub.com/loi/alha))

2) Studies in Higher Education ([https://www.tandfonline.com/toc/cshe20/current](https://www.tandfonline.com/toc/cshe20/current))

3) Teaching in Higher Education ([https://www.tandfonline.com/toc/cthe20/current](https://www.tandfonline.com/toc/cthe20/current))

4) Internet and Higher Education ([https://www.sciencedirect.com/journal/the-internet-and-higher-education/issues](https://www.sciencedirect.com/journal/the-internet-and-higher-education/issues))

## 4. Results And Discussion

This study’s first objective is to determine the most studied topics in the field of teaching and learning in higher education over the last two years in 2018 and 2019. For this, the top 20 keywords were selected through the process of semantic network analysis among 587 keywords appearing in 285 abstracts of research papers in four top journals related to the issues of teaching and learning in 2018 ~ 2019. The result is as shown in table 2.
According to the results of this study, the main 'top 20' keywords of teaching and learning in higher education covered the topics of 'students-centered or student-led learning' rather than teacher-led, in addition to that, research, experience, group, development, practice, and engagement are identifiable. Especially, the word 'student' composed 7.11% of the total 797 times as a leading keyword showing the highest frequency, and it follows by study, learning, education, research, university, and experience. They were 2.97%, 2.41%, 2.04%, 1.81%, 1.81%, and 1.18%, respectively. In this study, a directional link (Directed Network) based on the 'Binary Network', which does not weight the connecting line, was created. Here, the frequency of a node is an amount defined for each node and means the number of connection lines of each node that exists as a neighbor. In-degree refers to the number of edges coming towards a vertex in a directed graph; out-degree refers to the number of arcs directed away from the vertex. Although table 2 shows the keywords in the top 20 ranks, it is observed that few keywords in the top and the other keywords show a great difference in the number of nodes in- and out-degree. Accordingly, for the detailed view at a glance,

| Rank | Word   | Frequency (%) | In-Degree | Out-Degree | Rank | Word   | Frequency (%) | In-Degree | Out-Degree |
|------|--------|---------------|-----------|------------|------|--------|---------------|-----------|------------|
| 1    | student| 797 (7.11%)   | 144       | 141        | 11   | practice| 124 (1.11%)   | 20        | 12         |
| 2    | study  | 333 (2.97%)   | 55        | 39         | 12   | teaching| 103 (0.92%)   | 18        | 20         |
| 3    | learning| 270 (2.41%)  | 33        | 52         | 13   | result  | 102 (0.91%)   | 20        | 11         |
| 4    | education| 228 (2.04%)  | 34        | 28         | 14   | finding | 99  (0.88%)   | 14        | 13         |
| 5    | research| 203 (1.81%)  | 40        | 35         | 15   | analysis| 98  (0.87%)   | 20        | 11         |
| 6    | university| 203 (1.81%) | 33        | 29         | 16   | approach| 94  (0.84%)   | 6         | 12         |
| 7    | experience| 132 (1.18%) | 12        | 14         | 17   | process | 83  (0.74%)   | 10        | 11         |
| 8    | course  | 128 (1.14%)   | 21        | 20         | 18   | teacher | 83  (0.74%)   | 12        | 12         |
| 9    | group   | 127 (1.13%)   | 20        | 19         | 19   | development| 81 (0.72%) | 8         | 15         |
| 10   | paper   | 126 (1.12%)   | 21        | 8          | 20   | engagement| 80 (0.71%)  | 9         | 14         |
word cloud was created to check the quantitative importance of each keyword. Then, it considered the relationship and features of keywords in more detail through network map and topic modeling. Word Cloud is a visualization tool that illustrates the size of letters according to the importance of keywords. Based on that, we can notice the difference between relatively meaningful words, in brief, to understand how much difference is there. In this study, the word cloud node attributes were used to display information as frequency and a large number of words by entering the maximum number of words as 100. The result of the word cloud is as follows.

Meanwhile, the word-to-word network was visualized with a network map to understand the data analysis results intuitively. This means that the network data is calculated and arranged according to the program of NetMiner’s layout algorithm. A layout algorithm is a method of calculating where to place nodes to visualize network data. Among representative methods, Spring Layout was chosen as it can show the connection structure most effectively. Spring layout can be expressed by various algorithms such as Kamada & Kawai, Stress Majorization, and Clustered Eades, Fruchterman & Reingold, GEM, HDE, etc.

Among them, Kamada & Kawai, Stress Majorization, and Eades were chosen as these algorithms fit the need for data analysis and representation, then compared them as preliminary work to consider the number of various cases of subtopic extraction inherent in a given text. In this study, the isolated nodes are shown at the edge of the network map and visualized comparing the ‘Kamada & Kawai,’ ‘Stress Majorization,’ and ‘Clustered Eades’ network maps deselecting isolated nodes. The layout of the analysis results is as follows.

After importing unstructured data, a 2-mode network between words and sentences/paragraphs/documents generated in the program of NetMiner transforms into the keyword-keyword 1-mode system of the research presented in the major journals about teaching and learning. Here’s a look at the detailed layout with keywords from the three core types of network maps.
Table 3  
Top 20 Word Network

| Rank | Source       | Target     | TF-IDF (Weight) | # of Sentences/Paragraphs/Documents | Gini Coefficient |
|------|--------------|------------|-----------------|-------------------------------------|------------------|
| 1    | student      | experience | 28              | 22                                  | 0.9              |
| 2    | learning     | environment| 26              | 19                                  | 0.9              |
| 3    | case         | study      | 26              | 22                                  | 0.9              |
| 4    | student      | engagement | 25              | 13                                  | 1                |
| 5    | university   | student    | 25              | 22                                  | 0.9              |
| 6    | student      | perception | 24              | 16                                  | 1                |
| 7    | student      | learning   | 22              | 18                                  | 0.9              |
| 8    | study        | student    | 22              | 22                                  | 0.9              |
| 9    | learning     | student    | 20              | 18                                  | 0.9              |
| 10   | education    | institution| 17              | 17                                  | 0.9              |
| 11   | teaching     | learning   | 16              | 12                                  | 1                |
| 12   | student      | course     | 16              | 13                                  | 1                |
| 13   | student      | university | 16              | 14                                  | 1                |
| 14   | education    | student    | 15              | 15                                  | 0.9              |
| 15   | experience   | student    | 13              | 13                                  | 1                |
| 16   | student      | staff      | 12              | 9                                   | 1                |
| 17   | learning     | experience | 11              | 11                                  | 1                |
| 18   | learning     | process    | 11              | 9                                   | 1                |
| 19   | student      | teacher    | 11              | 6                                   | 1                |
| 20   | focus        | group      | 11              | 11                                  | 1                |

In the NetMiner program, a 1-mode network generates by using word-to-word distance information. In this study, the nearness of two words was calculated, and based on that, a method of creating links between words located close together was used. The number of words included when setting the link generation range between words is called ‘Window Size.’ In this study, the maximum of 3 words were included in the link generation range by entering Window Size as 3. Links create between words according to the Window Size set as above, and the two linked words are displayed as Source and Target, respectively.

The term of TF (Term Frequency) describes above indicates how often a particular word appears in a document. It means the higher the value, the more critical the word. However, a term that is commonly used (for example, do) may have a high TF value even though it is not an important word. To avoid this, we can measure how many documents
appear in a text by Document Frequency (DF). In conclusion, TF-IDF (Inverse Document Frequency) provides information to determine how valuable a word is in a particular document based on word frequency and document frequency. The value of weight in general marks the TF-IDF. This TF-IDF score is calculated as follows.

\[ W_{i,j} = tf_{i,j} \times \log\left( \frac{N}{df_i} \right) \]

\( tf_{i,j} \) = number of occurrences of \( i \) in \( j \)

\( df_i \) = number of documents containing \( i \)

\( N \) = total number of documents

Weight is the link frequency of generated word pairs, meaning that the words of 'student' and 'experience' have a weight of 28, and the word pair appears 28 times in the entire text. # of Sentences / Paragraphs / Documents is the number of sentences / paragraphs / documents in which the word pair appears. In this study, the word pair of 'learning' and 'environment' appeared 26 times, with a weight of 26 and # of documents of 19. Gini Coefficient is an indicator of how concentrated the word pair is intensely in a few sentences, paragraphs, and documents. It is also how evenly it appears in multiple sentences, paragraphs, and documents. A value closer to 1 means that the more focused it is on a few sentences, paragraphs, and documents, the more important the word pair is. In this case, the criterion for sentences, paragraphs, and documents is a co-occurrence unit selected when creating a 1-mode network.

Lastly, the method of LDA (Latent Dirichlet Allocation), which is a machine learning algorithm, was used to extract subtopics embedded in the text (Steyvers and Griffiths, 2007). Latent Dirichlet Allocation is the most popular and influential topic model, a method for analyzing a broad set of unstructured documents. The basic idea is that unstructured documents are represented as a topic distribution where each topic is characterized by a word distribution (Cyram NetMiner, 2019; Steyvers and Griffiths, 2007).

We can denote \( p(z_i | d_i) \), \( p(w_i | z_i) \) as the topic distribution for each document \( i \) and the word distribution for a topic allocated to \( j \)th word of document \( i \), respectively. In the learning phase, LDA fits \( p(z_i | d_i) \), \( p(w_i | z_i) \) to a pair of documents (i.e., a document-by-word sparse matrix). Given these distributions, the LDA can generate a new document with the following generative process (Cyram NetMiner, 2019):

\[
\text{for } j^{\text{th}} \text{ word in the } i^{\text{th}} \text{ document:}
\]

Choose a topic \( z_{i,j} \sim \text{Multinomial} \left( p(z | d_i) \right) \)

Choose a topic \( w_{i,j} \sim \text{Multinomial} \left( p(w | z_{i,j}) \right) \)
For each topic, the top nodes from the main nodes show in the table below. Moreover, this table shows the number of nodes and probability included for each topic, when the classification labels of nodes in a Subnodeset are assigned to the topic that maximizes the topic proportion from 'SubNode'.

| Topic  | 1st Keyword  | 2nd Keyword  | 3rd Keyword  | 4th Keyword  | 5th Keyword  | # of documents |
|--------|--------------|--------------|--------------|--------------|--------------|----------------|
| Topic-1| learning     | practice     | assessment   | activity     | community    | 226            |
|        | (0.113)      | (0.037)      | (0.034)      | (0.028)      | (0.023)      |                |
| Topic-2| student      | university   | experience   | classroom    | staff        | 199            |
|        | (0.149)      | (0.085)      | (0.049)      | (0.016)      | (0.01)       |                |
| Topic-3| research     | paper        | supervisor   | context      | academic     | 198            |
|        | (0.099)      | (0.045)      | (0.023)      | (0.023)      | (0.02)       |                |
| Topic-4| education    | approach     | institution  | system       | study        | 188            |
|        | (0.114)      | (0.036)      | (0.019)      | (0.014)      | (0.012)      |                |
| Topic-5| group        | result       | participant  | student      | effect       | 182            |
|        | (0.071)      | (0.038)      | (0.024)      | (0.023)      | (0.016)      |                |
| Topic-6| skill        | knowledge    | model        | performance  | role         | 174            |
|        | (0.039)      | (0.037)      | (0.029)      | (0.027)      | (0.026)      |                |
| Topic-7| student      | study        | emotion      | challenge    | perception   | 164            |
|        | (0.09)       | (0.082)      | (0.032)      | (0.025)      | (0.021)      |                |
| Topic-8| student      | analysis     | relationship | strategy     | feedback     | 154            |
|        | (0.085)      | (0.035)      | (0.032)      | (0.025)      | (0.024)      |                |
| Topic-9| student      | study        | course       | outcome      | case         | 132            |
|        | (0.073)      | (0.066)      | (0.048)      | (0.026)      | (0.019)      |                |
| Topic-10| teaching    | finding      | teacher      | student      | practice     | 126            |
|         | (0.048)      | (0.04)       | (0.034)      | (0.028)      | (0.027)      |                |

MainNode (it is a Keyword) and SubNode (it is a Document) show probability information about which topic to associate. By using this method, we can figure out that the more similar the values of the response variables are, the more likely they are to contain compatible subjects. In contrast, the more significant the differences between them, the more likely they are to include different topics. The results of the top 3-topic modeling, according to the # of documents, show as follows. The main subject of the first topic can be interpreted that practice and assessment of learning can be achieved through various activities and community activities. The second topic suggests that students’ college education can also achieve through experience-based classes as staff. Third, the supervisor's
research may indicate that topics in academic contexts can be addressed. In addition to that, several issues were revealed as uprising topics through the topic modeling of LDA. For example, a system-based education, the results or effects of group activity, how skills and knowledge can play a critical role in performance models, and how students’ perceptions or feelings can affect learning outcomes, relationships with students and their feedback that could be analyzed in developing learning strategies, learning outcomes using cases, and finding teaching strategies through students and teachers’ practice.

5. Implication And Conclusion

This study aspires to grasp the latest research agendas and academic trends in teaching and learning with the keywords of major international journals in higher education through semantic network analysis. Consequently, it turns out that this study obviously provides educators, researchers, and academic leaders with data-empowered insights and identifiable future agendas such as trend-based teaching and learning, research as well in higher education. In this regard, the significant implications of this study were outlined as follows.

First of all, traditionally, ‘teacher-centered’ or ‘teacher-led’ education in teaching and learning was the central theme of higher education in the past. A teacher or instructor mainly focused on delivering entire contents from his or her side to students unilaterally. However, now, the paradigm is wholly changed into ‘student-centered’ or ‘student-led’ education. Then, various issues such as learning, education, research, and experience that follow incidentally are broken down and spread to diverse subjects. This study is firmly reflected in this modern paradigm or educational trend by showing the result of analysis in a big data quantitatively and qualitatively. Furthermore, this research result will play a critical role in reshaping educational environments and key perspectives on teaching and learning.

Secondly, the world is changing faster than ever; accordingly, it is not easy to follow up on the current educational trends in higher education by mastering whole agendas. Most academic members in there are not adapting as quickly to keep them up-to-date in the double loop with strategic agility. Given that, this study allows us to identify the current flow of education and the educational issues to be followed at a glance. To best support this current situation, this study focused on the most recent two years of research data, rather than looking at old data such as ten or twenty-year past data. The results of this study are also observed and supported by experts who study trends. Thus, this research contributes to reflect best the current educational situations in teaching and learning of higher education.

Lastly, the method of semantic network analysis, a data-driven approach used in this paper, may shed light on the development of new techniques using the machine learning algorithm to get the whole picture of a new paradigm or shift in higher education. It proves that this method is a very compelling and effective tool to understand the key attributes of current flow and network map in teaching and learning thoroughly by extracting main issues and associated sub-topics. In this regard, this study enhances a more objective view of the actual educational reality and phenomena through big data and machine learning models.

Meanwhile, although this research suggests several noteworthy and critical implications, there are still some limitations to be improved below. This will address in future research.

First, in this study, 285 scholarly articles from the top-ranked international journals related to teaching and learning in 2018~2019 were gathered and analyzed to recognize the most recent research agendas and trends. Although it intended to see only up-to-date data given that the trend is changing quickly, however, it is a fact that studies using
huge data improve the results, the level of validity, and reliability of analysis in general, and it still works in the academic world. Accordingly, future research is needed to collect more research data by increasing the number of articles on teaching and learning.

Next, approaching individually or together with a holistic perspective in various education sectors such as law, engineering, business, computer science, or any other studies in higher education is worth doing for future research. The discovery and comparison of the most recent issues or keywords on teaching and learning in each field of higher education will help drive innovation and change in teaching and learning. Furthermore, it encourages academic leaders, more senior or higher management teams to have effective leadership by realizing the trend-based education and following up the directions in the future.

Last, although semantic network analysis or semantic mining technique performs quantitatively statistical, logical, and rule-based analysis of semantic networks of graph structures and qualitatively, the research method still leaves room for consideration. In the past, traditional network analysis techniques analyzed physical world relationships simply based on distance (such as centrality), strength, and direction, etc. However, recently network analysis has been developed continuously. The giant network is continually forming and flowing subsequent knowledge as large as 1: N link for real-time communication through social media such as Snapchat, Instagram, and YouTube, etc. Thus, it should notice that recent network analysis is very complicated, like the social network web with a huge amount of data flowing through the network structure. Also, it is necessary to derive and analyze sub-networks aiming to the purpose of use to apply them to diverse sectors by reflecting those attributes of a network into the research world.

Declarations

Availability of data and material

The data supporting the findings of this study are openly available in four journals (Active Learning in Higher Education, Studies in Higher Education, Teaching in Higher Education, and Internet and Higher Education) at https://journals.sagepub.com/loi/alha, https://www.tandfonline.com/toc/cshe20/current, https://www.tandfonline.com/toc/cthe20/current, https://www.sciencedirect.com/journal/the-internet-and-higher-education/issues respectively. These data were derived from the articles of each journal in the public domain.

Competing Interest (Disclosure statement)

The author reported no potential conflict of interest.

Funding

Not applicable

(This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.)

Author’s contributions

The author confirms the sole responsibility for this manuscript fully as a single author for the following:
study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Acknowledgements

Not applicable

(No funding to declare.)

References

1. Atteveldt, W. V. (2008). *Semantic Network Analysis: Techniques for Extracting, Representing, and Querying Media Content*. BookSurge Publishers, Charleston SC.

2. Angelo, T.A. (1996). Transforming assessment: High standards for higher learning. *AAHE Bulletin*, April, 3 - 4.

3. American Assembly of Collegiate Schools of Business (AACSB) (1996). *Achieving quality and continuous improvement through self-evaluation and peer review. Accreditation Handbook of the American Assembly of Collegiate Schools of Business*, St Louis, MO.

4. Ademola, O. (2000). Strategies for reducing the financial constraints of business education. *Nigerian educational system Business Education Journal, 3*(3).

5. Arain, F.M & Tipu, S.A.A. (2007). Emerging trends in management education. *International business schools*. J. Educ. Res and Rev. 2 (12), 325 -331.

6. Ausubel, D. P. (1968). *Educational Psychology: A Cognitive View* (London, Holt, Rhinehart & Winston).

7. Azuka, A.R. (2000). Career opportunities in business education. *Nigeria Business Education Journal. 111*(3).

8. Banta, T., Land, J., Black, K. & Olander, F. (1996). *Assessment in practice: Putting principles to work on college campuses*, Jossey - Bass, San Francisco, CA.

9. Barrie, S.C., & Prosser, M. (2002). *Aligning research on student learning with institutional policies and practices on evaluation and quality assurance*, Paper presented at the 11th ISL Conference, Brussels, 4-6 September.

10. Bauer, M., & Henkel, M. (1997). Responses of Academe to Quality Reforms in Higher Education: A Comparative Study of England and Sweden, *Tertiary Education and Management, 3*(3), 211-228.

11. Blei, D., Ng, A. & Jordan, M. (2003). Latent Dirichlet allocation, *Journal of Machine Learning Research, 3*:993-1022.

12. CABS (2019). *The changing shape of business education provision*. Chartered Association of Business Schools, March 2019. Carringtoncrisp. Charteredabs.org.

13. Cyram NetMiner (2019). *NetMiner Semantic Network Analysis Manual*. Cyram. Retrieved from https://www.NetMiner.Com

14. Deng, R., Benckendorff, P., & Gannaway, D. (2019). Progress and new directions for teaching and learning in MOOCs. *Computers & Education, 129*, 48-60.

15. Doerfel, M. L. (1998). What constitutes semantic network analysis? A Comparison of Research and Methodologies. *Connections, 21*(2), 16-26.

16. Edwards, D.E. & Brannen, D.E. (1990). Current status of outcomes assessment at the MBA level. *Journal of Educational Business, 65*(1), 206-212.

17. Elton, L. R. B., & Laurillard, D. M. (1979). Trends in research on student learning. *Studies in Higher Education, 4*(1), 87-102. https://doi.org/10.1080/03075077912331377131
18. Entwistle, N.J. (1973). *Complementary paradigms for research and development work in higher education*, Conference of the European Association for Research and Development in Higher Education, Rotterdam.

19. Executive Core (2015). *Future Trends in Business Education*. Summer 2015. Executive Core, LLC.

20. Foster J. (2019). *Key Trends Influencing Graduate Business Education in 2019*. Retrieved from https://www.mba.com/article-and-announcements/articles/why-business-school/key-trends-influencing-graduate-business-education-in-2019

21. Guri-Rozenblit, S. (1991). Distance/Open Learning-trends and developments as reflected in recent literature. *Studies in Higher Education, 16*(1), 83-90.

22. Heilstra, T. M., & Siguroardottir, M. S. (2017). The flipped classroom: Does viewing the recordings matter? *Active Learning in Higher Education, 19*(3), 211-223. https://doi.org/10.1177/1469787417723217

23. Henderson, M., Selwyn, N., & Aston, R. (2017). What works and why? Student perceptions of ‘useful’ digital technology in university teaching and learning. *Studies in Higher Education, 42*(8), 1567-1579, https://doi.org/10.1080/03075079.2015.1007946

24. Iniguez, S. (2015). Major trends in business education. MBA Journal. 2015 12:16. Retrieved from https://www.mba -journal.de/major-trends-in-business-education/

25. Kharlamov, A., Gradoselskaya, G., & Dokuka, S. (2018). Dynamic Semantic Network Analysis of Unstructured Text Corpora. *Lecture Notes in Computer Science book series* (LNCS, volume 10716), 392-403.

26. Kim, H. M. (2015). Analysis of Research Trends of South Korean Music Education through Semantic Network Analysis. *Korean Journal of Research in Music Education, 44*(4), 49~68.

27. Kim, N. D., & SNU Consumer Trend Analysis Center (2019). *Trends Korea 2020*. Futuristic window (Milaeui Chang): Seoul, Korea.

28. Kim, M., Choi, M., & Youm, Y. (2017). Semantic Network Analysis of Online News and Social Media Text Related to Comprehensive Nursing Care Service. *Journal of Korean Academy of Nursing, 47*(6), 806-816, http://doi.org/10.4040/jkan.2017.47.6.806.

29. Lee, S., Choi, J. H., and Kim, H.W. (2010). Semantic network analysis on the MIS research keywords: APJIS and MIS Quarterly 2005-2009. *Asian Pacific Journal of Information System, 20*(4), 25-51.

30. Levin, D. (2019). Trends in Technology: How we work, live and consume. USA Trends Day Keynote. Retrieved from https://www.daniellevine.com/

31. Lomer, S. & Anthony-Okeke, L. (2019). Ethically engaging international students: student generated material in an active blended learning model. *Teaching in Higher Education, 24*(5), 613-632. https://doi.org/10.1080/13562517.2019.1617264

32. Martin, F., Wang, C. & Sadaf, A. (2018). Student perception of helpfulness of facilitation strategies that enhance instructor presence, connectedness, engagement and learning in online courses. *The Internet and Higher Education*. 37. 52-65. https://doi.org/10.1016/j.iheduc.2018.01.003

33. Maxwell, S. (2019). *Top 3 MBA Trends in 2019*. Hiperpool. Retrieved from https://hiperpool.com/blog/top-3-mba-trends.

34. Nikitina, T. & Lapina I. (2017). Overview of Trends and Developments in Business Education, *The 21st World Multi-Conference on Systemics, Cybernetics and Informatics: WMSCI 2017*, Vol.2, USA, Orlando

35. Nomuoja, J.O. (2010). *Current trends in business education in higher institutions*. www.globalacademicgroup.com
36. Nulty, P. (2017). Semantic Network Analysis of Contested Political Concepts. *International Conference on Computational Semantics (IWCS 2017)*, Retrieved from http://www.aclweb.org/anthology/W/W17/#6800
37. OECD (2019). *Trends Shaping Education 2019 Spotlight 18 Play!* OEDC Publishing, Paris.
38. Park, S. Y. (2009). An analysis of the Technology Acceptance Model in understanding university students’ behavioral intention to use e-Learning. *Educational Technology & Society, 12*(3), 150–162.
39. Park, Y. E. (2019). Data Empowered Insights for Sustainability of Korean MNEs. *Journal of Asian Finance, Economics and Business, 6*(3), 173-183. doi:10.13106/jafeb.2019.vol6.no3.173
40. Pitan, O.S. & Muller, C. (2019). University reputation and undergraduates’ self-perceived employability: mediating influence of experiential learning activities. *Higher Education Research & Development, 38*(6), 1269-1284. https://doi.org/10.1080/07294360.2019.1634678
41. Price, L., & Kirkwood, A. (2014). Using technology for teaching and learning in higher education: A critical review of the role of evidence in informing practice. *Higher Education Research and Development, 33*(3), 549–564. https://doi.org/10.1080/07294360.2013.841643.
42. Rice, R. E., & Danowski, J. A. (1991). *Comparing comments and semantic networks about voicemail.* Proceedings of the American Society for Information Science, 28, 134-138.
43. Shen, C. W. & Ho, J. T. (2020). Technology-enhanced learning in higher education: A bibliometric analysis with latent semantic approach. *Computers in Human Behavior 104*. https://doi.org/10.1016/j.chb.2019.106177
44. Shneiderman, B., & Aris, A. (2006). Network visualization by semantic substrates. *IEEE Transactions on Visualization and Computer Graphics, 12*(5), 733-740.
45. Steyvers, M. & Tenenbaum, J.B. (2005). The large-scale structure of semantic networks: Statistical analyses and a model of semantic growth. *Cognitive science, 29*(1), 41-78.
46. Tierney, A. (2020). The scholarship of teaching and learning and pedagogic research within the disciplines: should it be included in the research excellence framework?. *Studies in Higher Education, 45*(1), 176-186. https://doi.org/10.1080/03075079.2019.1574732
47. Wood, A., Galloway, R. K., Sinclair, C., & Hardy, J. (2018). Teacher-student discourse in active learning lectures: case studies from undergraduate physics. *Teaching in Higher Education, 23*(7), 818-834. https://doi.org/10.1080/13562517.2017.1421630
48. Wright, J. (2018). Methodology Review, Part2: Text Mining and Semantic Network Analysis. Retrieved from https://jaredmwr.wordpress.com/2018/03/13/methodology-review-part-2-text-mining-and-semantic-network-analysis/
49. Xing, W., Tang, H., & Pei, B. (2019). Beyond positive and negative emotions: Looking into the role of achievement emotions in discussion forums of MOOCs. *The Internet and Higher Education. 43*. https://doi.org/10.1016/j.iheduc.2019.100690
50. Yun, E. & Park, Y. (2018). Extraction of scientific semantic networks from science textbooks and comparison with science teachers’ spoken language by text network analysis. *International Journal of Science Education. 40*(17), 2118-2136. https://doi.org/10.1080/09500693.2018.1521536
51. Zainuddin, Z., & Halili, S. H. (2016). Flipped classroom research and trends from different fields of study. *International Review of Research in Open and Distance Learning, 17*(3), 313–340.
52. Zaki, M. J., & Meira W. (2014). *Data Mining and Analysis: Fundamental Concepts and Algorithms.* London, LD: Cambridge University Press.
Figures

Figure 1

The proposed framework of this study

Figure 2

Word Cloud of Top 100 keywords
Figure 3

Layout after deselecting isolated nodes (Kamada & Kawai vs. Stress Majorization vs. Eades)

Figure 4

The detailed layout view of network maps