Heliyon 10 (2024) e28107

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

A social network analysis of college students' online learning during the epidemic era: A triadic reciprocal determinism perspective

Jun Chai [a], Jian-Hong Ye [b,c,*]

[a] Department of Public Physical Education, Ningbo University of Finance and Economics, Ningbo, China
[b] Faculty of Education, Beijing Normal University, Beijing, China
[c] National Institute of Vocational Education, Beijing Normal University, Beijing, China

ARTICLE INFO

Keywords:
Data science applications in education
Distance education
Learning experience
Online learning
Teaching/learning strategies

ABSTRACT

The way in which college students learn online has dramatically altered due to the COVID-19 pandemic. Using the triadic reciprocal determinism (TRD) theory, this study aimed to identify the key factors influencing college students' online learning experience through sentiment analysis, text mining, and social network analysis (SNA). Macro- and micro-level parsing was conducted on the SNA model, which was divided into core, mantle, and shell layers to determine the most influential factors in the core layer. This study found that learners' personal factors, learning behaviors, and related elements in the online learning environment significantly influenced the learning outcomes of college students enrolled in online courses. Additionally, this study explored the distribution of SNA model elements in the mantle and peripheral shell layers, which also impact the online learning experience of college students. Overall, this study provides a comprehensive overview of the various factors affecting college students' online learning experience, and highlights the importance of considering these factors when designing online learning environments for college students.

1. Introduction

1.1. Background

The COVID-19 pandemic has had and will continue to have a huge impact on the way the world works. Distance learning is extremely important and is now as important as face-to-face learning [1]. The outbreak has raised serious concerns for education systems worldwide. National efforts to curb COVID-19 led to unplanned school closures in more than 100 countries worldwide [2]. Due to the epidemic, university students relied on online learning platforms to continue their studies, and online learning platforms have since been recognized as an irreplaceable tool for emergency education [3]. The COVID-19 pandemic has created opportunities for large-scale experimentation with online courses in university settings [4]. During the home quarantine caused by the epidemic, all teaching became virtual, testing the sustainability of education systems [5].

Online learning can provide support for students and schools, and can create unique opportunities under emergency management

* Corresponding author. No.19, Xinjiekouwai St, Haidian District, Beijing, 100875, China.
E-mail addresses: chaijun@nbufe.edu.cn (J. Chai), kimpo30107@hotmail.com (J.-H. Ye).

https://doi.org/10.1016/j.heliyon.2024.e28107
Received 11 February 2023; Received in revised form 6 March 2024; Accepted 12 March 2024

[6]. Higher education institutions must ensure inclusive, equitable, and quality education that bridges the digital divide and promotes sustainable activities [5].

The current understanding of students' online learning experiences during the pandemic reveals several key findings. Firstly, students' perceptions of emergency remote teaching changed over time, with three stages of online learning identified [7]. Factors that facilitated effective online learning included student-content interaction, strong teacher support, and a high level of digital inclusion [8]. Conversely, lack of interaction with teachers and peers has been cited as a barrier to online learning [9]. Additionally, student engagement in virtual learning was identified as a major challenge for teachers, with various strategies and theories explored in the literature [10]. The literature also examined the impact of prior online learning experiences on the successful completion of online coursework, highlighting the potential influence of these experiences on students' adaptability during the pandemic [11]. Additionally, students' resources and skills play a significant role in their online learning experiences, with positive and negative aspects identified. The challenges faced by students included lack of physical touch, solitary learning, and technological issues.

As the epidemic transitions to a post-pandemic era and teaching gradually returns to the classroom, the primary issue that still requires attention is emergency education readiness. The second most important issue is to help universities build online learning resources that can be applied sustainably, which is also a topic that many governments and education scholars are focusing on. Therefore, if we can provide suitable decision-making methods, we should be able to help learners successfully carry out online learning.

Online distance education requires a significant investment in the planning phase, and emergency distance learning can serve as a temporary supplement to external crises [12]. Some scholars view educational technology as a neutral facilitation tool to deliver content online, and a contextually rich longitudinal study can reveal the impact of time on distance learning [13].

When exploring the innovative design of big data approaches, there are opportunities to apply relevant models to the design of big data-based learning environments to facilitate the online learning of information and knowledge in higher education settings [14]. Smart devices and smart technologies drive personalized and adaptive learning through smart learning environments, in line with the accelerating convergence of the two [15]. The three factors of self-directed learning, technology readiness, and motivation to learn have effects on the social, instructional, and cognitive presence of students studying subjects in blended and non-blended instructional settings [16].

Education based on technology-enhanced learning requires ongoing applications to support the transition from traditional learning space environments to web-based learning platforms. Factors such as Internet access and infrastructure contribute significantly to the challenge or level of adoption of digital technologies for education in higher education institutions [17]. The disruption caused by the pandemic has challenged the academic community, as faculty needed to become familiar with digital technology pedagogy and transfer their courses to online mode in a short period of time. Pedagogical approaches to technology-enhanced learning and teaching inform the development of blended and online learning in higher education [13].

Triadic reciprocal determinism is the idea that people generate environmental conditions that influence their behavior in a reciprocal manner, primarily through their behavior. From the interactive social learning perspective, known as a reciprocal deterministic process, triadic reciprocal determinism can be regarded as the interaction between individual behavior, personal factors and environmental challenges [18]. Therefore, within the framework of triadic reciprocal determinism (TRD) in social cognitive theory, a deterministic dynamic systems approach is proposed to model the interaction between individual behavior, personal factors, and environmental challenges [19].

Bandura's theoretical model suggests that individual behavior, cognition, emotion, biology, environmental events, and behavior are interconnected determinants that reciprocally influence each other [18,20]. This conceptual framework has had a profound impact on the social cognitive and self-efficacy theories that followed. Thus, the current study aimed to explore the relationship between learning and behavior, as well as the effect of environmental, behavioral, and personal factors on learning outcomes. Of these factors, self-efficacy is a crucial concept that pertains to an individual's beliefs and confidence in their ability to perform a task [21,22]. As noted in Bandura's model, learning is an ongoing process that involves information processing and can bring about changes in both behavior and thought patterns [20].

With the rapid shift to online education prompted by the COVID-19 pandemic, there has been an urgent need to adapt and comprehend online learning [23]. To address this, the research amalgamates Triadic Reciprocal Determinism (TRD) with Social Network Analysis (SNA), aiming to provide a more granular understanding of how individual behaviors, personal factors, and environmental contexts interact within online learning networks. The technical methodology of this study is multifaceted, involving advanced data acquisition, processing, and analysis techniques. By leveraging social network analysis (SNA), we propose a novel approach to explore how the interactions within educational networks influence learning outcomes. This reconstruction of TRD through an SNA model provides a unique lens to examine the complex interplay of personal factors, behavioral patterns, and environmental influences in online education.

Recognizing the limitations of traditional Social Network Analysis (SNA), our study seeks to advance the methodology by directly addressing these constraints. Traditional SNA, while groundbreaking, often grapples with data collection challenges, labor-intensive processes, and the absence of temporal and spatial dynamics. It may also impose arbitrary boundaries that neglect key participants or interactions, while subjective biases can skew the analysis and impede the generalization of results [24].

To overcome these issues, the research incorporates a temporal dimension into the SNA framework, offering a dynamic perspective that captures the evolution of social interactions over time. By integrating big data technologies, researchers are able to process massive amounts of information more efficiently and go beyond the traditional barriers to data collection.

The research method streamlines the acquisition of academic literature by utilizing a Python-based data crawler and the Zotero API for efficient exportation and database integration [25,26]. Following this, we conducted a comprehensive data preprocessing that included bibliometric analysis, data cleaning, deduplication, and annotation [27]. We then employed sentiment analysis and TF-IDF algorithms to extract sentiment scores and keywords, which are instrumental in discerning the central themes within the literature [28, 29], effectively merging qualitative insights with quantitative analysis in our research framework.

In the domain of learning, social network analysis models are extensively used to investigate interactions and information exchange among students. These models allow researchers to examine knowledge sharing and cooperative behavior among students, as well as to discern influential individuals and information dissemination pathways within a network [30]. Furthermore, social network analysis models are also useful in exploring social networks among students, and to investigate information transfer and influence dynamics among them [31]. Chen argues that the SNA model is an effective method for studying the network structure and interaction characteristics of MOOC forum discussions [32]. This model can depict the specifics of forum discussions and participants' interactive behaviours, providing important reference and guidance for MOOC teaching practice. SNA is an effective method for analysing instructor-student interactions in online courses. The degree and pattern of interaction and engagement may impact learning satisfaction or cognitive presence. The results of SNA analyses can help educational pedagogues better serve learners in the online classroom and course design [33].

Social network analysis models are also useful in studying the structure and dynamics of learning communities. For instance, experts have proposed the notion of "weak ties" to describe less close yet still cohesive interpersonal relationships within a learning community, such as those between students from different classes or majors. By scrutinizing weak ties, researchers can better understand their effects on learning communities [34]. Furthermore, the concept of "structural holes" has been introduced in related fields, describing interpersonal relationships that bridge different subgroups. These structural holes can enhance information flow and knowledge sharing, and are therefore essential to the functioning of learning communities [35].

Social network analysis models can be employed to investigate learners' behaviors and learning outcomes. SNA is an effective tool for analyzing instructor-student interactions and can enhance understanding of online classroom dynamics. The research shows that increased student interaction is positively linked to learning satisfaction, with cognitive presence serving as a mediating factor. Therefore, higher levels of interactive communication in online classrooms correlate with elevated learning satisfaction and cognitive presence [36]. By identifying the central figures within a learning group, researchers can examine their influence on learning behaviors and outcomes. One key indicator of influence is "centrality," which refers to nodes that occupy core positions within a social network. These nodes generally have access to more information and resources, as well as greater control over information transfer and influence [37]. Moreover, studies exploring the influence of homogeneity on social networks have revealed that individuals are more likely to connect with those who share similar characteristics. This homogeneity can also impact learners' learning behaviors and outcomes [38].

In summary, social network analysis models are a valuable tool for gaining insights into the structure, dynamics, behaviors, and outcomes of learning groups. Further research on the application of social network analysis in the field of learning could facilitate learners' development and improve their learning outcomes.

Social network analysis models and traditional statistical methods differ in terms of data structure, variable types, data types, and theoretical foundations. Social network analysis focuses on network structure and topological features, studying the location and association of nodes and edges, while traditional statistical methods pay attention to numerical variables, correlation properties, concentration trends, and variability within statistical datasets [39].

When it comes to data analysis and model building, social network analysis and traditional statistical methods exhibit notable differences. Although both methods can be useful for data analysis and modeling, social network analysis is better suited to analyzing intricate and large-scale network data. There are also discernible differences between social network analysis models and traditional statistical methods in terms of theoretical foundations, data types, fundamental characteristics, and analysis techniques. Although both techniques aim to explain and describe data entities, they adopt different approaches to achieve their objectives [39,40].

1.2. Study motivation

Past studies generally performed quantitative analysis of questionnaires and conducted interview-based qualitative research, while individual researchers performed meta-analyses of previous studies. The research data of these studies tended to be limited to a small number of databases. In this current study, social cognitive theory and the hybrid approach of big data analysis, text mining, sentiment analysis and social network analysis, as well as research modeling with a far greater number of big data equivalents were used to conduct an in-depth study of online education.

Exploring students' online learning triadic reciprocal interaction results through artificial intelligence techniques and big data mining was motivation I. This study explored the factors of college students' online learning as motivation II through text mining by using artificial intelligence and big data analysis based on the framework of triadic reciprocity theory. Through a mixture of big data, sentiment analysis and other research triadic reciprocity theoretical frameworks, as motivation III, this study examined the impact of ternary interactions and its core indicators in the elemental hierarchy of college students' online learning, which can be used to help teachers improve online education through a social network analysis model.

1.3. Study purposes

This study aimed to help solve research problems by using artificial intelligence and big data related techniques, and drew on theories related to TRD to explain the influencing factors of college students' online learning, to classify the hierarchy, and to produce the results. This new idea is proposed for the study of college students' online learning. The following purposes guided this study.

Factors and their underlying elements influencing college students' online learning were examined through the TRD theoretical framework. Specifically, this study endeavored to elucidate the interrelationships and impacts among factors associated with the research theme, aiming to comprehensively understand its intricate attributes, dominant trends, and prospective advancements. The online environment, learning behaviors, and learners of TRD in technology-enhanced learning in colleges and universities in the epidemic era affect the results of online learning, and the relevant results were analyzed using big data text mining techniques. Specifically, this study aimed to answer the following questions.

- RQ1 What are the influencing factors and elements of online learning for college students through the lens of the TRD theory, and what are the relevant elements of these and possible other factors?
- RQ2 What is the elemental hierarchy of the social network analysis model, and what is the relevant elemental content of the influencing factors?

2. Methodology

2.1. Data source

In this study, a big data bibliometric approach was employed; this is a commonly adopted method in social sciences research. This systematic approach involves synthesizing and analyzing existing literature to summarize research results and conclusions in related disciplines. Such a method enables researchers to efficiently comprehend the research progress and trends in a specific field, while also providing valuable insights and suggestions for future research.

This study drew on the theory of triadic reciprocal determinism (TRD) as its conceptual framework of this study to investigate the effect of personal, behavioral, and environmental factors on learning. Learning is defined as the process of acquiring knowledge and skillsets, which can be achieved through observing others' actions, practicing with feedback, and following instructions (Bandura, 1985) [20]. The TRD framework provides a comprehensive understanding of the multifaceted influences on learning. However, to further delve into the intricate dynamics of these influences, especially in an interconnected learning environment, this study performed social network analysis (SNA) as SNA can be used in conjunction with other research methods to provide a richer and more nuanced understanding of online learning dynamics [41].

Social network analysis models differ from traditional statistical methods in various ways, including data structure and analysis, variable types and measurement, data type and size, as well as theoretical foundation and research areas [39]. According to experts, two intuitive views of the core-edge structure are presented: the discrete model that divides the network into core and edge members with a high degree of social interaction and connectivity between core members, and the continuous model that divides the network into core, semi-edge, and edge tiers. The core tier is composed of members with high connectivity and mutual support, often valuable, influential, and prestigious individuals that play a vital role in the entire network. Therefore, core members are considered vital to the overall network. In terms of social network analysis models, the centrality measure is one of the core levels and indicates the importance of social network nodes. The edge level refers to non-core nodes in the social network, that is, nodes with lower centrality metrics values that determine the importance of social network nodes [39,42,43].

This study reconstructed the TRD theory through a social network analysis model, and incorporated big data mining techniques to explore college students' online learning. The TRD theory framework offers a novel perspective that can be leveraged with big data tools to gain deeper insights into the essential characteristics of online learning and its relationship with students' interactive behaviors. This study recognizes that data in the actual research process is more complex compared to traditional statistical methods. In many cases, data are power-law distributed, and individuals are not independent or mutually unaffected, rendering traditional statistical methods insufficient for calculation and measurement purposes.

This study searched for research-related literature published in academic journals through the Web of Science (WOS) Social Science Citation Index (SSCI) and Science Citation Index Expanded (SCIE) databases on August 15, 2022. The steps of the literature search with advanced search criteria are as follows:"((((((((((((((((((TS=(artifical intelligence)) OR TS=(machine intelligence)) OR TS=(intelligent support)) OR TS=(intelligent virtual reality)) OR TS=(chat bot*)) OR TS=(machine learning)) OR TS=(automated tutor*)) OR TS=(personal tutor*)) OR TS=(intelligent agent*)) OR TS=(expert system*)) OR TS=(neural network)) OR TS=(natural language processing)) OR TS=(chatbot*)) OR TS=(intelligent system)) OR TS=(intelligent tutor*)) AND TS=(college students)) OR TS=(university students)) AND TS=(covid-19)) AND TS=(online learning)) OR ALL=(technology-enhanced learning environments)" [44].

The WOS advanced search query consists of multiple components. TS=(artificial intelligence) searches for articles that contain "artificial intelligence" in the text field. The OR operator combines multiple search terms, allowing any of them to be selected if satisfied. TS=(machine intelligence) searches for articles with "machine intelligence" in the text field, while TS=(intelligent support) and TS=(intelligent virtual reality) search for articles with "intelligent support" and "intelligent virtual reality," respectively. TS=(chat bot*) searches for articles with keywords starting with "chat bot" in the text field. TS=(machine learning) searches for articles containing "machine learning," while TS=(automated tutor*) and TS=(personal tutor*) search for articles with keywords starting with "automated tutor" and "personal tutor," respectively. TS=(intelligent agent*) and TS=(expert system*) search for articles with keywords starting with "intelligent agent" and "expert system," respectively. TS=(neural network) searches for articles containing "neural network," while "TS=(natural language processing) searches for articles containing "natural language processing. TS=(intelligent system) searches for articles containing "intelligent system," while TS=(intelligent tutor*) searches for articles with keywords starting with "intelligent tutor."

TS=(college students) and TS=(university students) search for articles containing "college students" and "university students," respectively. TS=(covid-19) searches for articles containing “covid-19,” and TS=(online learning) searches for articles containing “online learning” in the text field. Finally, all components indicate that the articles to be searched for must contain “technology-enhanced learning environments.”

First search group: ((((((((((((((((((TS=(artificial intelligence)) OR TS=(machine intelligence)) OR TS=(intelligent support)) OR TS=(intelligent virtual reality)) OR TS=(chat bot*)) OR TS=(machine learning)) OR TS=(automated tutor*)) OR TS=(personal tutor*)) OR TS=(intelligent agent*)) OR TS=(intelligent agent*)) (expert system*)) OR TS=(neural network)) OR TS=(natural language processing)) OR TS=(chatbot*)) OR TS=(intelligent system)) OR TS=(intelligent tutor*)

Multiple OR operators are used in the search; any condition between these operators will be selected when satisfied. TS = indicates a search for articles that contain a keyword or phrase in the text field. Keywords included in the text search are: artificial intelligence, machine intelligence, intelligent support, intelligent virtual reality, chat bot*, machine learning, automated tutor*, personal tutor*, intelligent agent*, expert system*, neural network, natural language processing, chatbot*, intelligent system, intelligent tutor*.

The second search group: AND (((TS=(college students)) OR TS=(university students)) AND TS=(covid-19)) AND TS=(online learning).

The AND operator indicates that two or more search criteria must be satisfied at the same time, and returns articles that contain all of the keywords. With the OR operator, any article that includes one of these operators can be selected. The OR operator concatenates the following conditions: college students, university students. The AND operator indicates that both the preceding and following search conditions must be met for the search to be successful. The following conditions must be satisfied at the same time: covid-19, online learning.

The third search group: OR ALL=(technology-enhanced learning environments)

The searched article will be returned if it contains the phrase listed in ALL = . ALL = means that the phrase “technology-enhanced learning environments” must be included in order to be selected, and the OR operator means that the article can be selected if one of the conditions is met.

After qualifying by "document type," "field," and "time," a total of 1283 valid documents were obtained. As shown in Fig. 1, 210 research articles with 373 citations were published in 2020; 657 research articles with 4639 citations were published in 2021; and 416 research articles with 5159 citations were published in 2022. These data clearly demonstrate the rapid development and continued in-depth research in this field in recent years.

2.2. Application analysis

Although research has entered the post-pandemic era, analyzing research related to the pandemic can make up for the shortcomings of research that uses artificial intelligence technology to delve into educational theories. These analyses can assist governments and educational institutions in emergency education and provide support for the continuous application of online education. This study employed methods such as bibliometric analysis, text mining, sentiment analysis, and social network analysis.

Specific tools used include Citespace, VOSviewer, Bibliometrix, Python, R language, word clouds, Spssau, Ucinet, and Netdraw. Bibliometric analysis includes direct citation and keyword co-occurrence analysis [45]. Keyword co-occurrence analysis is a co-occurrence analysis method used to discover thematic relationships between keywords in literature [46].

Bibliometric analysis can help us understand unstructured data in a rigorous way and reveal the accumulated scientific knowledge and slight evolutionary differences in mature fields. Therefore, conducting text mining and sentiment analysis of big data can lay a solid foundation for advancing the field. This study used social network analysis (SNA) to analyze and visualize research on university

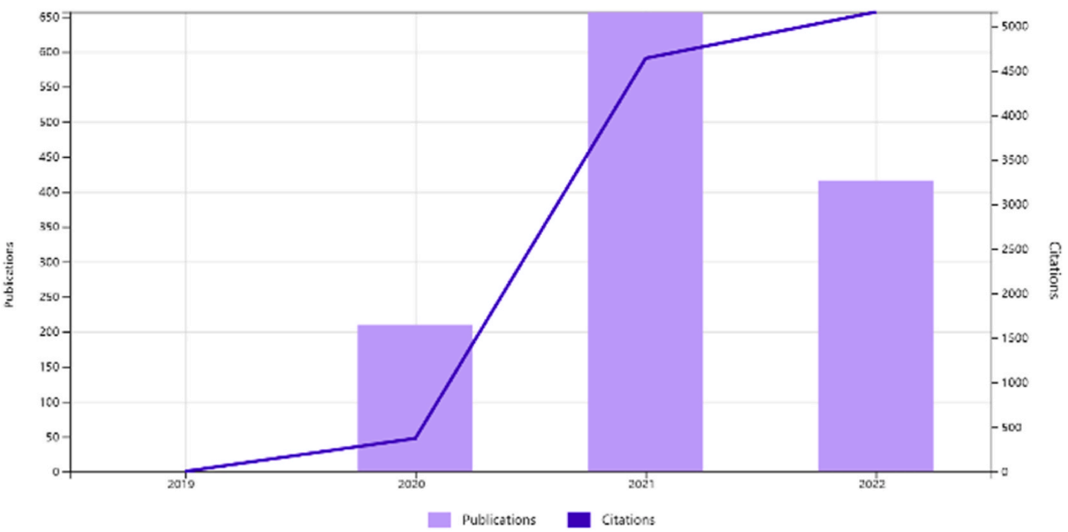

Fig. 1. Number of relevant published and cited articles.

students' online learning. Macro- and micro-level indicators such as density and clustering coefficients were used to measure at the macro level, while centrality, closeness, and betweenness were used as micro-level central indicators [47].

2.3. Distribution of online learning research

This was a study conducted to categorize and analyze research published in a number of databases. The results revealed that over 100 research articles were published across seven distinct categories, as illustrated in detail in Fig. 2, Section 2.3. Specifically, there were 366 articles (29% of the total) in Educational Research, 203 articles (16%) in Scientific Disciplines in Education, 184 articles (14%) in Environmental Sciences, 127 articles (10%) in Green Sustainable Science Technology, 126 articles (10%) in Environmental Studies, 114 articles (9%) in Psychology/Multidisciplinary, and 109 articles (8%) in Public/Environmental/Occupational Health. These data highlight the diversity of the database research field, which encompasses multiple disciplines and emphasizes the interconnections and integrations across different domains. The categorizations and quantitative distribution demonstrated the rapid development and continued in-depth research undertaken in this field in recent years.

In this investigation, a meticulous cluster analysis was conducted, categorizing authors based on distinct characteristics. For this analysis, the node count parameter was set to 50, indicating a potential division of authors into a maximum of 50 clusters. Through a refined algorithmic approach, four distinct clusters were successfully identified, as shown in Fig. 3.

The first cluster is prominently represented by the node "Cao, 2020." Authors within this cluster exhibit highly congruent research interests and backgrounds. Their scholarly contributions are substantial, reflecting a high degree of coherence in their research directions. Typically, these authors command significant recognition in their respective domains, having made numerous pioneering contributions.

The second cluster is anchored by the node "Fornell, 1981." Authors in this cluster demonstrate a broad spectrum of research domains and interests. While their research directions and methodologies vary, each has achieved notable outcomes in their respective fields. This cluster showcases authors with exceptional innovative capacities and interdisciplinary research prowess.

The third cluster is characterized by the node "Hodges, 2021." Authors within this cluster tend to have a more concentrated research domain and interest, primarily focusing on a specific research trajectory. Despite variations in their research methodologies and specific directions, their contributions are marked by high levels of innovation and applicability. Typically, these authors hold a leading position in global research outcomes within their domain.

The final cluster, represented by the node "Khalil, 2020," encompasses authors with a diverse range of research domains and interests. They exhibit significant variation, not only in their research directions and methodologies but also in their academic backgrounds and experiences. While their contributions might not be as pronounced as those of authors in the first three clusters, they have played a pivotal role in advancing their respective fields and innovating research methodologies.

The demarcation of these four clusters provides a comprehensive insight into the differences and similarities among authors in terms of research domains, interests, directions, methodologies, and outcomes. This delineation offers valuable insights for understanding the evolution of the relevant field and potential future research trajectories.

This study conducted a comprehensive examination of the research papers authored by various scholars, and discovered that an online questionnaire survey clearly demonstrated that students had fundamentally positive views of e-learning, leading them to embrace this new learning system. This phenomenon was further reinforced by the fact that the survey results provided empirical evidence for the importance of e-learning during the COVID-19 crisis period. It is noteworthy that e-learning has emerged as a transformative tool that can enhance the overall learning process, and social media platforms can further optimize learning outputs.

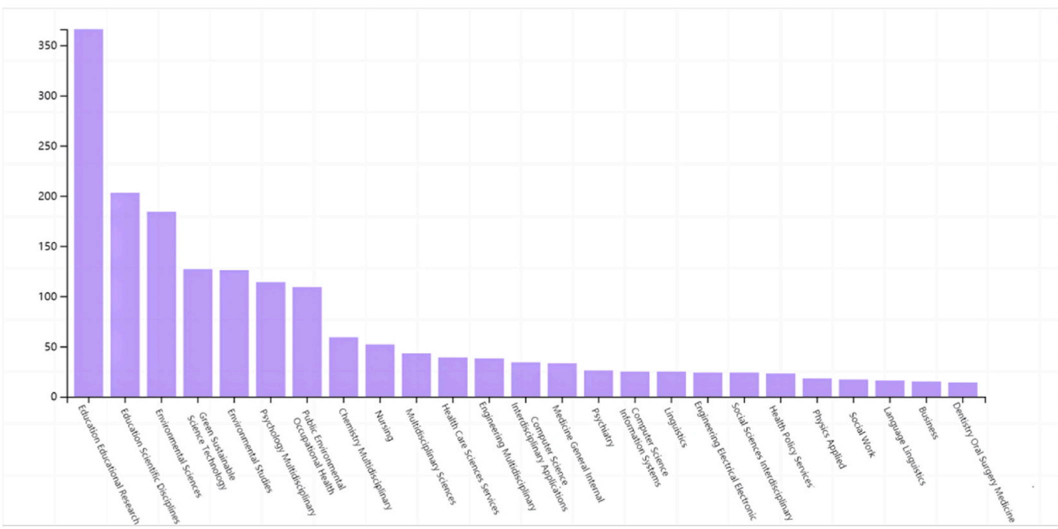

Fig. 2. Top 25 categories for number of related research articles.

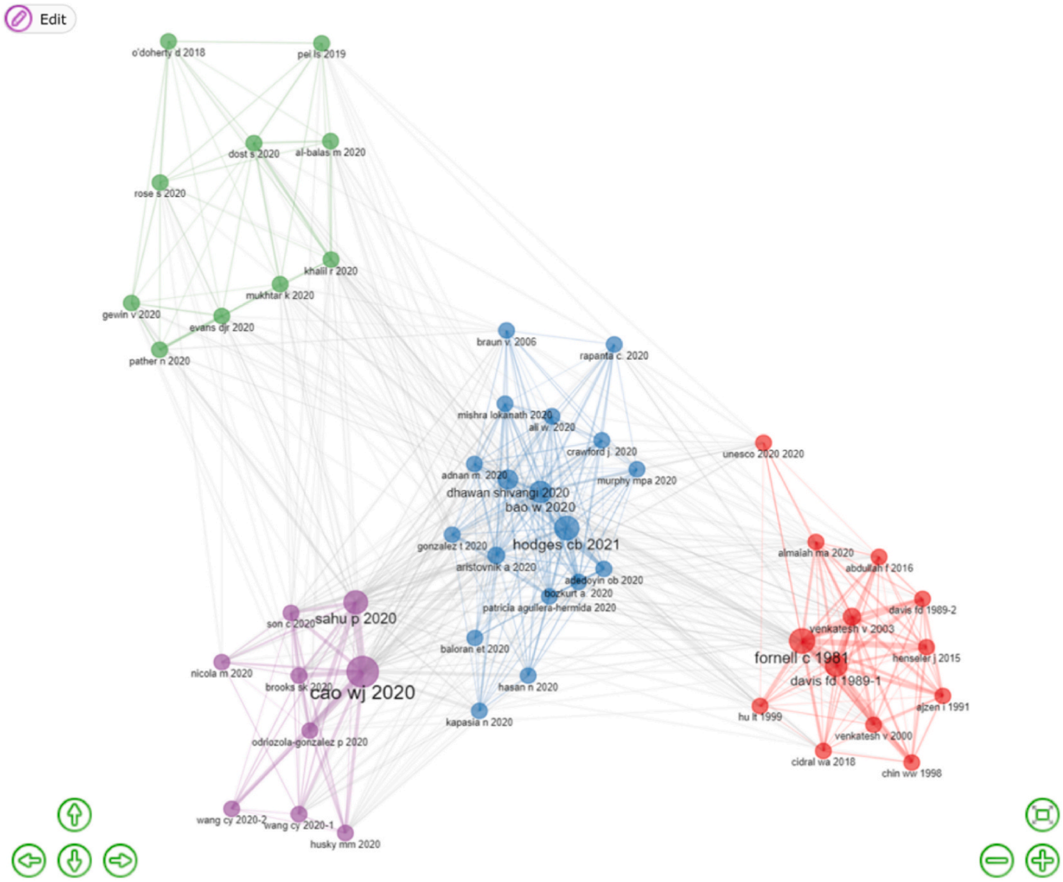

Fig. 3. Author subgroup network map.

Khan et al. conducted a research study that involved a questionnaire survey which included a large sample of Chinese university students [48]. The results of this study revealed that these students were experiencing significant anxiety and worry about the COVID-19 pandemic [49].

A global survey that included participants from diverse sociodemographic backgrounds provided evidence that male, part-time, first-year, Applied Science students, individuals with lower standards of living, and individuals from Africa or Asia were significantly less satisfied with their academic work/life during the pandemic compared to other cohorts. Conversely, female, full-time first-year students, and students facing economic hardships were found to be more emotionally affected by the pandemic in terms of their personal situation and lives. Aristovnik et al. published a study that supported these findings [50], recommending that targeted interventions should be implemented to create a positive learning environment for students from disadvantaged groups [51].

Qualitative research has also shown that students who are older, reside in rural areas, have work and family commitments, and have limited access to electronic resources can experience difficulties when it comes to implementing e-learning. Ramos-Morcillo et al. conducted a meta-synthesis analysis of existing research studies, finding that while an online learning shift is feasible, the pandemic nature of the educational shift requires future research to delve deeper into the structure of education [52]. Camargo et al. published a study that echoed these findings, recommending that future research should continue to explore and understand the complexities of e-learning implementation and its impact on students from diverse backgrounds [53].

3. Results and analysis

3.1. Article and citation analysis

In the period 2020–2022, 1238 relevant studies were published in 385 journals. The top 10 journals in terms of number of articles were Sustainability with 123 articles, Frontiers in Psychology with 85 articles, International Journal of Environmental Research and Public Health (55 articles), Education and Information Technologies (54 articles), Journal of Chemical Education (49 articles), BMC Medical Education (47 articles), Interactive Learning Environments (33 articles), Frontiers in Public Health (21 articles), Plos One (21 articles), and Nurse Education Today (15 articles).

The co-cited source journals and journal source clustering were analyzed, and the results showed that there were 145 academic journals with at least 50 citations.

Table 1 shows the top 10 journals with the highest total number of citations ranked according to the total number of citations they had received at the time the search was performed. The journal with the highest total number of citations is "Computers in Human Behavior" with 1474. The second highest is "Sustainable Development-Basel" with 716. The "Journal of Chemical Education" has 705 citations, making it the third highest, the "International Journal of Environmental Research and Public Health" has 548, making it fourth, the "International Journal of Environmental Research and Public Health" has 548, making it fifth, "BMC Medical Education" has 460, making it sixth, "Frontiers in Psychology" has 450, making it seventh, and the "British Journal of Educational Technology" and "Educational and Information Technologies" are tied for eighth highest with 426 citations each. Finally, "Internet and Higher Education" has 419 citations, making it 10th highest.

The top 10 journals with the highest total number of citations are mostly related to education, technology, and health. "Computers in Human Behavior" has the highest number of citations, indicating its significant impact in the field. "Sustainable Development-Basel" and "Journal of Chemical Education" also have a high number of citations, indicating their importance in their respective fields. The rankings of the journals can be used as a reference for researchers to identify the most influential journals in their field of study.

When performing source clustering analysis according to Bradford's law [54], the core layer is defined as zone 1 and the mantle layer is positioned as zone 2. Table 2 shows that the top seven journals in the core layer are Sustainability (rank value of 1, freq value of 123, cumreq value of 123, zone value of 1), Frontiers in Psychology (rank value of 2, freq value of 85, cumreq value of 208, and zone value of 1), the International Journal of Environmental Research and Public Health (rank value of 3, freq value of 55, cumreq value of 263, and zone value of 1), Education and Information Technologies (rank 4, freq 54, cumreq 317, zone 1), the Journal of Chemical Education (rank 5, freq 49, cumreq 366, zone 1), Bmc Medical Education (rank 6, freq 47, cumreq 413, zone 1), and Interactive Learning Environments (rank 7, freq 33, cumreq 446, zone 1). The frequency in the table refers to the frequency of publication (Publication frequency), which indicates the number of papers published by an author or organization in a given period of time. Cumfreq stands for cumulative publication frequency. It represents the cumulative annual number of publications since an author or institution engaged in academic research.

Table 2 shows the top 10 journals in the core region ranking. The ranking is based on the frequency of articles published in each journal. The table also includes the cumulative frequency and layer of each journal. The top-ranked journal is Sustainability with a frequency of 123 published articles. The second-ranked journal is Frontiers in Psychology with a frequency of 85, and third-ranked is the International Journal of Environmental Research and Public Health with a frequency of 55. The table shows that the top three journals are all in layer 1, indicating their high impact and influence in the field. The remaining seven journals are in layer 2, which still signifies a good level of impact and influence.

Sustainability is the most popular journal in the core region ranking, indicating its significance in the field. The top three journals are all related to sustainability, environmental research, and public health, highlighting the importance of these topics in the current research. The table can be used as a reference for researchers to identify the most influential journals in their field of study.

3.2. Common keyword analysis

The basic function of keywords, reflecting the research topic of academic journal articles, is that they can be used to understand the direction of the related field [55]. To clarify the current status of related research topics, the study used VOSviewer, a Java-based platform, for keyword clustering analysis. From the analysis results, 3342 keywords were generated from related studies during 2020–2022, among which 166 appeared more than five times together.

Applying the R language environment for text mining, a total of 1283 research documents related to the application of cognitive AI education in college students' online learning were used to generate word clouds, and 200 documents were selected as the upper limit of the number. The word cloud and related word frequency tables were obtained as shown in Fig. 4 below.

3.3. Time dimension

In this study, co-citation analysis of related studies was performed. The rapid growth in the number of scientific publications requires new methods to understand the direction of scientific research within the field of study, to determine the importance of specific

Table 1
Top 10 journals by total citations.

Journals	Total number of citations
Computer Education	1474
Computers in Human Behavior	716
Sustainable Development-Basel	705
Journal of Chemical Education	618
International Journal of Environmental Research and Public Health	548
BMC Medical Education	460
Frontiers in Psychology	450
British Journal of Educational Technology	426
Educational and Information Technologies	426
Internet and Higher Education	419

Table 2
Top 10 journals in core region ranking.

Journals	Rank	req	CumFreq	Zone
Sustainability	1	23	123	1
Frontiers in Psychology	2	5	208	1
International Journal of Environmental Research and Public Health	3	55	263	1
Education and Information Technologies	4	4	317	1
Journal of Chemical Education	5	9	366	1
Bmc Medical Education	6	7	413	1
Interactive Learning Environments	7	3	446	1
Frontiers in Public Health	8	1	467	2
Plos One	9	1	488	2
Nurse Education Today	10	5	503	2

Fig. 4. Related research word cloud map.

groups, authors or institutions, and to calculate metrics such as centrality to determine the importance (centrality) of a particular precise paper.

The keyword frequency ranking in the literature quantification obtains the research hotspot labels; the point degree centrality, near centrality, and intermediate centrality ranking in the social network analysis obtains the influential actors in the network; and the keyword ranking in the clusters in Fig. 5 obtains the labels of the clusters. During 2012–2022, many relevant studies were conducted. As shown in Fig. 5, the related areas in recent years have focused on dental education, self-regulated learning, critical factors, college students, educational processes, and general chemistry. The following is an overview of the major studies in the literature. The content of each cluster is the keywords in the co-occurrence network, and the largest value in the same cluster is elected as the representative of

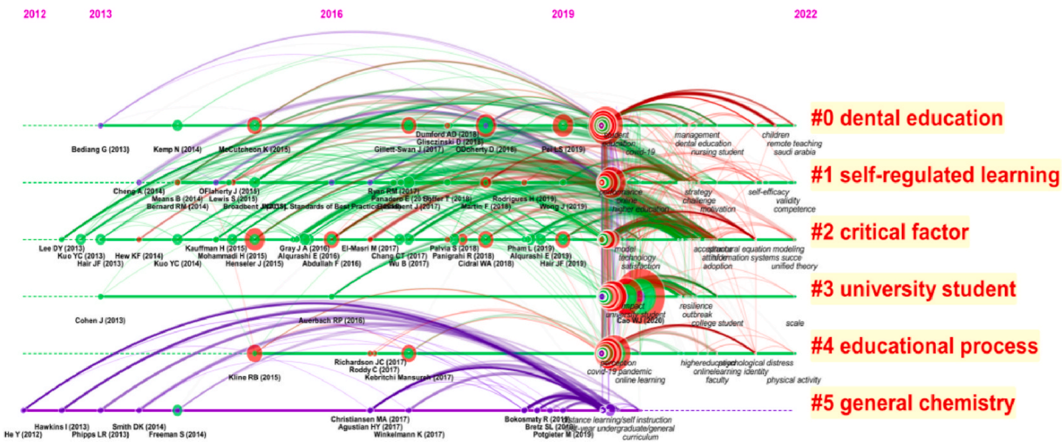

Fig. 5. Author, citation, keyword co-citation timeline.

the category and is labeled. There are six groups of cluster labels, and the frequency of the studied words are from dental education to general chemistry from the highest to the lowest, where dental education has the highest percentage in the clusters.

Online learning can be considered as a potential teaching method because of its advantages for improving the knowledge and skills of undergraduate students compared to offline learning [56]. A partially flipped learning model helps increase student engagement, supports learning, and positively impacts retention and academic performance [57].

3.4. Content dimension

This study performed data pre-processing on the literature material, using big data mining and sentiment analysis, word separation, de-duplication, deactivation of words, text feature extraction and TF-IDF calculation.

The TF-IDF method originated from information retrieval research in the 1950s and 1960s. It combines term frequency and inverse document frequency to weight individual terms. The TF-IDF metric assigns a weight to each word that is proportional to its frequency of occurrence in a given document, and is inversely proportional to its frequency in the document set as a whole. This weighting scheme aims to identify words with unique, meaningful features across the entire collection of documents, and to increase their importance. TF-IDF is widely used in information retrieval and text mining [29].

TF stands for term frequency, indicating the number of times a particular word appears in a document, and IDF stands for inverse document frequency, which measures the rarity of the word across the set of documents. The TF-IDF weight of a word can be calculated using the formula: TF-IDF = TF * log(N/DF), where TF is term frequency, N is the total number of documents in the set, DF is the number of documents containing the word, and log is the natural logarithm.

The distribution of the sentiment value and number of related data are shown in Fig. 6 below, with 26,685 sentiment values of 0; 8652 sentiment values of 1; 1521 sentiment values of 2; 36 sentiment values of 3; and 1 sentiment value of 4 in the period. The positive word cloud is shown in Fig. 7 below.

The sentiment value of −1 is 2894; the value of −2 is 255; the value of −3 is 16; and the value of −4 is 1. The negative word cloud is shown in Fig. 8 below. The total number of words for keywords related to data processing is 3,242,383, and 186 words were obtained after mining and analysis and selection of related keywords. Since it is always easy to find highly reliable items, the main concern of the test maker is the tail ratio of 27%, which would be the most suitable [58]. This study used 27% as the percentage for selection, which identified 50 words, as shown in Fig. 9. The top 10 are Student, Education, University, Teaching, Courses, Teachers, Online, Technology, Pandemic and Experience.

3.5. Spatial dimension

The most common form of matrix in social network analysis is a very simple square matrix with the same number of rows and columns as the number of elements in the data set. The elements or fractions in the matrix cells record information about the relationship between each pair of elements. The simplest and most common matrix is binary. If there is a connection, enter 1 in the cell; if there is no connection, enter 0. The "adjacency matrix" is the starting point for almost all network analysis, and represents who is next to whom or adjacent to whom in the "social space" mapped by the relationship being measured [43]. The data were mined by big data text and the study established the adjacency matrix of elements, with the specification of a 50*50 matrix of 0 and 1, through analysis to obtain the adjacency matrix in Fig. 10below.

3.6. Technical operation

The research process involves various technical operations to provide better access to relevant literature in a given field and to improve the accuracy and comprehensiveness of the analysis. The specific process can be summarized as follows.

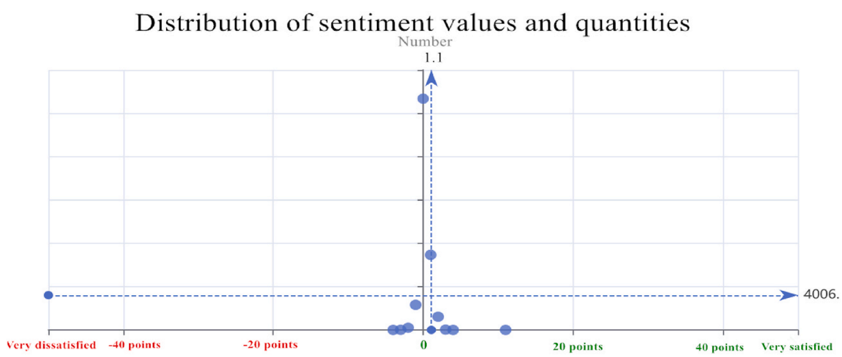

Fig. 6. Distribution of sentiment values.

Fig. 7. Word cloud of positive emotional values.

Fig. 8. Emotional value negative word cloud.

Fig. 9. Keyword word cloud.

Step 1 Paper text acquisition. Specific relevant literature is batch exported and integrated into a literature base for pre-processing using a data crawler library including Python and a related crawler framework, combined with the API of the literature management software, Zotero [25,26].

Step 2 Data preprocessing. Based on bibliometric analysis of the literature collection, literature data cleaning and preprocessing operations include journal paper de-weighting, screening, and taxonomic annotation with standardized literature data. These operations can also use natural language processing (NLP) methods to remove useless information such as stop words,

	S	U	T	S	P	C	T	E	E	A	P	T	A	P	H	M	S	S	R	F	P	T	L	G	I	A	S	D	K	S	I	C	O	E	A	P	R	A	P	C	P	E	E	N	M	L	F	S	A	E
Student	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
University	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	0	1	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0
Teaching	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	0	0	1	1	1	1	1	1	0	0	1	0	1	1	0	1	0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	0
Study	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1	1	0
Perception	1	0	1	1	0	0	1	1	0	1	1	1	0	1	1	1	0	0	1	1	0	1	0	0	0	0	1	0	1	1	1	1	1	0	1	0	1	1	0	1	0	1	1	0	1	1	0	0	0	0
Curriculum	1	1	1	1	0	0	0	1	1	1	0	0	1	0	1	0	0	0	1	1	0	0	1	1	0	0	1	0	0	1	0	0	0	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0
Teacher	1	1	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	0	1	0	1	1	0	1	0	1	1	0	1	0	1	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0	1	1	1	0
Experience	1	1	1	1	1	1	1	0	1	1	1	0	0	0	1	1	0	1	1	0	0	0	1	1	1	0	1	0	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0
Environment	1	1	1	1	0	1	1	1	0	1	1	0	0	1	1	0	1	1	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0
Academic	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	1	1	0	0	1	1	0	1	0	0	0	1	1	1	0	0	1
Pandemic	1	1	1	1	1	0	0	1	1	0	0	1	0	0	1	0	1	0	1	0	0	1	0	1	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	0
Technology	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	0	1	0	0	0	1	0	1	1	1	0	1	1	1	0	1	1	0	0	0	0	0	0	0	1	0	0
Activity	1	1	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0
Participate	1	1	1	1	1	0	1	0	1	1	0	0	1	0	0	0	1	0	1	1	1	1	1	0	1	0	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
Health	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	1	0	1	1	1	0	0	1	1	0	1	0	1	1	0	1	1	1	0	1	0	0	1	0	1	0	1	0	0	0	0	1	1	1
Model	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Social	1	1	1	1	0	0	0	0	1	1	1	1	0	1	1	0	0	0	0	1	0	0	0	1	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
Systems	1	1	0	1	0	0	0	1	1	1	0	1	0	0	0	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
Reporting	1	1	0	1	1	1	1	1	0	0	1	1	1	1	1	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0	1	0	0	1	0	0	0	0	1	0	0
Factors	0	1	0	1	1	1	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0
Planning	1	1	1	1	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0
Time	1	0	1	1	1	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Laboratory	1	1	1	1	0	1	0	1	1	1	0	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	1	1	0	0	0	1	0	1	0	0
Global	1	1	1	1	0	1	1	1	1	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0
Individual	1	1	1	1	0	0	0	1	1	1	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	0	0	1	0	0	0	0	0	1	1	1	0	0
Advice	1	0	1	1	0	0	1	0	1	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Strategy	1	1	0	1	1	1	1	1	1	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0
Distance Education	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Knowledge	1	0	1	0	1	0	1	0	0	0	1	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0
Service	1	1	0	1	1	1	0	0	0	0	0	0	1	0	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0
Interaction	1	1	1	1	1	1	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	1	1	0	0	0	1	0	1	0	0	0	0	1	0	0	1	0	1
Challenge	1	1	0	1	1	0	0	1	1	1	1	0	0	0	1	0	1	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	1	0	0	1	0
Online	1	0	0	1	1	0	1	0	1	0	0	1	0	1	1	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
Education	1	1	1	1	0	1	1	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	1	0	0	0	1	0	0	1	1	1	1	0	0	0	1	0	1	1	1
Anxiety	1	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
Problem	1	0	0	1	0	1	1	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0
Resources	1	1	0	1	1	0	0	0	1	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Active	1	0	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Practice	0	0	1	1	0	0	0	0	1	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0
Content	1	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Professional	1	1	1	1	0	0	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
Exam	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Emotions	1	0	0	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
National	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Motivation	1	0	0	1	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
Life	1	1	0	1	1	0	0	1	0	1	0	0	1	0	0	0	1	0	0	1	1	0	1	1	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Feedback	1	0	0	1	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Safety	1	0	0	1	0	0	1	0	1	0	0	1	0	0	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0	1	1	0	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
Adaptive	1	0	1	1	0	1	0	1	0	0	1	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Empirical	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 10. Adjacency matrix.

punctuation, and numbers, and perform stemming extraction and word form reduction operations to standardize the vocabulary [27].

Step 3 Sentiment analysis and keyword extraction. Based on the cleaned and pre-processed literature data, sentiment scores of titles, abstracts and texts were calculated using corresponding sentiment analysis methods. The cleaned literature data were then processed using TF-IDF to compute keywords [28,29].

Step 4 SNA modeling. SNA models for network analysis were constructed based on sentiment score and keyword data, and keyword co-occurrence networks were built. Node and edge relationship graphs were constructed based on keyword co-occurrence, and SNA methods were used for analysis [31,40].

Step 5 Results analysis. The above analysis results were integrated, presented using graphs, visualizations and analytical calculations, and interpreted to provide a reference for further research.

In general, combining article crawling with various analysis methods can provide better access to relevant literature and improve the accuracy and comprehensiveness of the analysis.

3.7. Summary of insights

TRD stands for Triadic Reciprocal Determinism, which is a concept from social cognitive theory. This framework postulates that a person's behavior is the result of interactions among personal factors, environmental influences, and the behavior itself. These three components are considered to be in constant reciprocal interaction with one another. According to the principles of Triadic Reciprocal Determinism (TRD) as applied to online learning for college students, factors influencing the learning experience are categorized into three primary aspects: Personal (P), Behavioral (B), and Environmental (E) factors [21]. Bridging TRD and Social Network Analysis (SNA), the research employs SNA to further stratify these factors into a hierarchical model comprising core, mantle, and shell layers. This hierarchy reflects the varying degrees of influence and centrality of the elements within the learning network: core layer elements are central to network stability, mantle layer elements are active but less central, and shell layer elements remain the least engaged and most peripheral [25,26,28,29].

The study mentioned the three levels included in the TRD model (core, mantle, and crust) and the three levels in social network analysis (core, periphery, and shell), which consist of several elements. Specifically, the core level (core) includes personal factors such as "students" and "health," as well as learning environment and social factors like "school," "teaching," "learning," etc. The mantle level (periphery) includes learning-related factors such as "courses," "technology," "social," etc. The crust level (shell) includes factors such as "services," "advice," "practice," etc. These elements are considered to be key factors that influence online learning experiences. In social network analysis, different node types also reflect different elements and roles in the network, such as core nodes being the most important ones in the entire network, periphery nodes being the ones that connect core nodes and shell nodes, and shell nodes being the less active or less connected nodes in the entire network.

In the TRD model, the factors influencing online learning among college students can be categorized into core, meso and shell layers, where the core elements are the main promoters of the content, the meso elements are mainly the more active participants, beneficiaries and indirect promoters, and the shell elements are mainly the silent participants or bystanders. Thus, in this model, the core, middle and shell layers correspond to the core, thin and shell layers in SNA. Elements in the core layer have higher centrality, tightness, and mediation in the SNA, whereas the shell layer tends to be the largest layer in the SNA, with the fewest connections and contributions. Thus, the TRD model provides a theoretical foundation that provides a framework for studying the relationships and influences of different layers in a network.

4. Results and discussion

4.1. Factor and element distribution

Influencing Factors on Online Learning for College Students: 50 Elements and Three Causal Factors. This study classified the data through TRD combined with big data analysis and sentiment analysis. The relevant factors can be divided into Personal (P), which includes connotations such as Cognitive, Emotional, and Physiological; Behavior (B), which includes connotations such as Frequency, Intensity, and Duration; and Environment (E), which includes connotations such as Culture, Society, and Facilities [21].

Influencing Factors on Online Learning for College Students: 50 Elements and Three Causal Factors provide a comprehensive examination of the various factors that impact the online learning experience of college students. Through a combination of literature review and data analysis, the article's authors employed TRD combined with advanced forms of data analysis, including sentiment analysis, to classify and organize relevant information.

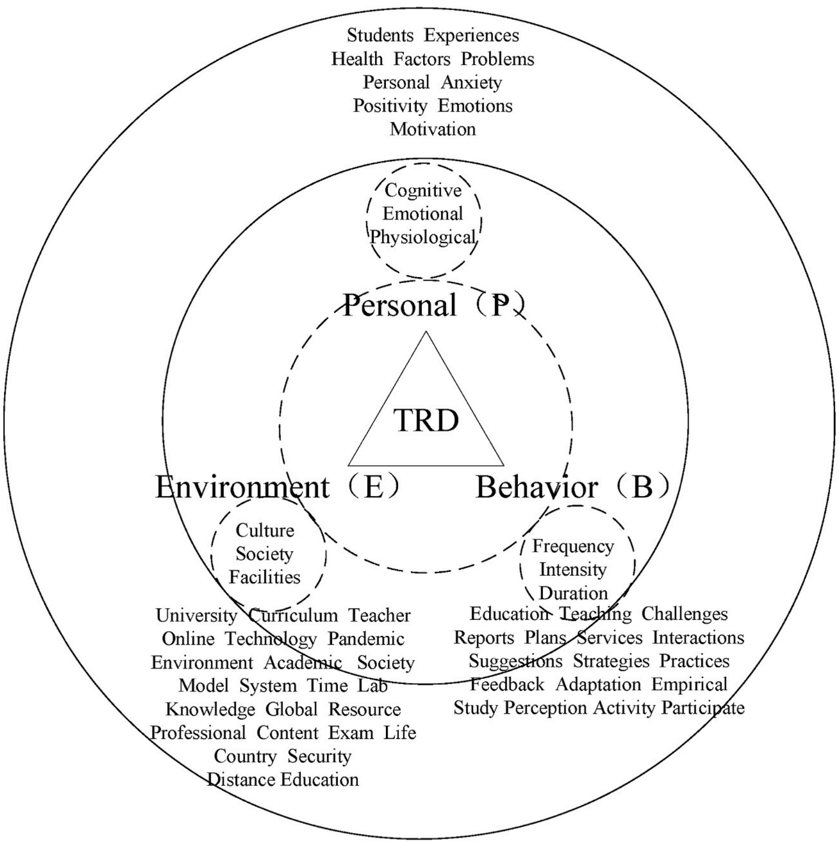

Fig. 11. Factor and element distribution according to TRD theory.

The classification system identified three main causal factors—Personal (P), Behavior (B), and Environment (E)—each containing various elements that cumulatively shape the online learning experience. Personal factors, which include cognitive, emotional, and physiological aspects, were found to have a significant impact on a student's ability to engage and succeed in an online learning environment. Behavioral factors, which encompass frequency, intensity, and duration of participation and activity, also contribute significantly to the overall learning experience. Finally, Environmental factors—covering cultural, social, and facility-related considerations—were also found to have a significant impact on the online learning experience.

The distribution of the 50 elements across the three causal factors is organized based on the connotations of each factor. The personal factor contains 15 elements that focus on students' individual attributes and characteristics that are essential for effective online learning. The Behavior factor contains 18 elements related to the student's level of participation, activity, and study habits. Finally, the Environment factor contains 17 elements that consider external conditions such as cultural norms, social pressures, and technological resources that shape the online learning environment.

Fig. 11 presents this classification system visually, highlighting the three causal factors and the distribution of the 50 elements within each factor. The image depicts how these elements interact and intersect to create a comprehensive framework for understanding the complexities of online learning success.

4.2. Influencing factors

In this study, the researchers utilized Social Network Analysis (SNA) to discern the principal factors influencing student engagement in online learning, guided by the framework of Triadic Reciprocal Determinism (TRD). The investigatory procedure commenced with the systematic aggregation of pertinent literature via Python-based data crawlers and the Zotero API [25,26], succeeded by meticulous data preprocessing that included text normalization through Natural Language Processing (NLP) techniques [27]. Subsequent sentiment analysis and TF-IDF computations facilitated the extraction of sentiment scores and pivotal keywords [28,29]. SNA modeling was then applied to elucidate the interconnections among the identified keyword [31,40], culminating in an integrative analysis that merged visualization with analytical calculations. This rigorous process illuminated the complex interactions among personal, behavioral, and environmental elements as postulated by TRD, thereby augmenting the precision and comprehensiveness of the literature analysis within the domain of online learning.

The elements of influencing factors of college students' online learning under TRD were analyzed by macro and micro level indicators; there are three core indicators at the micro level, and the elements to construct the SNA model can be divided into the nuclear and peripheral layers. Density is usually defined as the sum of the values of all ties divided by the number of possible ties. That is, for valuable data, density is usually defined as the average strength of all possible (rather than all actual) connections. The weighted average neighborhood density is called the clustering coefficient, and it is often wise to compare the clustering coefficient with the overall density when assessing the degree of clustering [43]. Macro-level indicators were analyzed and the network density of the SNA model was obtained as 0.3694 with a clustering coefficient of 0.550. Network density is defined as the ratio of possible ties identified between network participants, and it measures the degree of consistency of nodes. Densities are scored between 0 and 1, with densities close to 1 indicating a more coherent network and denser relationships between nodes. The clustering coefficient is defined as the ratio of the number of links in a network to the number of nodes and possible links. This index is also scored between 0 and 1. Numbers close to 1 show higher rates of association with and within elements [47,59,60].

Micro-level indicator analysis yields three core indicators, centrality, intimacy, and intermediation, as shown in Table 3. The centrality is 36.490 and the standard centrality is 16.355, which is the number of each node in the network in relation to other nodes. Higher centrality is the more active element, and the influence is more capable of influencing other elements. The closeness was 61.484 for In-closeness and 61.501 for Out-closeness, a metric that emphasizes the location of nodes in the structured network, and is defined as the total measured ground distance to all other nodes. Highly intimate central network elements provide fast access to information and provide distribution and accessibility throughout the network. With an intermediate degree of 1.327 and a standard intermediate degree of 1.993, this metric is based on the number of crossings through the shortest paths of the nodes. The most influential elements are in high intermediate networks, most of which connect different element groups [47,59–61].

In this study, analysis was carried out using Ucinet6, and the core and periphery were analyzed using the network function from the software menu. The core and peripheral layer elements of the SNA network can be obtained from Fig. 12, where 1 is the core layer and 2 is the peripheral layer. The relevant elements of each layer were obtained by software identification.

4.3. The social network

The social network analysis model was constructed based on the theory of TRD, and the factors affecting college students' online

Table 3
Centrality, closeness, and intermediate degree of SNA.

	Mean (Standard Deviation)	Minimum	Maximum
Degree	37.551 (17.418)	6.122	93.878
In-closeness	62.096 (7.988)	51.042	94.231
Out-closeness	62.096 (7.973)	50.000	94.231
Betweenness	1.304 (2.005)	0.008	12.094

learning can be divided into core, mantle and shell layers, with the most influential layers and elements in the core layer. There are three states of factors and their elements in the model, that is, the core layer, mantle layer, and shell layer. The core layer elements are the main promoters of content; the mantle layer elements are mainly the more active participants, beneficiaries and indirect promoters; and the shell layer elements are mainly silent participants or bystanders [62].

After applying the Ucinet6 software tool to the adjacency matrix, the reachable matrix was derived, which clearly showed the connection paths between elements. This matrix is a crucial tool that indicates whether there is a connection between any two elements in a network. It is a numerical representation of the topological structure of the network, and each element in the matrix represents whether there is a connection path between the corresponding pair of nodes. A value of 1 indicates the existence of a path, while a value of 0 indicates the absence of any path between the nodes. This matrix is often used to study complex networks, such as social, biological, and communication networks [63].

Fig. 13 below displays the reachable matrix derived using Ucinet6. It is observed that the matrix is symmetric, indicating that the connection between any pair of nodes is mutual. The diagonal elements are all 1s, as each node is connected to itself. The off-diagonal elements represent the connection between different pairs of nodes. For example, element (i, j) has a value of 1 if node i can reach node j, and vice versa.

Fig. 11 serves as a categorical breakdown of the 50 elements impacting online learning for college students, classified according to the Triadic Reciprocal Determinism (TRD) theory. These elements are organized into three causal factors: Personal (P), which encompasses cognitive, emotional, and physiological aspects; Behavior (B), which includes frequency, intensity, and duration of activities; and Environment (E), which covers cultural, societal, and infrastructural considerations. This figure is designed to visually represent the distribution of these elements across the three factors, illustrating how they collectively contribute to the online learning experience.

In contrast, conversion through the Spssau platform results in the directed graph shown in Fig. 14 below, which is a three-dimensional vector sphere with a collection of vectors composed of keywords of related elements. The directed graph is a graphical representation of the adjacency matrix. It is a mapping of the matrix elements to arrows on the graph. A value of 1 in the adjacency matrix indicates an arrow from one node to another in the graph, while a value of 0 does not have an arrow. The three layers—shell, mantle, and core—are interpreted with the help of three-layer indicators. Each layer has its own set of nodes and edges, representing different levels of connectivity within the network [43].

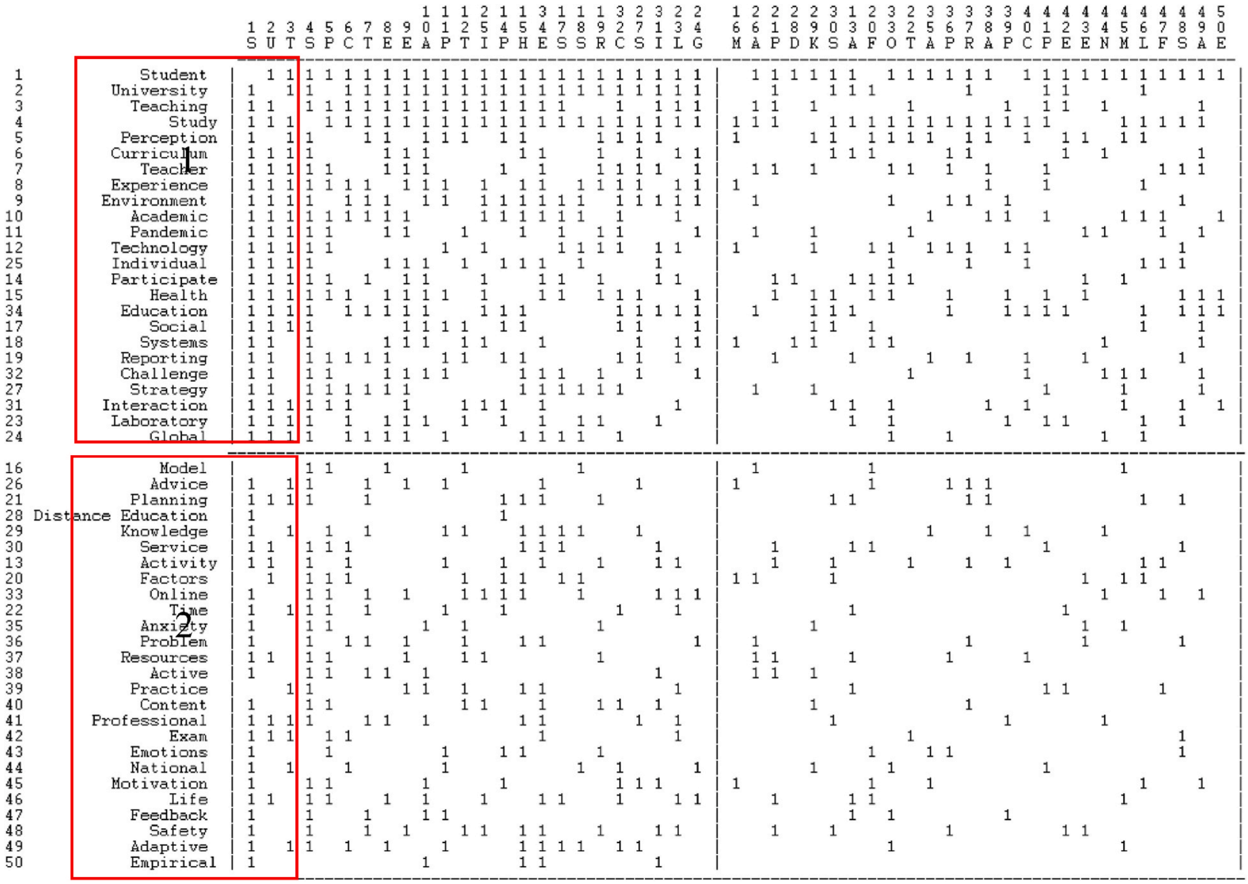

Fig. 12. The nuclear and peripheral layers of the elemental SNA model according to TRD theory.

		1 S	2 U	3 T	4 S	5 P	6 C	7 T	8 E	9 E	10 A	11 P	12 T	13 A	14 P	15 H	16 M	17 S	18 S	19 R	20 F	21 P	22 T	23 L	24 G	25 I	26 A	27 S	28 D	29 K	30 S	31 I	32 C	33 O	34 E	35 A	36 P	37 R	38 A	39 P	40 C	41 P	42 E	43 E	44 N	45 M	46 L	47 F	48 S	49 A	50 E
1	Student	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	University	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	Teaching	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	Study	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	Perception	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6	Curriculum	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	Teacher	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
8	Experience	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	Environment	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
10	Academic	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	Pandemic	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	Technology	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
13	Activity	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14	Participate	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
15	Health	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	Model	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	Social	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
18	Systems	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19	Reporting	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	Factors	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
21	Planning	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
22	Time	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	Laboratory	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
24	Global	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
25	Individual	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
26	Advice	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
27	Strategy	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
28	Distance Education	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
29	Knowledge	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
30	Service	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
31	Interaction	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
32	Challenge	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
33	Online	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
34	Education	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
35	Anxiety	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
36	Problem	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
37	Resources	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
38	Active	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
39	Practice	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
40	Content	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
41	Professional	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
42	Exam	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1
43	Emotions	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
44	National	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
45	Motivation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
46	Life	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
47	Feedback	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
48	Safety	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
49	Adaptive	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
50	Empirical	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Fig. 13. Reachability matrix.

The shell layer nodes in this three-layer model have low participation and are more easily affected by external factors compared to the mantle layer nodes, which have medium participation and are relatively more stable than the shell layer nodes. The core layer nodes, on the other hand, have high participation and serve as key factors that help maintain network stability. Moreover, the model assumes that there is a role displacement effect between the three identity states, meaning that the three states of the factor and its elements are not static and can undergo transitions as participation increases. Specifically, with an increase in participation, nodes can break through the boundary from the shell layer and penetrate to the mantle layer. Subsequently, with further increases in participation and promotion, nodes will break through from the mantle layer to the core layer. Additionally, the core layer elements will change from the core layer to the mantle layer as participation or activeness decreases. If participation and activeness continue to decrease, they will change from the mantle layer to the shell layer and thus be at the edge of the activity [62]. This three-layer model can help us better understand how different factors affect network behavior and stability, shedding light on the complex dynamic processes that occur within social networks.

4.4. Core layer effects

Elements related to the influences of college students' online learning under the triadic interaction are presented. Through the three core indicators of the elements' influence, online learning influences the results of the 10 elements in the core layer. The core layer elements are related to the fields of Student, University, Teaching, Study, Teacher, Experience, Environment, Academy, Pandemic, Health, and Education. The core layer of the social network analysis (SNA) model is obtained by classifying the teaching-related factors (TRD factors) into different groups. The elements that belong to category B are Teaching, Study, Experience, and Education. In colleges and universities, it is necessary to have a comprehensive perspective on the teaching methods of online education and to integrate technology to support teaching and learning [64]. The elements that belong to category E are University, Teacher, Environment, Academy, and Pandemic. The various barriers to online learning that students encounter affect teachers, learning environments, and personal health, work and information overload from teachers. Lack of adaptation and unfamiliarity with the new online learning environment and personal health challenges related to stress and anxiety [65] are also factors that need to be considered. The elements that belong to category P are Student and Health.

Social network analysis aims to unveil the inherent patterns and structures of social relationships within a given network. The core-

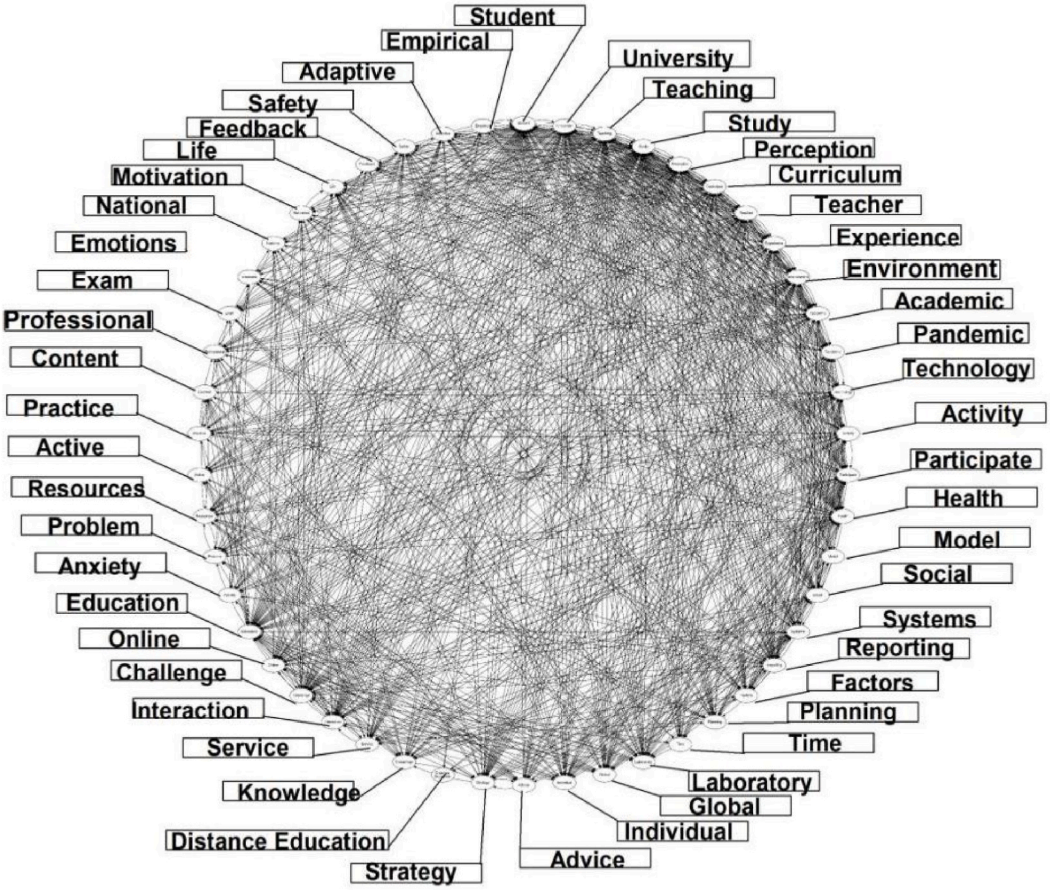

Fig. 14. Directed graph of elements according to TRD theory.

edge structure is a crucial feature that social network analysis can reveal [66]. This structure often displays a configuration where network nodes are clustered into more densely connected core nodes and less connected peripheral nodes. Core nodes occupy a key position in the flow of information and exert greater influence on the network's behavior, making them crucial to identifying the core-edge structure of social networks [67].

Nodes in social networks are often classified based on their centrality, with higher centrality nodes considered to be key, core, or central, and lower centrality nodes considered as edge, isolated, or peripheral [39]. Identifying the central core nodes in a network involves node centrality measures such as degree centrality, mediator centrality, and feature vector centrality. The central nodes in the core-edge structure tend to be consistently higher in degree centrality and other centrality measures than the nodes in the peripheral structure [40]. In the core-edge structure, central nodes interact with surrounding nodes to form dense subgroups, which increases the network's cohesion and facilitates more efficient information dissemination and coordination [35].

In summary, studying social networks with core-edge structures can help identify the central core nodes of the network by analyzing node connections. These central nodes occupy a critical position in the core-edge structure, contributing to greater influence on network behavior. Considering the specificity of core-edge structures in social networks is crucial to more accurately reveal the network's dynamics.

Experts have presented two intuitive views of the core-edge structure: a discrete model that segregates the network into core and edge members, where core members have high social interaction and connectivity; and a continuous model that segregates the network into core, semi-edge, and edge tiers, with core tier members being similarly highly connected and mutually supportive individuals. In both models, core members are considered to be of critical importance to the overall network [67].

Research on SNA has shown that student performance is influenced by the network's SNA coefficients [68]. SNA is a tool that can be used to study and analyze the structure of social learning networks (SLNs). It describes specific communities or groups and their relationships within SLNs. SNA also identifies and analyses the position and influence of key individuals in SLNs throughout the network [69]. The influence of college students' online learning according to TRD is a complex process that involves multiple elements and interactions between them. The higher education system is a complex system, and at the bottom of the complex system there is a rich network of interconnected components that determine the relational properties of the system. Understanding the educational system as an interconnected network of people (student), degree programs (teaching), and institutions requires methods (universities) and concepts from the computational social sciences. SNA methods have broad applications in educational systems research and practice, and SNA can reveal the complexity and implications of these relationships [70]. These elements can be classified into three groups: students, universities, and teaching. These three groups of elements are shown in Fig. 15. Each group plays a crucial role in the process of online learning, and their interactions with each other create a triadic relationship that shapes the overall influence.

Student: This category includes elements related to the student's personal experience in the educational process. It includes "Student," "Study," "Education," "Experience," and "Health." These elements encompass the student's academic journey, their learning process, the educational system they are part of, their overall experience in the academic setting, and their health, which can significantly impact their academic performance [71,72].

University: This category includes elements that pertain to the broader university setting and its impact on the educational process. It includes "University," "Environment," and "Pandemic." These elements refer to the physical and social environment of the university, as well as the impact of external factors such as the COVID-19 pandemic on the university setting [71].

Teaching: This category includes elements related to the methods and approaches used in teaching. It includes "Teaching," "Teacher," and "Academic." These elements encompass the strategies, techniques, and methods used by teachers in the educational process, as well as the academic standards and expectations set by the educational institution [71,73,74].

The influence of these elements on online learning is primarily manifested through 10 core indicators that measure the effects of online learning on student outcomes. These indicators are grouped into three categories: student-level indicators, program-level indicators, and institutional-level indicators. Student-level indicators focus on individual student factors that may affect online learning success, such as student demographics, academic preparedness, and technology access. Program-level indicators examine the quality and effectiveness of the online program itself, including measures of curriculum quality, teacher quality, and student-teacher interaction. Institutional-level indicators consider the role of the university in supporting students' online learning, including factors such as university resources, administrative support, and campus culture.

To analyze the influence of these elements on online learning, the study employed social network analysis (SNA) to explore the relationships among the various elements and their effects on student outcomes. SNA is a valuable tool for studying complex systems composed of multiple interconnected elements, such as the social networks of individuals or groups. It can help identify patterns of connection and interaction among elements and measure the importance of each element within the network.

To conduct our SNA, this study used the Ucinet6 software, which includes a range of network analysis techniques and visualization tools. This study imported our data into Ucinet6 and used the software's network analysis capabilities to calculate various measures of centrality for each element in our network. Centrality measures indicate an element's relative importance within the network, and can help identify key players or "hubs" that may have a disproportionate impact on the network's overall function. This study calculated three types of centrality measure: degree centrality, closeness centrality, and betweenness centrality. Degree centrality indicates the

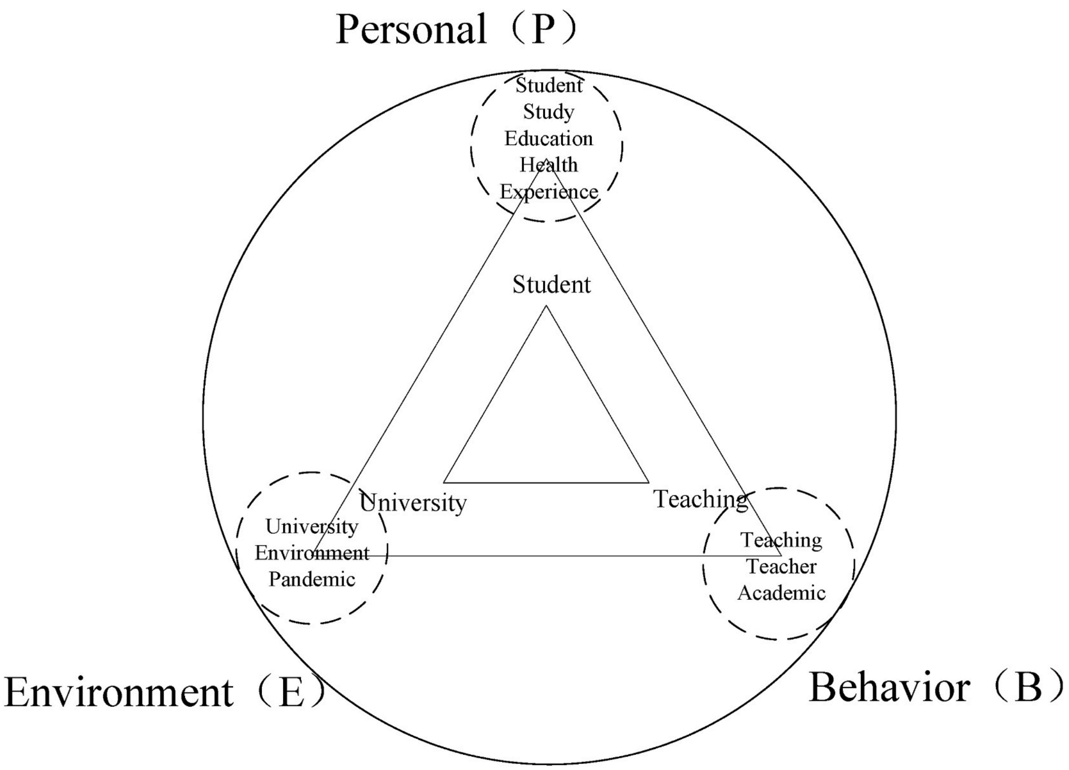

Fig. 15. The three groups of elements of the education system.

number of connections an element has to other elements in the network, closeness centrality measures how close an element is to all other elements in the network, and betweenness centrality assesses an element's control over information flow within the network.

This study visualized our SNA results using the Netdraw software, which enabled us to clearly display the structure and relationships within our network model. Our analysis identified three distinct layers within the overall network: a core layer, mantle layer, and shell layer (Figs. 16 and 17). The core layer includes those elements that have a strong impact on student outcomes through their direct connections to one another and to student outcomes: Student, University, Teaching, Study, Perception, Curriculum, Teacher, Experience, Environment, and Academic. The mantle layer includes elements that are connected to the core layer but do not have as strong an impact on student outcomes. Finally, the shell layer includes elements that are only indirectly connected to the core layer and have little direct impact on student outcomes.

By isolating each layer of our SNA model, this study was able to identify those elements that play a particularly important role in shaping student outcomes through their interactions with other elements within the core layer. Our analysis suggests that Student has

Normalized Centrality Measures

		1 Degree	2 Closeness	3 Betweenness	4 Eigenvector
1	Student	93.878	94.231	12.094	39.143
2	University	61.224	72.059	2.060	30.324
3	Teaching	59.184	71.014	2.278	28.885
4	Study	87.755	89.091	7.732	38.200
5	Perception	57.143	70.000	3.396	24.716
6	Curriculum	44.898	64.474	1.373	22.437
7	Teacher	53.061	68.056	1.984	25.465
8	Experience	48.980	66.216	1.263	25.485
9	Environment	53.061	68.056	1.413	27.011
10	Academic	51.020	67.123	2.137	24.847
11	Pandemic	42.857	63.636	1.419	20.682
12	Technology	46.939	65.333	1.999	21.137
13	Activity	34.694	60.494	0.764	16.765
14	Participate	44.898	64.474	1.865	21.779
15	Health	59.184	71.014	2.987	27.790
16	Model	16.327	53.846	0.115	7.701
17	Social	36.735	61.250	0.569	19.369
18	Systems	38.776	62.025	1.634	18.481
19	Reporting	42.857	63.636	1.134	21.076
20	Factors	30.612	59.036	0.805	13.768
21	Planning	30.612	59.036	0.407	16.247
22	Time	22.449	56.322	0.159	12.527
23	Laboratory	44.898	64.474	1.099	22.446
24	Global	36.735	61.250	0.501	19.981
25	Individual	38.776	62.025	0.751	20.247
26	Advice	26.531	57.647	0.526	13.352
27	Strategy	38.776	62.025	0.633	20.527
28	Distance Education	6.122	51.042	0.008	3.640
29	Knowledge	30.612	59.036	0.693	14.645
30	Service	28.571	58.333	0.329	15.250
31	Interaction	42.857	63.636	1.337	21.092
32	Challenge	46.939	65.333	1.167	24.160
33	Online	32.653	59.756	0.584	16.709
34	Education	65.306	74.242	3.537	30.165
35	Anxiety	18.367	55.056	0.152	9.452
36	Problem	26.531	57.647	0.321	13.997
37	Resources	28.571	58.333	0.410	14.533
38	Active	20.408	55.682	0.159	11.150
39	Practice	24.490	56.322	0.318	12.570
40	Content	22.449	56.322	0.148	12.338
41	Professional	28.571	58.333	0.343	16.103
42	Exam	20.408	55.682	0.172	10.990
43	Emotions	20.408	55.682	0.238	9.577
44	National	20.408	55.682	0.189	10.143
45	Motivation	26.531	57.647	0.468	12.825
46	Life	32.653	59.756	0.488	17.362
47	Feedback	18.367	55.056	0.146	9.840
48	Safety	32.653	59.756	0.600	16.497
49	Adaptive	30.612	59.036	0.306	16.978
50	Empirical	10.204	52.128	0.012	6.558

Fig. 16. Normalized centrality measures for each element.

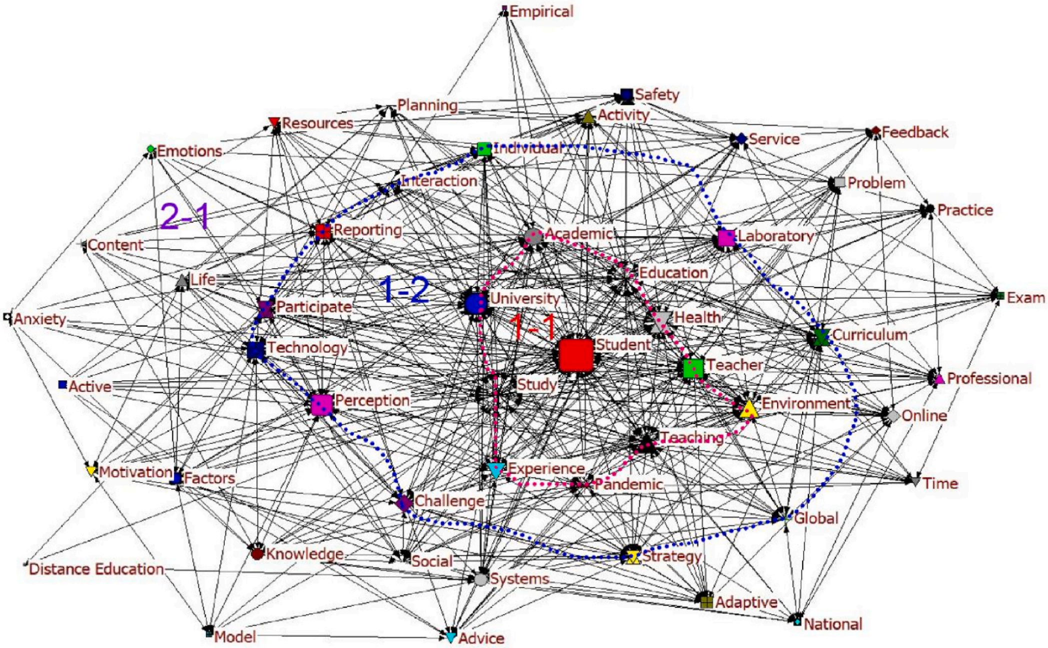

Fig. 17. Core-mantle-shell layer distribution of the elemental SNA model according to TRD theory.

the highest degree centrality within the core layer and is therefore likely to have a strong impact on other elements within the mantle and shell layers. Similarly, University and Teaching have high levels of betweenness centrality within the core layer, indicating their potential to control information flow within the mantle and shell layers and thus their importance in determining overall network function.

Prior to SNA analysis, the matrix was imported, and then the numerical centrality was generated through Ucinet6, followed by software drawing to derive the final centrality graphical model, with the square as the centrality indicator. A larger range indicates greater impact, and after visual analysis of the matrix centrality through the Netdraw software, the results were obtained as shown in Fig. 17. The Ucinet6 software was used for correlation analysis, with the aim of presenting the spatial structure of the elements that influence university students' online learning. According to the diagram, it can be concluded that there are three levels of structure: the shell layer, mantle layer and core layer.

The core layer elements as detailed in Table 4 are related to the fields of Student, University, Teaching, Study, Teacher, Experience, Environment, Academy, Pandemic, Health, and Education. The core layer of the social network analysis (SNA) model is obtained by classifying the teaching-related factors (TRD factors) into different groups. The elements that belong to category B are Teaching, Study, Experience, and Education. In colleges and universities, it is necessary to have a comprehensive perspective on the teaching methods of online education and to integrate technology to support teaching and learning [64]. The elements that belong to category E are University, Teacher, Environment, Academy, and Pandemic. The various barriers to online learning that students encounter are affected by teachers, learning environments, personal health, and teachers' workload and information overload. Lack of adaptation and unfamiliarity with the new online learning environment and personal health challenges related to stress and anxiety [65]are also factors that need to be considered. The elements that belong to category P are Student and Health.

Table 4
Centrality, closeness, and intermediation of core layer elements (E = environment, B = behavior, and P = person).

Elements	TRD	Levels	Degree	Closeness	Betweenness
Student	P	1–1	93.878	94.231	12.094
University	E	1–1	61.224	72.059	2.06
Teaching	B	1–1	59.184	71.014	2.278
Study	B	1–1	87.755	89.091	7.732
Teacher	E	1–1	53.061	68.056	1.984
Experience	B	1–1	48.98	66.216	1.263
Environment	E	1–1	53.061	68.056	1.413
Academic	E	1–1	51.02	67.123	2.137
Pandemic	E	1–1	42.857	63.636	1.419
Health	P	1–1	59.184	71.014	2.987
Education	B	1–1	65.306	74.242	3.537

During the COVID-19 pandemic, online learning platforms in universities played a crucial and irreplaceable role in enabling large-scale online learning practices [3]. The analysis of the core layer elements, which are characterized by their centrality size, showed that these elements can be ranked in descending order of activity of related elements, moving from Student to Pandemic, as summarized in Table 4. In terms of the online learning of students in higher education, personal factors related to learners, Student, and Health have the highest centrality among the related P factors. Among the related E factors, online learning environment elements have the highest centrality, progressing from largest to smallest as University, Teacher, Environment, Academy, and Pandemic. Finally, among the related B factors, elements related to learning behavior have the highest centrality, moving from largest to smallest as Study, Education, Teaching, and Experience. The results of this analysis provide valuable insights into the design and implementation of effective online learning platforms that can support students during the pandemic and beyond.

As shown in Table 4, the related elements are arranged in descending order of Student to Pandemic based on the degree of closeness, which is a measure of how closely related the elements are to each other. The greater the closeness value, the closer the distance between the elements, indicating a higher likelihood of their interaction and connection. This pattern holds true even when considering elements with the same order and centrality, as the greater the closeness, the closer the distance to other elements, and the more frequent the interaction of elements. Therefore, closeness is an important factor in determining how related elements are to each other.

Table 4 below shows the ranking of elements according to their degree of influence and mediating role, starting from high to low. The factors related to the pandemic have the lowest level of influence and mediating role, while the factors related to students have the highest level of influence and mediating role. The personal factors of learners, Student and Health, have the highest centrality and the strongest element influence and mediation. The elements of online learning environment have the highest centrality from large to small: Academy, University, Teacher, Pandemic, and Environment. The elements of learning behavior have the highest centrality from large to small: Study, Education, Teaching, and Experience.

The distribution of the elements of the mantle layer of the nuclear layer in the SNA model is explained as follows. The elements belonging to B are Participation, Challenge, Reporting, Interaction, and Strategy. Interaction with peers is so important to students that face-to-face learning cannot disappear completely, but it can eventually be complemented by e-learning [75]. Students are dealing with online learning through the challenges and requests for support involved in learning, and what is needed is a positive response to their emotional, technological, and socioeconomic needs [76]. The elements belonging to E are Curriculum, Technology, Social, Laboratory, and Global. Due to the epidemic, teachers and school administrators should prioritize the quality of course content, course platform services, and materials when selecting course platforms and content, all of which are very important indicators of the usefulness of the platform to students [6]. The elements belonging to P are Individual and Perception. The factors and elements related to college students' online learning in this tier are weaker than in the core tier in terms of activity, element interaction, influence, and intermediate role.

The elements in the outer shell layer that belong to B are Activity, Service, Advice, Anxiety, Activity, Practice, Feedback, and Empirical Study. Online learning practices during the epidemic are considered unprecedented in the history of global higher education in terms of scale, scope, and depth [3]. Regarding the positive aspects of online learning, students identified time saving as the main advantage, followed by the comfort provided by staying at home, and the accessibility offered by the online environment [75]. Elements of E include Being Online, Time, Knowledge, Resources, Professional community, Content, Life, Safety, and Distance Education. The COVID-19 pandemic led to several changes in the teaching and learning process, and changes such as online courses may be associated with some mental health problems and negatively impact the quality of life and academic performance of college students [77]. University learning should encourage students to engage in independent learning through a wide range of methods and media. Resources for distance learning need to be enhanced, and students should have access to more reading materials [78]. The elements belonging to P are Factors and Motivation; and the elements belonging to O are Model, Planning, and Examinations. The factors and elements related to college students' online learning in this layer are the degree of activity, element interaction, and influence. They are far weaker than the mantle layer and core layer in the nuclear layer, but still have some influence.

5. Conclusions and recommendations

5.1. Conclusions

Bandura's triadic reciprocal determinism model posits that learning is influenced by environmental, behavioral, and personal factors that interact with each other [79]. Therefore, it is crucial to find ways to encourage students' positive learning behaviors in online education and learning. Moreover, creating an environment that supports learning and facilitates the learning process can also foster positive outcomes for students [79].

Social structures play a crucial role in shaping an individual's behavior by providing resources, constraining human affairs, and regulating people's behavior. However, social structures are not absolute authorities to which people passively submit. As Bandura noted, individuals tend to explore variations within the rules and try to change them [80]. Effective individuals are more able to take advantage of the opportunities and resources provided by the social system and actively adapt or change their practices [21,22]. This perspective highlights the autonomy and initiative of individuals in the social structure, and suggests ways to increase individual efficacy and positive social adaptation [21].

This study is based on the premise that in online education and learning, there should be a focus on creating a supportive learning environment that facilitates the students' learning process, following Bandura's theoretical framework and research findings [21]. In social network analysis models within the field of learning, the core-marginal structure represents one of the most prevalent architectures. This structure consists of a subset of highly connected core nodes, surrounded by a number of edge nodes, which can be further subdivided into semi-edge and edge nodes, also known as weakly connected nodes. Identifying the core hierarchy typically requires selecting appropriate centrality and core metrics while taking into account the network's overall structure and context [37,39,66,67,81–83].

This study proposes an SNA model that includes several core-layer elements such as Student, University, Teaching, Study, Teacher, Experience, Environment, Academy, Pandemic, and Health. By employing this model, it was discovered that college students' online learning outcomes are significantly influenced by their personal factors (e.g., student and health), the online learning environment (e.g., university, teacher, environment, academy, and pandemic), and learning behaviors (e.g., study, education, teaching, and experience). The study also investigated the distribution of elements in the mantle and peripheral shell layers of the SNA model, which also have an impact on online learning among college students. Overall, this study offers a fresh perspective and approach to exploring online learning in higher education institutions, utilizing big data approaches and SNA models.

Now that the world has clearly entered the post-epidemic era, this study was oriented to research epidemics, and utilized technologies such as artificial intelligence to delve into the bottlenecks of theoretical research on education and teaching to explore and make up for the shortcomings. This can help relevant departments and universities to provide emergency education in the case of emergencies, and also perform their own exploratory practices in the continued application of online education. Therefore, this study conducted an in-depth study of college students' online learning in the epidemic era using SNA modeling from the perspective of TRD theory, with the aim of identifying the influencing factors and achieving the corresponding results. The main work of this study is summarized as follows.

This study analyzed and pre-processed the literature journal information. A comprehensive analysis of the literature data was performed to understand the structure of the literature data on the one hand, and transformed the data interpretation through big data technology on the other hand, to better mine the literature data and identify the factors that influence college students' online learning through the lens of the TRD theory.

An SNA model was developed based on a comprehensive understanding of all literature data and structure. At least six hybrid research tools, namely bibliometric analysis, big data analysis, text mining, sentiment analysis, linear algebraic modeling, and social network analysis, were used as tools for the study to interpret the data from three dimensions: temporal, spatial, and content, and to analyze the macro- and micro-level indicators.

The core and peripheral layers were analyzed for the layers of the model; the layers can be divided into core, mantle and shell layers. The classification and generalization of elements in the core, mantle and shell layers were realized by the three factors of network environment, learners and learner behavior under the role of the SNA model. The factors of network environment, individual learners and learner behavior were analyzed to calculate and analyze the centrality, closeness and intermediate degree of elements. This study aimed to provide theoretical and technically sustainable support for online learning for university students in the epidemic era.

5.2. Implications

Based on the results of the above analysis, it can be seen that the study of online learning for college students, which effectively utilizes tools such as big data technology, distinguishes itself from other studies limited to SPSS, AMOS or qualitative coding. The relevant research surface is small, distinguishing it from other studies that focused on a single research method such as questionnaires and interviews. Past studies using bibliometric methods did not delve into the factors and elements of the triadic reciprocity theory and did not conduct detailed analysis or interpretation. The relevant studies basically stayed in the simple organization of knowledge maps and did not study in-depth big data text mining in conjunction with the triadic reciprocity determinism. This study made an attempt, using approaches such as text mining, to investigate the factors affecting college students' online learning by drawing on the theoretical construct of TRD. This study constructed the SNA model to analyze the element hierarchy distribution and to identify the most influential core elements. In the three dimensions of time, space and content, starting from the macro and micro levels of the model, in this study, three analyses of degree, closeness, and betweenness were performed at the micro level of the model. This study explains the elements of the core, mantle, and shell layers of the SNA model. It sought to incorporate big data text mining for sentiment analysis and SNA modeling, and to process the data and analyze it thoroughly. This may achieve a mixture of quantitative and qualitative approaches which can decipher the relevant factors.

In the three dimensions of time, space and content, starting from the macro and micro levels of the model, the micro level has been studied in depth, and the three centrality weights have been analyzed. The positive and negative emotion weights of emotion mining can be introduced into the new methods of weighted stratification, such as the EWM entropy weight method, the AHP hierarchical analysis method, the ISM explanatory structural model stratification method, and so on, to explain the relevant educational laws through the analysis of subjective and objective elements. For positive and negative emotional elements, the PACT polarity management method can be introduced for mixed research, introducing mixed methods such as expert advice questionnaires, interviews, and so on, to deepen the artificial intelligence and big data foundation.

5.3. Limitations and future research

The first research limitation is the theoretical limitation, the triadic reciprocal deterministic theory, which goes from three facets to do research that can be done more oriented in the future, such as adding Time-Space-Content (TSC) theory. Future research can be optimized using algorithms such as neural networks. The second research limitation is that the study focused on online learning during the epidemic, but a comparative analysis was not performed on research materials from the post-epidemic era, and nor was an analysis of hybrid courses and purely online courses performed. This approach can be used in the future to enhance the shortcomings of studies that have not been analyzed in a comprehensive and in-depth manner. The third research limitation is the limitation of anti-crawler technology and many information sites which have related technical limitations, resulting in text material that may not achieve truly comprehensive coverage.

Other shortcomings include the fact that this study does not go into enough detail on SNA modeling in terms of the variables of influencing factors and positive and negative affective weighting elements. Subsequent research could incorporate more relevant studies to analyze the effects and weights in detail. In addition, given the effects of other latent variables, such as negative, positive, neutral affect and other elements on students' online learning effectiveness, further attention and in-depth analysis are needed. There are also differences in the epidemic and post-epidemic eras; therefore, the application of online learning can be analyzed in depth for positive and negative affective weights using polarity management and entropy weighting methods.

Ternary reciprocal determinism has limitations in terms of selecting objects, descriptive properties, lack of operational guidance, and model parameter settings. To overcome these limitations, future research can leverage multiple theoretical models for comparison and combined use. New algorithms or techniques can also be explored to address the lack of operational guidance and uncertainty in model parameter settings. While TF-IDF is easy to compute and use, its limitation lies in its inability to handle some special cases. Moreover, future research should delve further into the weak relationships between the mantle and shell layers in the edge layer of the social network analysis model and explore their implications for big data applications. Hence, future research should integrate the advantages of multiple text processing methods and use TF-IDF in combination with other methods to improve the research results. Additionally, more empirical studies should be conducted in the future to validate the main influences on students' online learning. The research themes and findings of this study should be further refined and augmented.

While the study employed a meticulous approach in the selection and synthesis of research articles, it is pertinent to highlight the absence of strict adherence to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The PRISMA framework offers a structured methodology that enhances the transparency and comprehensiveness of reviews. The decision was driven by a tailored review method, specifically designed for the research questions at hand. Although rigorous, this method did not align precisely with the PRISMA framework. Nonetheless, the significance of such guidelines is recognized, and their full adoption is advocated for future research to ensure more standardized reporting.

As the realm of education continues to evolve, it is imperative to delve into the transformative potential of digitalization. The digital transformation, coupled with the rapid advancements in artificial intelligence, presents a plethora of opportunities for reshaping the educational landscape. Embracing the concept of Smart Education—where learning is adaptive, personalized, and data-driven—can revolutionize pedagogical approaches and outcomes. These themes, being at the forefront of educational innovation, warrant in-depth exploration and research. Future studies should focus on harnessing these cutting-edge technologies and methodologies to foster a more responsive and dynamic educational environment.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors upon reasonable request. The data were derived from the WOS database and are secondary data which can be obtained through the database.

Ethics statement

This study did not involve human subjects and was not subject to ethical review.

CRediT authorship contribution statement

Jun Chai: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jian-Hong Ye:** Writing – review & editing, Writing – original draft, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jian-Hong Ye reports financial support was provided by Beijing Normal University. Jian-Hong Ye reports a relationship with Beijing Normal University that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by Fundamental Research Funds for the Central Universities in China (Grant Number: 2022NTSS52) and Beijing Normal University's First-class Discipline Cultivation Project for Educational Science (Grant Numbers: YLXKPY-XSDW202211,

YLXKPY-ZYSB202201).

References

[1] S.A. Ahmed, N.N. Hegazy, H.W. Abdel Malak, W. Cliff Kayser, N.M. Elrafie, M. Hassanien, A.A. Al-Hayani, S.A. El Saadany, A.O. Ai-Youbi, M.H. Shehata, Model for utilizing distance learning post COVID-19 using (PACT)TM a cross sectional qualitative study, BMC Med. Educ. 20 (1) (2020) 400, https://doi.org/10.1186/s12909-020-02311-1.
[2] I.A. Basheti, R.I. Nassar, İ. Halalşah, The impact of the coronavirus pandemic on the learning process among students: a comparison between Jordan and Turkey, Educ. Sci. 12 (5) (2022), https://doi.org/10.3390/educsci12050365. Art. 5.
[3] H. Jiang, A.Y.M.A. Islam, X. Gu, J.M. Spector, Online learning satisfaction in higher education during the COVID-19 pandemic: a regional comparison between Eastern and Western Chinese universities, Educ. Inf. Technol. 26 (6) (2021) 6747–6769, https://doi.org/10.1007/s10639-021-10519-x.
[4] E.-J. Kim, J.J. Kim, S.-H. Han, Understanding student acceptance of online learning systems in higher education: application of social psychology theories with consideration of user innovativeness, Sustainability 13 (2) (2021) 896, https://doi.org/10.3390/su13020896.
[5] U. Faura-Martínez, M. Lafuente-Lechuga, J. Cifuentes-Faura, Sustainability of the Spanish university system during the pandemic caused by COVID-19, Educ. Rev. 74 (3) (2022) 645–663, https://doi.org/10.1080/00131911.2021.1978399.
[6] T. Wang, C.-L. Lin, Y.-S. Su, Continuance intention of university students and online learning during the covid-19 pandemic: a modified expectation confirmation model perspective, Sustainability 13 (8) (2021) 4586, https://doi.org/10.3390/su13084586.
[7] Y. Cao, Understanding Chinese students' online learning experiences with emergency remote teaching: a case study, Asia Pac. J. Educ. (2023) 1–19, https://doi.org/10.1080/02188791.2023.2206548.
[8] R. Bansal, N. Pruthi, A systematic literature review on student engagement in online learning amid COVID-19, Asia Pac. J. Educ. (2023), https://doi.org/10.4018/978-1-6684-7639-0.ch011.
[9] D. Spencer, T. Temple, Examining students' online course perceptions and comparing student performance outcomes in online and face-to-face classrooms, Online Learn. 25 (2) (2021) 233–261.
[10] L. Peculea, Online learning experiences of engineering students in the post-pandemic perspective, J. Educ. 32 (1/2023) (2023) 118–132, https://doi.org/10.24250/jpe/Vol.321/2023/LP.
[11] F. Puteh Behak, H. Abdullah, H. Ismail, R. Saimin, Z.A. Zakaria, Norhaili Massari, Harshness of the online learning": the journey of Malaysian tertiary students during covid-19 pandemic, Al-Azkiyaa - Jurnal Antarabangsa Bahasa Dan Pendidikan 1 (2) (2022) 67–83, https://doi.org/10.33102/alazkiyaa.v1i2.27.
[12] C. Hodges, S. Moore, B. Lockee, T. Trust, A. Bond, The difference between emergency remote teaching and online learning, Educ. Rev. 12 (2020).
[13] T. Almpanis, P. Joseph-Richard, Lecturing from home: exploring academics' experiences of remote teaching during a pandemic, International Journal of Educational Research Open 3 (2022) 100133, https://doi.org/10.1016/j.ijedro.2022.100133.
[14] A. Maseleno, M. Huda, K.S. Mat Teh, A.G. Don, B. Basiron, K.A. Jasmi, M.I. Mustari, B.M. Nasir, R. Ahmad, Understanding modern learning environment (MLE) in big data era, International Journal of Emerging Technologies in Learning (iJET) 13 (5) (2018) 71, https://doi.org/10.3991/ijet.v13i05.8042.
[15] W. Di, X. Danxia, L. Chun, The effects of learner factors on higher-order thinking in the smart classroom environment, Journal of Computers in Education 6 (4) (2019) 483–498, https://doi.org/10.1007/s40692-019-00146-4.
[16] S. Geng, K.M.Y. Law, B. Niu, Investigating self-directed learning and technology readiness in blending learning environment, International Journal of Educational Technology in Higher Education 16 (1) (2019) 17, https://doi.org/10.1186/s41239-019-0147-0.
[17] K. Okoye, H. Hussein, A. Arrona-Palacios, H.N. Quintero, L.O.P. Ortega, A.L. Sanchez, E.A. Ortiz, J. Escamilla, S. Hosseini, Impact of digital technologies upon teaching and learning in higher education in Latin America: an outlook on the reach, barriers, and bottlenecks, Educ. Inf. Technol. (2022) 1–70, https://doi.org/10.1007/s10639-022-11214-1.
[18] A. Bandura, The self system in reciprocal determinism, Am. Psychol. 33 (4) (1978) 344–358, https://doi.org/10.1037/0003-066X.33.4.344.
[19] M. Lo Schiavo, B. Prinari, I. Saito, K. Shoji, C.C. Benight, A dynamical systems approach to triadic reciprocal determinism of social cognitive theory, Math. Comput. Simulat. 159 (2019) 18–38, https://doi.org/10.1016/j.matcom.2018.10.006.
[20] A. Bandura, Social Foundations of Thought and Action: A Social Cognitive Yheory, Prentice Hall, 1985. https://book.douban.com/subject/3918843/.
[21] A. Bandura, in: A. Bandura (Ed.), Self-efficacy: the Exercise of Control. Clinical Functioning: Alcohol and Drug Abuse, 1997, pp. 357–368.
[22] A. Bandura, Social cognitive theory: an agentic perspective, Asian J. Soc. Psychol. 2 (1) (1999) 21–41, https://doi.org/10.1111/1467-839X.00024.
[23] A. Aristovnik, K. Karampelas, L. Umek, D. Ravšelj, Impact of the COVID-19 pandemic on online learning in higher education: a bibliometric analysis, Frontiers in Education 8 (2023) 1225834, https://doi.org/10.3389/feduc.2023.1225834.
[24] M.E.J. Newman, D.J. Watts, S.H. Strogatz, Random graph models of social networks, in: Proceedings of the National Academy of Sciences of the United States of America, 2002, pp. 2566–2572, https://doi.org/10.1073/pnas.012582999, 99(Suppl_1).
[25] J. Beel, B. Gipp, Google Scholar's ranking algorithm: an introductory overview, in: Proceedings of the 12th International Conference on Scientometrics and Informetrics (ISSI'09), 2009, July, pp. 230–241, vol. 1.
[26] M. Ryan, Web Scraping with Python: Collecting More Data from the Modern Web, OReilly Media Inc., United States of America, 2018, pp. 20–45.
[27] C. Manning, H. Schutze, Foundations of Statistical Natural Language Processing, MIT press, 1999.
[28] B. Pang, L. Lee, Opinion mining and sentiment analysis, Foundations and Trends in Information Retrieval 2 (1–2) (2008) 1–135, https://doi.org/10.1561/1500000011.
[29] G. Salton, C. Buckley, Term-weighting approaches in automatic text retrieval, Inf. Process. Manag. 24 (5) (1988) 513–523, https://doi.org/10.1016/0306-4573(88)90021-0.
[30] S.P. Borgatti, A. Mehra, D.J. Brass, G. Labianca, Network analysis in the social sciences, Science 323 (5916) (2009) 892–895, https://doi.org/10.1126/science.1165821.
[31] A. Korshunov, I. Beloborodov, N. Buzun, V. Avanesov, R. Pastukhov, K. Chykhradze, I. Kozlov, A. Gomzin, I. Andrianov, A. Sysoev, S. Ipatov, I. Filonenko, C. Chuprina, D. Turdakov, S. Kuznetsov, Social network analysis: methods and applications, in: Proceedings of the Institute for System Programming of RAS, 2014, pp. 439–456, https://doi.org/10.15514/ISPRAS-2014-26(1)-19, 26.
[32] W. Chen, Effect of instruction intervention on MOOC forum discussion: student engagement and interaction characteristics, in: In International Conference on Technology in Education, Springer Nature Singapore, Singapore, 2023, pp. 94–105.
[33] A. Steinmaurer, R. Savic, J. Krugel, C. Gütl, Analyzing social networks and learning content on a discussion forum of an introductory programming MOOC in higher education, in: 2023 IEEE Learning with MOOCS (LWMOOCS), IEEE, 2023, pp. 1–6, https://doi.org/10.1109/LWMOOCS58322.2023.10305937.
[34] M.S. Granovetter, The Strength of Weak Ties11This study originated in discussions with Harrison White, to whom I am indebted for many suggestions and ideas. Earlier drafts were read by Ivan Chase, James Davis, William Michelson, Nancy Lee, Peter Rossi, Charles Tilly, and an anonymous referee; their criticisms resulted in significant improvements, in: S. Leinhardt (Ed.), Social Networks, Academic Press, 1977, pp. 347–367, https://doi.org/10.1016/B978-0-12-442450-0.50025-0.
[35] R.S. Burt, Structural Holes: The Social Structure of Competition, Harvard University Press, 1992. https://www.jstor.org/stable/j.ctv1kz4h78.
[36] J. Lim, Students' interaction, satisfaction and cognitive presence in online discussions, Educ. Technol. Soc. 27 (1) (2024) 35–49, https://doi.org/10.30191/ETS.202401_27(1).RP03.
[37] L.C. Freeman, Centrality in social networks conceptual clarification, Soc. Network. 1 (3) (1978) 215–239, https://doi.org/10.1016/0378-8733(78)90021-7.
[38] M. Mcpherson, L. Smith-Lovin, J. Cook, Birds of a feather: homophily in social networks, Annu. Rev. Sociol. 27 (2001) 415, https://doi.org/10.1146/annurev.soc.27.1.415.
[39] M. Newman, Networks, vol. 1, Oxford University Press, 2018, https://doi.org/10.1093/oso/9780198805090.001.0001.
[40] M. Newman, Networks: an Introduction, Oxford University Press, 2010, https://doi.org/10.1093/acprof:oso/9780199206650.001.0001.

[41] S. Jan, P. Vlachopoulos, M. Parsell, Social network analysis and online learning communities in higher education: a systematic literature review, Online Learn. 23 (1) (2019), https://doi.org/10.24059/olj.v23i1.1398.
[42] R.S. Burt, The network structure of social capital, Res. Organ. Behav. 22 (2000) 345–423, https://doi.org/10.1016/S0191-3085(00)22009-1.
[43] R. Hanneman, Introduction to social network methods, Sociology, Computer Science (2001). https://www.semanticscholar.org/paper/Introduction-to-Social-Network-Methods-Hanneman/58896e4e56c54b640a8a2a0abca0d2dbab45a1bc.
[44] Gwo-Jen Hwang, Jianwen Fang, Yunfang Tu, Global picture and trend of artificial intelligence education application research, Modern Distance Education Studies 34 (3) (2022) 3–14.
[45] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, W.M. Lim, How to conduct a bibliometric analysis: an overview and guidelines, J. Bus. Res. 133 (2021) 285–296, https://doi.org/10.1016/j.jbusres.2021.04.070.
[46] E. Abad-Segura, M.-D. González-Zamar, E. Meneses, E. Vázquez-Cano, Financial technology: review of trends, approaches and management, Mathematics 8 (2020) 951, https://doi.org/10.3390/math8060951.
[47] H. Hazrati, S. Bigdeli, S.K.S. Arabshahi, V.Z. Gavgani, N. Vahed, Visualization of clinical teaching citations using social network analysis, BMC Med. Educ. 21 (1) (2021) 349, https://doi.org/10.1186/s12909-021-02643-6.
[48] M.A. Khan, V. Vivek, M.K. Nabi, M. Khojah, M. Tahir, Students' perception towards e-learning during COVID-19 pandemic in India: an empirical study, Sustainability 13 (1) (2020) 57, https://doi.org/10.3390/su13010057.
[49] C. Wang, H. Zhao, The impact of COVID-19 on anxiety in Chinese university students, Front. Psychol. 11 (2020) 1168, https://doi.org/10.3389/fpsyg.2020.01168.
[50] A. Aristovnik, D. Keržič, D. Ravšelj, N. Tomaževič, L. Umek, Impacts of the COVID-19 pandemic on life of higher education students: a global perspective, Sustainability 12 (20) (2020) 8438, https://doi.org/10.3390/su12208438.
[51] N. Kapasia, P. Paul, A. Roy, J. Saha, A. Zaveri, R. Mallick, B. Barman, P. Das, P. Chouhan, Impact of lockdown on learning status of undergraduate and postgraduate students during COVID-19 pandemic in West Bengal, India, Child. Youth Serv. Rev. 116 (2020) 105194, https://doi.org/10.1016/j.childyouth.2020.105194.
[52] A.J. Ramos-Morcillo, C. Leal-Costa, J.E. Moral-García, M. Ruzafa-Martínez, Experiences of nursing students during the abrupt change from face-to-face to e-learning education during the first month of confinement due to COVID-19 in Spain, Int. J. Environ. Res. Publ. Health 17 (15) (2020) 5519, https://doi.org/10.3390/ijerph17155519.
[53] C.P. Camargo, P.Z. Tempski, F.F. Busnardo, M. de Arruda Martins, R. Gemperli, Online learning and COVID-19: a meta-synthesis analysis, Clinics 75 (2020) e2286, https://doi.org/10.6061/clinics/2020/e2286.
[54] S.C. Bradford, Sources of information on specific subjects, Engineering 137 (1934) 85–86.
[55] R. Bodily, H. Leary, R.E. West, Research trends in instructional design and technology journals, Br. J. Educ. Technol. 50 (1) (2019) 64–79, https://doi.org/10.1111/bjet.12712.
[56] L. Pei, H. Wu, Does online learning work better than offline learning in undergraduate medical education? A systematic review and meta-analysis, Med. Educ. Online 24 (1) (2019) 1666538, https://doi.org/10.1080/10872981.2019.1666538.
[57] R. Bokosmaty, A. Bridgeman, M. Muir, Using a partially flipped learning model to teach first year undergraduate chemistry, J. Chem. Educ. 96 (4) (2019) 629–639, https://doi.org/10.1021/acs.jchemed.8b00414.
[58] T.L. Kelley, The selection of upper and lower groups for the validation of test items, J. Educ. Psychol. 30 (1) (1939) 17.
[59] N. Vahed, V.Z. Gavgani, R. Jafarzadeh, Z. Tusi, M. Erfanmanesh, Visualization of the scholarly output on evidence based librarianship: a social network analysis, Evid. Base Libr. Inf. Pract. 13 (4) (2018) 50–69, https://doi.org/10.18438/eblip29396.
[60] Z. Yang, M. Zhu, Z. Qu, Y. Zhang, Research on organization of mathematics knowledge in good mathematical cognitive structure, Eurasia J. Math. Sci. Technol. Educ. 14 (1) (2018) 291–302, https://doi.org/10.12973/ejmste/78242.
[61] S. Bhattacharya, Some salient aspects of machine learning research: a bibliometric analysis, Journal of Scientometric Research 8 (2s) (2019) s85–s92, https://doi.org/10.5530/jscires.8.2.26.
[62] Wei Yao, Shuxian Wu, Ping Ke, Bin Sun, Jing Zhang, Research on knowledge mobilization patterns in network communities based on tsc theory, Intelligence Theory and Practice 43 (4) (2020) 4754, https://doi.org/10.16353/j.cnki.1000-7490.2020.04.008.
[63] S. Boccaletti, G. Bianconi, R. Criado, C.I. Del Genio, J. Gómez-Gardenes, M. Romance, M. Zanin, The structure and dynamics of multilayer networks, Phys. Rep. 544 (1) (2014) 1–122.
[64] C. Carrillo, M.A. Flores, COVID-19 and teacher education: a literature review of online teaching and learning practices, Eur. J. Teach. Educ. 43 (4) (2020) 466–487, https://doi.org/10.1080/02619768.2020.1821184.
[65] N.H. Al-Kumaim, A.K. Alhazmi, F. Mohammed, N.A. Gazem, M.S. Shabbir, Y. Fazea, Exploring the impact of the COVID-19 pandemic on university students' learning life: an integrated conceptual motivational model for sustainable and healthy online learning, Sustainability 13 (5) (2021) 2546, https://doi.org/10.3390/su13052546.
[66] R.A. Hanneman, M. Riddle, Introduction to Social Network Methods, University of California, 2005. https://www.researchgate.net/publication/235737492_Introduction_to_Social_Network_Methods.
[67] S.P. Borgatti, M.G. Everett, Models of core/periphery structures, Soc. Network. 21 (4) (2000) 375–395, https://doi.org/10.1016/S0378-8733(99)00019-2.
[68] S. Samudra, C. Walters, D. Williams-Dobosz, A. Shah, P. Brickman, Try before you buy: are there benefits to a random trial period before students choose their collaborative teams? CBE-Life Sci. Educ. 23 (1) (2024) https://doi.org/10.1187/cbe.23-01-0011 ar2.
[69] R. Sahay, S. Nicoll, M. Zhang, T.Y. Yang, C. Joe-Wong, K.A. Douglas, C.G. Brinton, Predicting learning interactions in social learning networks: a deep learning enabled approach, IEEE/ACM Trans. Netw. (2023), https://doi.org/10.1109/TNET.2023.3237978.
[70] C. Candia, J. Pulgar, F.L. Pinheiro, Interconnectedness in education systems, Phys. Educ. (2022), https://doi.org/10.48550/arXiv.2203.05624.
[71] R.H.A.T. Perera, N. Abeysekera, Factors affecting learners' perception of e-learning during the COVID-19 pandemic, Asian Assoc. Open Univ. J. 17 (1) (2022) 84–100, https://doi.org/10.1108/AAOUJ-10-2021-0124.
[72] F. Saleem, W. AlNasrallah, M.I. Malik, S.U. Rehman, Factors affecting the quality of online learning during COVID-19: evidence from a developing economy, Frontiers in Education 7 (2022), https://doi.org/10.3389/feduc.2022.847571.
[73] Heejung An, Geraldine Mongillo, Woonhee Sung, David A. Fuentes, Factors affecting online learning during the COVID-19 pandemic: the lived experiences of parents, teachers, and administrators in U.S. High-needs K-12 schools, Journal of Online Learning Research 8 (2) (2022) 203–234.
[74] Q. Yu, Factors influencing online learning satisfaction, Front. Psychol. 13 (2022). https://www.frontiersin.org/articles/10.3389/fpsyg.2022.852360.
[75] V. Gherheș, C.E. Stoian, M.A. Fărcașiu, M. Stanici, E-learning vs face-to-face learning: analyzing students' preferences and behaviors, Sustainability 13 (8) (2021) 4381, https://doi.org/10.3390/su13084381.
[76] M.W.L. Yeung, A.H.Y. Yau, A thematic analysis of higher education students' perceptions of online learning in Hong Kong under COVID-19: challenges, strategies and support, Educ. Inf. Technol. 27 (1) (2022) 181–208, https://doi.org/10.1007/s10639-021-10656-3.
[77] D.V. Azzi, J. Melo, A. de A.C. Neto, P.M. Castelo, E.F. Andrade, L.J. Pereira, Quality of life, physical activity and burnout syndrome during online learning period in Brazilian university students during the COVID-19 pandemic: a cluster analysis, Psychol. Health Med. 27 (2) (2022) 466–480, https://doi.org/10.1080/13548506.2021.1944656.
[78] M.D.H. Rahiem, The emergency remote learning experience of university students in Indonesia amidst the COVID-19 crisis. International Journal of Learning, Teaching and Educational Research 19 (6) (2020) 1–26, https://doi.org/10.26803/ijlter.19.6.1.
[79] A. Bandura, Social cognitive theory: an agentic perspective, Annu. Rev. Psychol. 52 (1) (2001) 1–26, https://doi.org/10.1146/annurev.psych.52.1.1.
[80] A. Bandura, Human agency in social cognitive theory, Am. Psychol. (1989), https://doi.org/10.1037/0003-066X.44.9.1175.

[81] V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech. Theor. Exp. 2008 (10) (2008) P10008, https://doi.org/10.1088/1742-5468/2008/10/P10008.
[82] L. Freeman, A set of measures of centrality based on betweenness, Sociometry 40 (1977) 35–41, https://doi.org/10.2307/3033543.
[83] M. Kitsak, L.K. Gallos, S. Havlin, F. Liljeros, L. Muchnik, H.E. Stanley, H.A. Makse, Identification of influential spreaders in complex networks, Nat. Phys. 6 (11) (2010) 11, https://doi.org/10.1038/nphys1746.