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Bibliometric analysis of artificial intelligence techniques for predicting soil liquefaction: insights and MCDM evaluation

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Abstract

The geotechnical phenomenon of soil liquefaction has serious implications for infrastructure and human safety, making it crucial to develop effective prediction and mitigation strategies as urbanization and infrastructure development expand. Recently, there has been significant interest in the potential of artificial intelligence (AI) techniques to address complex geotechnical issues, such as soil liquefaction. This study provides a bibliometric analysis of research literature on AI applications in predicting soil liquefaction. By systematically searching the Web of Science database, we identified 258 relevant articles published between 1994 and 2023 and applied bibliometric indicators to analyze publication trends, authorship patterns, affiliated institutions, publication venues, and citation patterns. This study presents a novel approach to evaluating the results obtained from bibliometric analysis. The MULTIMOORA method, a Multi-Criteria Decision Making (MCDM) technique, was employed to analyze further the journals that contributed to creating an academic knowledge inventory regarding AI techniques in soil liquefaction. This study demonstrates the utility of MCDM techniques as aggregators of bibliometric analysis results and their ability to facilitate decision-making. The interdisciplinary nature of this field, combining geotechnical engineering, computer science, and machine learning, is highlighted. The study also reveals a steady rise in publications on AI in liquefaction, with a notable increase in 2011 and 2019. The Soil Dynamics and Earthquake Engineering journal is shown to be particularly significant in studies on soil liquefaction prediction with AI techniques, followed by the Bulletin of Engineering Geology and the Environment and Environmental Earth Sciences journals.

Keywords Artificial intelligence · Bibliometric analysis · Geotechnical engineering · Soil liquefaction · Machine learning · Multi-criteria decision making

Extended author information available on the last page of the article

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1 Introduction

Liquefaction is one of the most important, interesting, complex and controversial issues in geotechnical engineering. The great destruction caused by liquefaction in Alaska (Mw = 9.2) and Niigata (Ms = 7.5) earthquakes that occurred within three months in 1964 increased the interest of geotechnical engineers in this subject. Liquefaction has been studied by hundreds of researchers, especially after these two earthquakes, and different terminologies, methods and analysis methods have been suggested. Due to the negative effects of liquefaction on human life and the economy, research on this subject is increasing daily and gaining importance.

After defining the liquefaction phenomenon, researchers have focused on many approaches to determining liquefaction potential to predict the possibility of liquefaction. Some of the researchers have developed methods based on field test data such as Standard Penetration Test (SPT), Cone Penetration Test (CPT), Shear Wave velocity (Vs), and some have examined the liquefaction phenomenon with experiments modeled in the laboratory (cyclic triaxial test, cyclic simple shear, cyclic torsional shear test, centrifuge tests, shaking table test, etc.) (Youd et al. 2001; Boulanger and Idriss 2006; Alizadeh Mansouri and Dabiri 2021). It is a more common approach in geotechnical engineering to use methods based on field tests instead of laboratory tests in liquefaction risk analysis due to the difficulty of both obtaining an undisturbed sample from the ground where liquefaction risk is investigated and modeling the field conditions exactly in laboratory experiments. SPT-based liquefaction analysis is the most widely preferred approach among field experiments (Yılmaz et al. 2022; Ghani and Kumari 2022; Ghani et al. 2022). The most well-known is the “cyclic stress approach” (Seed and Idriss 1971; Seed et al. 1983, 1985; Youd et al. 2001). Determining the liquefaction potential is based on determining the safety coefficient of the soil against liquefaction. The factor of safety (FS) is found by dividing the cyclic resistance ratio (CRR) required for liquefaction of the ground by the cyclic stress ratio (CSR) created by the earthquake (Youd et al. 2001). However, in addition to correcting the raw SPT-N values obtained with the Standard Penetration Test according to the fine grain ratio and applied energy rate, they also need to be corrected according to other factors such as well diameter, overburden load, and groundwater level (Youd et al. 2001; Idriss and Boulanger 2010; Alizadeh Mansouri and Dabiri 2021). Additionally, in liquefaction analyses based on the SPT experiment, many parameters are used, including those obtained from laboratory and field tests and earthquake-related parameters. While empirical expressions obtained by previous earthquakes (Youd et al. 2001; Cetin et al. 2004; Idriss and Boulanger 2008, 2010; Boulanger and Idriss 2014) and field observations can be used to determine CSR and CRR parameters, it is difficult to find a single acceptable empirical expression due to the include numerous parameters and uncertainties (Cai et al. 2022; Zhou et al. 2022b). For these reasons, researchers have turned to Artificial intelligence (AI) techniques in estimating liquefaction potential that is more robust, understandable and predictive as a strong alternative to traditional approaches, especially in the last 20 years (Xue and Yang 2013, 2016; Xue and Xiao 2016). As a result of new developments in earthquake engineering and significant progress in computer technology, AI methods such as fuzzy logic, artificial neural networks, machine learning and optimization have been applied to liquefaction assessments. The evaluation of liquefaction potential with these new approaches has attracted the attention of researchers, and many researchers have conducted studies on these issues (Chik et al. 2014; Abdalla et al. 2015; Bui et al. 2018; Feng et al. 2020; Ahangari Nanehkaran et al. 2022; Díaz et al. 2022; Li et al. 2022; Ozsagir et al. 2022; Rehman et al. 2022; Wang et al. 2022; Zhu et al. 2022).

AI has emerged as a promising tool for addressing complex geotechnical problems, such as soil liquefaction (Baghbani et al. 2022) and geotechnical design of rock structures (Azarafza et al. 2022). AI techniques, such as machine learning (ML) algorithms and data-driven models, can enhance the accuracy and efficiency of liquefaction hazard assessment, site characterization, and mitigation measures. These techniques can leverage large datasets, incorporate diverse parameters, and identify complex relationships that traditional analytical methods may overlook. However, many of the AI techniques which are more effective than traditional methods in solving complex problems have several challenges and limitations, such as overfitting, underfitting, high computational cost, poor generalization, and slow convergence (Qi et al. 2018; Wang et al. 2019).Researchers have begun to prefer novel AI techniques in liquefaction assessments, as in many other geotechnical engineering topics, to improve the generalization ability of AI models and overcome limitations in recent years. Many AI-based approaches have been proposed for the prediction of the soil liquefaction potential by different researchers around the world (Samui and Karthikeyan 2013; Qi et al. 2018; Wang et al. 2019; Rahbarzare and Azadi 2019; Zhang et al. 2021; Alizadeh Mansouri and Dabiri 2021; Zhao et al. 2021; Ghani and Kumari 2022; Cai et al. 2022; Zhou et al. 2022ba).

Researchers are considering innovative AI methods in liquefaction assessments because of the challenges associated with conventional AI techniques. In this context, the main contributions of this study are as follows:

- To show how the rich results obtained through bibliometric analysis and targeting different purposes offer ease of evaluation to the decision maker by combining MCDM techniques,
- To conduct a comprehensive bibliometric analysis of the research literature on the application of AI in soil liquefaction,
- By examining publication trends, authorship patterns, affiliations, and citation patterns to provide an overview of the current state of AI in liquefaction research,
- To give ideas about popular trends to researchers who will conduct research in this field and to show important affiliations, effective studies and publication opportunities in this field,
- To compare the performances of scientific journals in this field that contribute to forming the academic knowledge inventory.

By showing that bibliometric analysis results can be evaluated with different MCDM techniques, the study will pioneer future studies using bibliometric analyses in geotechnical engineering and other fields. The remainder of this study is organized as follows. Section 2 describes the methodology employed for the bibliometric analysis. Section 3 presents the publication trends, highlighting the distribution of publications over time, authorship patterns, affiliated institutions, and publication venues. Section 4 discusses the analysis of citation patterns, identifying the most cited articles, influential works, and clusters of related topics through co-citation analysis. Section 5 provides a comprehensive discussion on the interdisciplinary nature of AI in liquefaction research, emphasizing the contributions from geotechnical engineering, computer science, and machine learning, as well as the role of research institutions and countries. Section 6 discusses the findings' implications and identifies future research and collaboration directions. Finally, the study concludes with a summary of the key insights and contributions obtained from the bibliometric analysis.

2 Methodology

The methodology of this study involves two main phases: bibliometric analysis followed by the application of MCDM. Firstly, data collection procedures will be outlined, detailing the sources utilized to gather relevant literature and citation data. Next, the methodology for bibliometric analysis will be explained in detail, clarifying the metrics and techniques used to evaluate the collected data. This includes quantitative analysis impact assessment and examination of authorship, collaboration, institutional analysis, and citation patterns. Following the bibliometric analysis, MCDM analysis methods, specifically MULTIMOORA, will be incorporated. MULTIMOORA will assess and rank the identified journals based on predetermined criteria. These combined methodologies will provide a comprehensive framework for conducting the study. A general flow diagram illustrating the methodology of the study is depicted in Fig. 1.

2.1 Bibliometric analysis

Pritchard (1969) introduced the concept of bibliometric analysis, which involves quantitatively assessing scientific research. It is employed to gauge and scrutinize the present research directions within a particular field to derive measurable and replicable data pertinent to policy administration (Mooghali et al. 2011). Bibliometric analysis offers a comprehensive perspective on a knowledge domain. It can pinpoint research inquiries that scientists might seek to address and the techniques authors have devised to reach their objectives (Su and Lee 2010). A systematic search was performed across the Web of Science Core Collection (WoS) database to analyze the research literature comprehensively. WoS includes content from more than 10,000 academic journals across various fields. It encompasses research articles and includes diverse bibliometric data such as article titles, author affiliations, geographical origins, publication years, subject categories, and keywords. The search used the following query in WoS to capture relevant articles published between 1994 and 2023.

> (TS=(liquefaction) AND TS=(soil)) AND (((TS=(machine) OR TS=(deep)) AND TS=(learn)) OR TS=(decision tree) OR TS=(support vector machine) OR TS=(neural network) OR TS=(artificial intelligence) OR TS=("soft computing"))

After searching WoS, a total of 304 studies were retrieved. Among these, only those written in English and classified as document types: articles, proceeding papers, review articles, early access, and book chapters were included. The selected studies underwent screening to eliminate irrelevant ones. Consequently, 258 works remained for bibliometric analysis, upon which subsequent analyses in the study were based. Articles were chosen based on their relevance to the application of AI in liquefaction, specifically focusing on studies utilizing AI techniques, particularly machine learning methods, for soil liquefaction. Inclusion

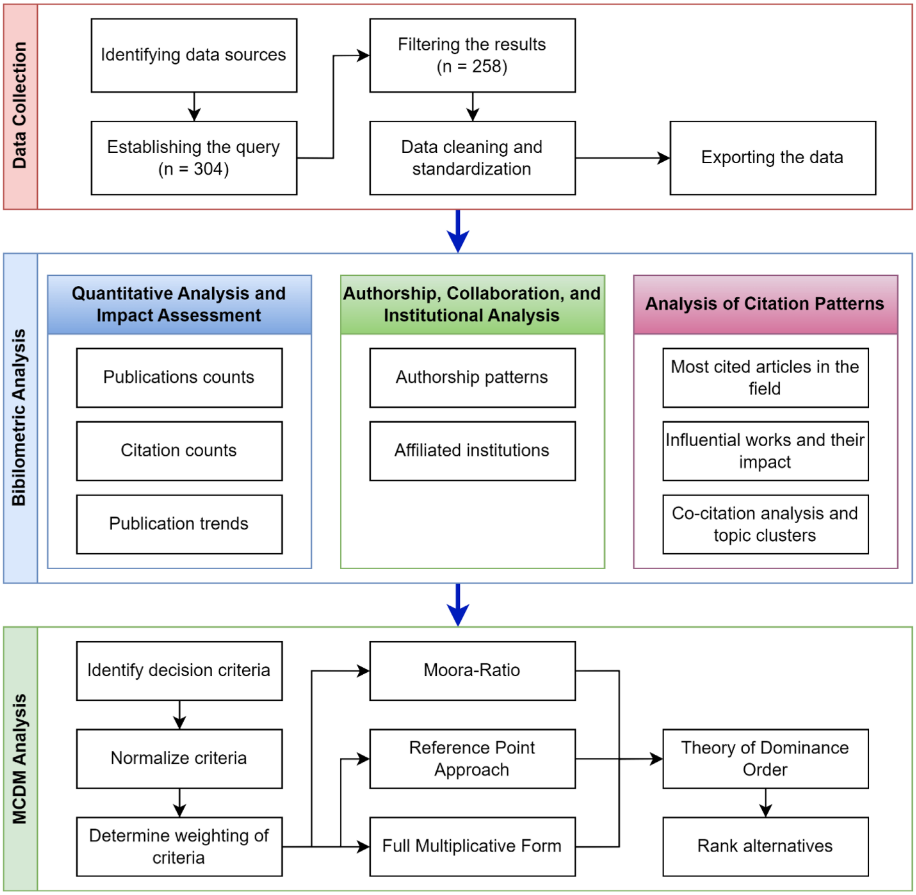

Fig. 1 General flow diagram of the study

criteria comprised studies that directly employed AI techniques for soil liquefaction. Exclusion criteria included articles unrelated to AI or liquefaction, duplicates, and publications not in English. The selected articles were subjected to data extraction, including information on publication year, authors, affiliations, publication venues, and citation counts. The data were then analyzed using bibliometric indicators to gain insights into publication trends, authorship patterns, affiliated institutions, and publication venues. Citation patterns were also examined to identify highly cited articles and influential works in the field.

In this study, bibliometric analysis was efficiently conducted using the Bibliometrix (Aria and Cuccurullo 2017), VOSviewer, and pyBibX (Pereira et al. 2023) packages. These packages provide researchers with powerful tools and algorithms to extract relevant information from scholarly publications and analyze various bibliometric indicators. Bibliometrix, a comprehensive R package, offers a wide range of functions for data retrieval, data cleaning, and the calculation of bibliometric measures. It allows researchers to collect publication data from online databases, preprocess it by removing duplicates or outliers, and then generate key bibliometric indicators such as citation counts, co-authorship networks, and journal impact factors. PyBibX, on the other hand, is a Python library that complements Bibliometrix by providing additional functionalities for bibliographic data analysis. It enables researchers to perform complex bibliometric analyses, including identifying research hotspots, co-citation analysis, and keyword co-occurrence analysis. Also, VOSviewer software (Van Eck and Waltman 2014) is used to visualize information such as network graphs. By leveraging the combined capabilities of Bibliometrix, pyBibX, and VOSviewer, researchers can gain valuable insights into the scientific landscape, identify influential authors or institutions, track research trends, and make informed decisions based on the quantitative analysis of scholarly literature.

The bibliometric analysis employed various indicators, including publication count over time, collaboration patterns, authorship distribution, institutional contributions, publication venue analysis, and citation analysis. These indicators provided quantitative data to understand the research's growth, patterns, and impact on AI in liquefaction.

Through this methodology, the study aimed to ensure a comprehensive and systematic analysis of the research literature on AI applications in liquefaction. The chosen indicators allowed for a holistic understanding of the research landscape and the contributions made by different stakeholders in advancing the field. Table 1 indicates the number of articles focusing on AI's utilization in soil liquefaction between 1996 and 2023.

Table 1 The distribution of publications by year between 1996–2023

Main Information	Results
Total Number of Countries	36
Total Number of Institutions	3
Total Number of Sources	100
Total Number of References	7808
Total Number of Languages	1
Total Number of Documents	258
Article	223
Article in Press	3
Article; Book Chapter	4
Proceedings Paper	23
Review	5
Average Documents per Author	1.36
Average Documents per Institution	276.33
Average Documents per Source	2.33
Average Documents per Year	9.56
Total Number of Authors	595
Total Number of Authors Keywords	616
Total Number of Authors Keywords Plus	435
Total Single-Authored Documents	18
Total Multi-Authored Documents	240
Average Collaboration Index	3.14
Max H-Index	8
Total Number of Citations	5468
Average Citations per Author	9.19
Average Citations per Institution	1822.67
Average Citations per Document	21.19
Average Citations per Source	53.82

2.2 MULTIMOORA method

The MULTIMOORA method is a Multi-Criteria Decision Making technique introduced by Brauers and Zavadskas in 2010 by adding the Full Multiplicative Form of Multiple Objectives method to the MOORA method (Brauers and Zavadskas 2010). Adding the order obtained from the Full Multiplicative Form method to the MOORA method, which consists of the Moora-Ratio and Reference Point Approach, the MULTIMOORA order is obtained by applying the Theory of Dominance Order. The method starts with the response matrix (Eq. 1) of the alternatives on different objectives or characteristics;

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & x_{m4} & x_{m5} & x_{m6} \end{bmatrix} \tag{1}$$

x_{ij} as the response of alternative *j* on objective or attribute *i*, *i*=1,2,…,*n* is the number of objectives; *j*=1,2,…,*m* is the number of alternatives.

With the Moora-Ratio method, for each objective in the response matrix, normalized values $\bar{x}_{ij}$ are obtained by dividing the values of the alternatives by the sum of the squares within the square root. Based on these normalized values obtained, for each alternative, the sum of the maximum objective ones is subtracted from the minimum objective ones (Eq. 2). The final ranking is obtained by sorting the obtained $\bar{y}_j$ values from largest to smallest.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^{2}}}, \bar{y}_j = \sum_{i=1}^{i=g} \bar{x}_{ij} - \sum_{i=g+1}^{i=n} \bar{x}_{ij} \tag{2}$$

$i = 1,2,\ldots,g$ as the objectives to be maximized$i = g+1, g+2, \ldots, n$ as the objectives to be mi

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with: $\bar{y}_j$ is the normalized assessment of alternative j with respect to all objectives.

In the Reference Point Approach, we still use $\bar{x}_{ij}$ normalized values. For each objective *i*, the reference points r_i are found, depending on whether they are minimization or maximization, and their absolute values are taken by subtracting them from all $\bar{x}_{ij}$ values (Eq. 3). The final ranking is obtained by taking the maximum values for each alternative *j* in the resulting matrix and sorting them from smallest to largest.

$$\left| r_i - \bar{x}_{ij} \right| \tag{3}$$

r_i is the ith coordinate of the reference point.

In the Full Multiplicative Form method, among the x_{ij} values of each *j* alternative for all objectives ,*i*, the maximization ones are multiplied by A_j, and the minimization ones are multiplied by B_j among themselves, and then divided by each other, U'_j is obtained (Eq. 4). The resulting values are sorted from largest to smallest to obtain the Full Multiplicative Form ranking.

$$U'_j = \frac{A_j}{B_j}, A_j = \prod_{g=1}^{i} x_{gi}, B_j = \prod_{k=i+1}^{n} x_{kj} \tag{4}$$

with: U'_j is the utility of alternative j with objectives to be maximized and objectives to be minimized (Kracka et al. 2010). The three rankings obtained from the Moora-Ratio, Reference Point Approach, and Full Multiplicative Form methods are transformed into a single ranking, the MULTIMOORA ranking, by applying the Theory of Dominance Order.

2.3 Evaluation of bibliometric analysis results with MCDM techniques

Bibliometric analysis provides reports containing the values of various alternatives in terms of different criteria. While the performance of the alternatives may be ranked differently in an analysis made in terms of one criterion, the performance of the alternatives may be ranked differently in the results of the analysis made in terms of another criterion. When evaluating the criteria, it is desired to optimize different objectives. While one criterion is aimed at being the maximum in the alternatives, a different criterion can be evaluated as the minimum value in the alternatives. These issues, combined with the fact that bibliometric analyses provide rich analysis reports, make it easier for those who evaluate the analyses to make a final evaluation. At this stage, MCDM techniques are recommended by this study. MCDM techniques will be able to play an aggregator role and provide the opportunity to evaluate different bibliometric analysis results by bringing them together, considering the maximum/minimum desired value in the alternative for each criterion. In this study, the MULTIMOORA method, which has an important place in the literature and has successful applications among the MCDM techniques, was applied as the MCDM technique. The main advantage of the MULTIMOORA method is that it includes the Moora-Ratio, Reference Point Approach and Full Multiplicative Form methods, which are three accepted methods in the literature and offer a single ranking with the theory of dominance order.

In the study, when applying MULTIMOORA to bibliometric analysis results, the performance indicators used in the evaluation of journals: H-index (HI), G-index (GI), and M-index (MI), Total Citation (TC), total Number of Publications (NP) and Publication Start Year (PYS) were considered as criteria. While having a minimum PYS value makes a journal stand out, having a maximum of other criteria values makes a journal more successful. The values obtained from the bibliometric analysis results were converted into the decision matrix (Eq. 5) and applied to MULTIMOORA.

$$X = \begin{bmatrix} \mathrm{HI} & \mathrm{GI} & \mathrm{MI} & \mathrm{TC} & \mathrm{NP} & \mathrm{PYS} \\ \mathrm{Max} & \mathrm{Max} & \mathrm{Max} & \mathrm{Max} & \mathrm{Max} & \mathrm{Min} \\ x_{11} & x_{12} & x_{13} & x_{14} & x_{15} & x_{16} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} & x_{26} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & x_{m4} & x_{m5} & x_{m6} \end{bmatrix} \tag{5}$$

3 Results and discussion

3.1 Distribution of publications by year

Analyzing publication trends provides insights into the growth and development of AI applications in liquefaction research over time. This section examines the distribution of publications by year, highlighting any significant changes or trends in research output. By analyzing the publication data, it is possible to identify periods of increased research activity and potential areas of emerging interest, as shown in Fig. 2. As expected, the number of publications has increased in recent years. The red lines in the graphs show the average numbers over the period. The number of publications remained low in 2023, as 2023 still needed to be finished when the analysis was made. The number of citations has decreased in recent years because the citations to the publications made in recent years have reached their actual numbers over the years. When interpreting Fig. 2, it becomes evident that the volume of publications on AI in liquefaction has exhibited a consistent upward trend, notably surging since 2011 and 2019. The publication peak was observed in 2022, underscoring a growing interest in this research area. Additionally, the substantial number of publications in 2023 indicates a sustained focus on AI applications in soil liquefaction.

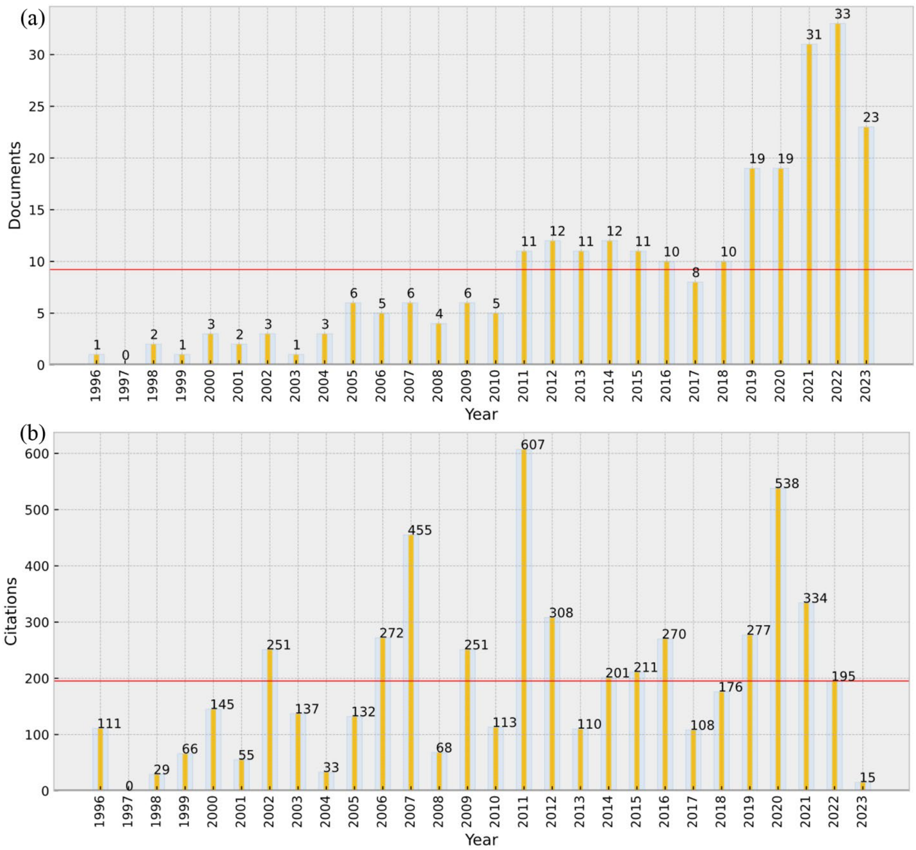

Fig. 2 (**a**) Documents and (**b**) citation numbers

3.2 Authorship patterns

Authorship patterns play a crucial role in understanding the collaborative nature of research in the field of AI in soil liquefaction. This section explores the number of authors per publication, the prevalence of single-authored versus multi-authored papers, and the identification of prolific authors. The analysis sheds light on the level of collaboration and the key contributors in the field.

In Fig. 3, "n" shows the number of authors and "CI" stands for "citation index." It represents the average number of citations per article for each respective year. A higher citation index suggests that the articles published in a specific year have received more citations, indicating their importance and contribution to the research community. Most publications have multiple authors, indicating a collaborative nature of research in the field. Also, the number of authors per publication tends to be relatively low, with most publications having fewer than five authors.

The most productive authors are given in Fig. 4, which illustrates the publication intervals and the specific years in which authors have contributed to the research, providing insights into their publication patterns over time. It also provides a breakdown of the number of publications authored by individuals in various years.

Figure 5 presents a network of authors who have collaborated at least five times. This visualization provides a comprehensive view of the research community's established working relationships and partnerships, shedding light on the most frequent and significant collaborative connections. Additionally, it serves as a valuable resource for understanding the dynamics of cooperation and knowledge exchange among authors in the field.

3.3 Affiliated institutions

Investigating authors' affiliations provides insights into the institutional landscape and identifies the institutions at the forefront of AI research in liquefaction. It examines the distri-

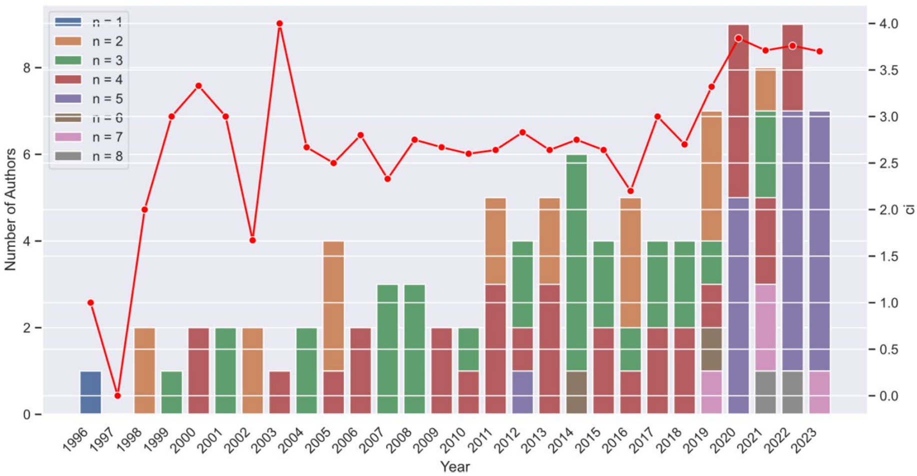

Fig. 3 Authorship and Citation Index (CI) trends in research publications

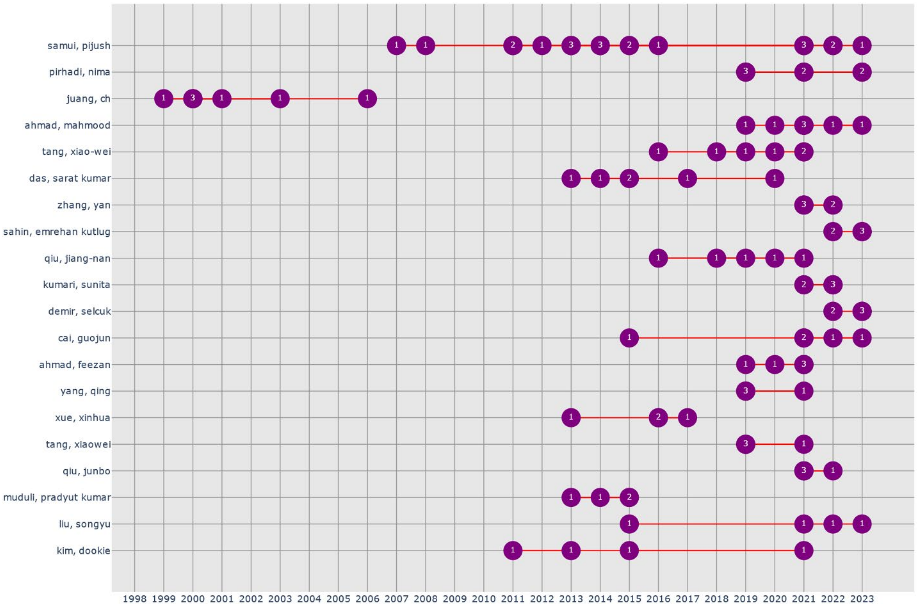

Fig. 4 Top authors and their publication numbers

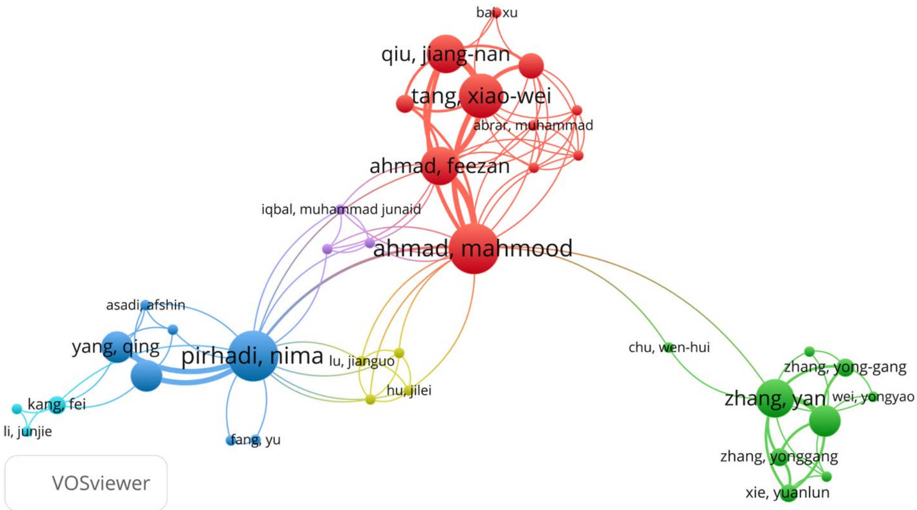

Fig. 5 Network graphs of the authors

bution of publications across different institutions, highlighting the leading institutions in terms of research output and their contributions to advancing the field, as shown in Fig. 6.

3.4 Publication trends

The choice of publication sources reflects the dissemination of research findings and the recognition of the contributions made in the field. This section analyzes the distribution of publications across different journals, conferences, and other publication outlets. By identifying the prominent publication sources, it is possible to understand the preferred platforms for sharing research on AI in liquefaction and the impact of these publications within the academic community.

By examining these publication trends, authorship patterns, affiliated institutions, and publication venues, a comprehensive understanding of the research landscape in AI applications for liquefaction can be obtained. These insights provide valuable information about the growth, collaboration, and dissemination of knowledge in the field, facilitating further analysis and discussion, as shown in Fig. 7.

The local impact of the sources is given in Table 2. In this study, we utilized H-index (HI), G-index (GI), M-index (MI), total citations (TC), total number of publications (NP), and publication start year (PYS) as specific performance criteria to evaluate the performance of journals.

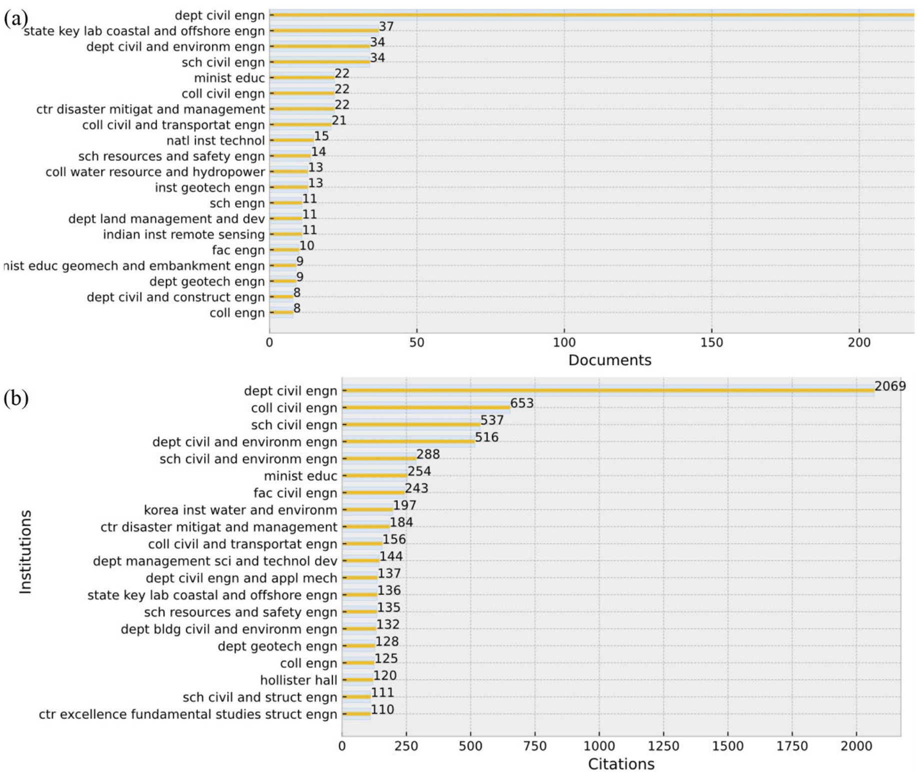

Fig. 6 (**a**) Document and (**b**) citation numbers for the institutions

HI represents the number h of times a researcher's publications have been cited at least h times. A researcher's h-index indicates where h publications have received h or more citations. For example, if a researcher's h-index is 10, at least ten publications have been cited ten times.

GI is an index weighted by the number of citations of a researcher's publications. This index considers the distribution of citations of the researcher's publications and the concentration factor of citations.

MI represents the ratio of the h-index to the NP. Represents the average number of citations of a researcher's publications. This index helps evaluate the overall citation performance of the researcher's publications.

TC indicates the total number of citations received by publications in the journals covered within the scope of the study.

PYS provides insights into the longevity and establishment of the journals in the field.

These indicators were selected based on their established significance in bibliometric analysis and their ability to provide comprehensive insights into the research landscape of AI applications in soil liquefaction prediction. By incorporating these performance indicators, we aim to provide a comprehensive evaluation of journal performance, considering both the quantity and impact of publications and the productivity of contributing authors.

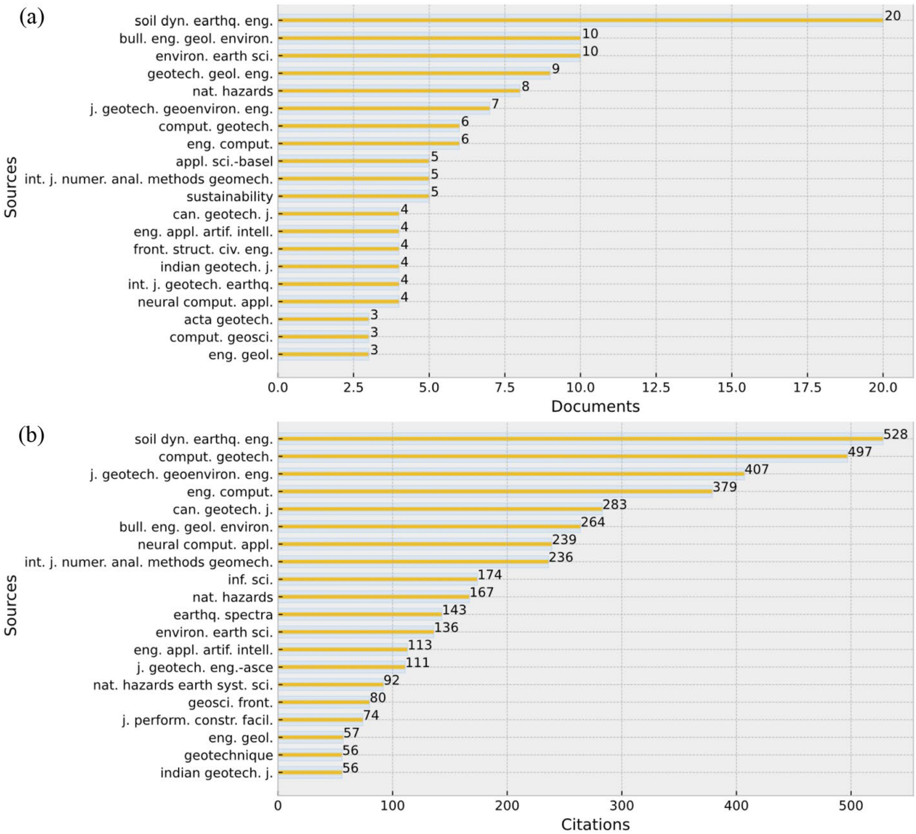

Fig. 7 (**a**) Document and (**b**) citation numbers for the sources

Table 2 Local impact of the sources

Publication	HI	GI	MI	TC	NP	PYS
Soil Dynamics and Earthquake Engineering (SOIL DYN EARTHQ ENG)	11	20	0.5	528	20	2002
Bulletin of Engineering Geology and The Environment (B ENG GEOL ENVIRON)	7	10	0.78	264	10	2015
Environmental Earth Sciences (ENVIRON EARTH SCI)	7	10	0.54	136	10	2011
Computers and Geotechnics (COMPUT GEOTECH)	5	6	0.26	497	6	2005
International Journal for Numerical and Analytical Methods In Geomechanics (INT J NUMER ANAL MET)	5	5	0.21	236	5	2000
Journal of Geotechnical and Geoenvironmental Engineering (J GEOTECH GEOENVIRON)	5	7	0.22	407	7	2001
Natural Hazards (NAT HAZARDS)	5	8	0.39	167	8	2011
Canadian Geotechnical Journal (CAN GEOTECH J)	4	4	0.16	283	4	1999
Engineering with Computers (ENG COMPUT)	4	4	1	147	4	2020
Indian Geotechnical Journal (INDIAN GEOTECH J)	4	4	0.4	56	4	2014

The findings extracted from the table can be briefly summarized as follows:

“Soil Dynamics and Earthquake Engineering” emerges as a standout in the field with the highest h-index (11) and g-index (20), underscoring its significant impact on research. Notably, “Bulletin of Engineering Geology and The Environment” and “Environmental Earth Sciences” also exhibit remarkable h-index and g-index scores, indicating their influential presence.

Furthermore, “Soil Dynamics and Earthquake Engineering” not only boasts the highest number of citations (528) but also leads in the number of publications (20), reflecting its substantial and extensive contributions to the field. Surprisingly, “Computers and Geotechnics” and “International Journal for Numerical and Analytical Methods in Geomechanics” achieved relatively high citation counts despite having a smaller publication volume.

Table 2 also reveals insights into the temporal aspect of these publications. “Canadian Geotechnical Journal” was first established in 1999, while “Engineering With Computers” emerged as a relatively newer entrant, commencing its publication in 2020.

Moreover, it is worth noting that “Soil Dynamics and Earthquake Engineering” takes the lead not only in citations and g-index but also in the number of articles, with 20 publications. This abundance of articles solidifies its status as a prominent and active source in the field. Similarly, “Bulletin of Engineering Geology and the Environment” and “Environmental Earth Sciences” are noteworthy contributors, with ten articles each emphasizing their significant and consistent contributions. “Geotechnical and Geological Engineering” closely follows suit with nine articles, highlighting its relevance and continued publication output.

Range of publication sources The list encompasses a diverse range of sources related to geotechnical engineering, environmental sciences, and geology. This diversity suggests a multidisciplinary approach and highlights the importance of various fields in addressing geotechnical challenges and understanding natural hazards.

Relatively lower publication activity Several sources, such as “Computers and Geotechnics,” “Applied Sciences-Basel,” and “International Journal for Numerical and Analytical Methods in Geomechanics,” have a lower number of articles (ranging from 5 to 7), as shown in Table 2. While their publication activity may be lower, it does not necessarily indicate lower quality or impact. It could be due to a more specialized focus or a newer journal.

Regarding high citation counts, “The Journal of Geotechnical and Geoenvironmental Engineering” emerges as the frontrunner, boasting the highest number of local citations at 802. Figure 8 underscores its status as a highly referenced source within the local geotechnical and environmental engineering community, highlighting its significant influence and recognition. Close on its heels is “Soil Dynamics and Earthquake Engineering,” with a substantial 675 local citations, signifying its noteworthy impact and relevance in the field. In contrast, the remaining sources exhibit a range of citation counts, varying from 554 to 157. These diverse counts reflect different levels of citation recognition within the local context, demonstrating the varying degrees of importance and influence among these sources. Within this spectrum, sources such as “J GEOTECH ENG-ASCE,” “Canadian Geotechnical Journal,” and “COMPUT GEOTECH” garner moderate citation counts, indicating their substantial relevance and contribution to the local geotechnical and engineering research landscape.

The number of publications across all journals has generally increased, indicating a growing interest and research activity in geotechnical and geological engineering. As illustrated in Fig. 9, “Soil Dynamics and Earthquake Engineering” consistently leads the way regarding publication counts over the entire observation period. This ongoing pattern underscores the journal’s enduring and significant presence in the field. Alongside, “Bulletin of Engineering Geology and The Environment” and “Environmental Earth Sciences” maintain relatively steady publication counts, reflecting their sustained level of research output.

Particularly in the case of “Natural Hazards,” which demonstrates a notable increase in publications from 2011 onwards. This upward trajectory suggests a growing emphasis on studying natural hazards and their impact on geotechnical and geological engineering, aligning with evolving research priorities and concerns in the field.

However, it is worth noting that fluctuations in publication counts are observed in other journals, such as “Geotechnical and Geological Engineering.” These journals exhibit varying activity levels over the years, with increased or decreased publication periods. These fluctuations may be attributed to specific research projects, collaborative endeavors, or

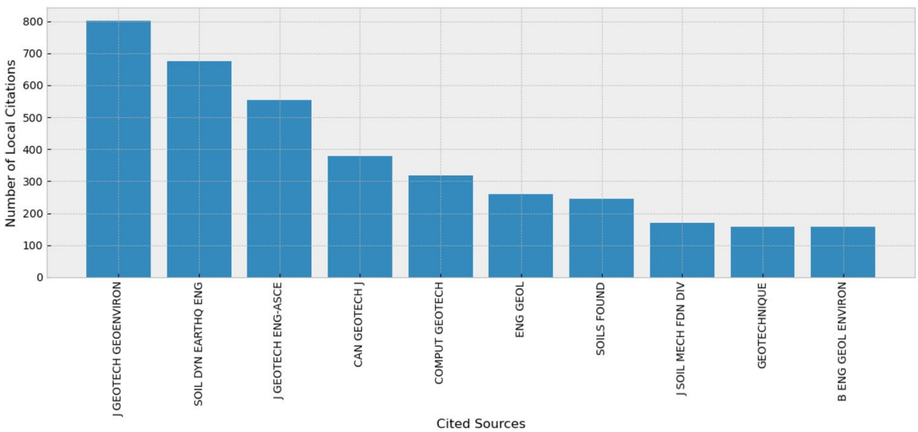

Fig. 8 Number of local citations for the sources

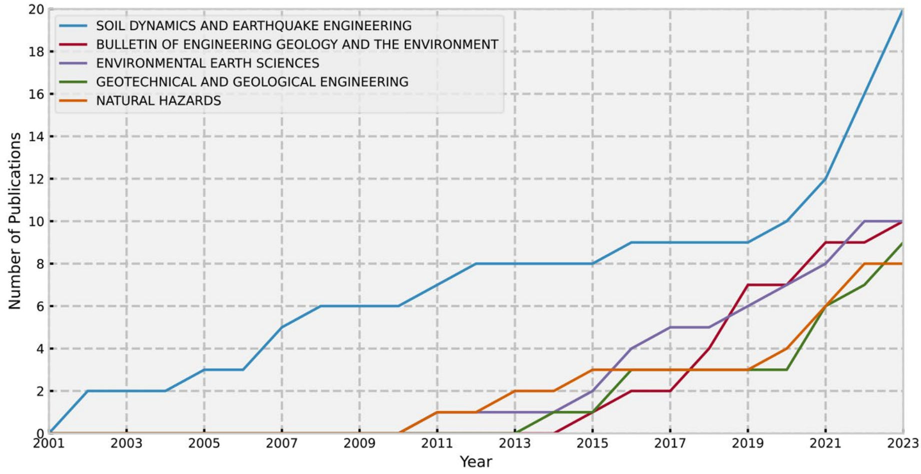

Fig. 9 Publication counts by source over time

the emergence of new areas of interest, emphasizing the dynamic and evolving nature of research in geotechnical and geological engineering.

When presenting a word cloud of key terms for AI and soil liquefaction publications, Fig. 10 provides insights into the frequency and prominence of specific keywords used in the literature. It offers a valuable glimpse into the most commonly utilized terms within the field, shedding light on the primary areas of focus and research themes.

Furthermore, Fig. 11 illustrates that the most frequently used keywords are "artificial neural networks" and "cone penetration test." This observation underscores their prominence as the predominant terms within the analyzed publications, highlighting their central role in the research discourse and indicating their significance as key areas of focus and exploration.

When we delve into the analysis of the keywords mentioned in the abstract, it becomes evident that a closer examination of the trends over the years can be facilitated by referencing Fig. 12. This graph illuminates that in recent years, terms such as "data set" and "data set validation" have been frequently employed, signifying their increased prevalence in the literature.

An insightful division of keywords into "soil liquefaction" and "artificial neural network" categories has led to the creation of Fig. 13, which is shared for reference. This graphical representation visually depicts the relative prominence and co-occurrence of these two key themes in the analyzed literature. This visualization also highlights the evolution of keywords over the years. The transition from blue to yellow represents the increasing usage of more recent terms.

3.5 Analysis of citation patterns

In this section, the article focuses on analyzing citation patterns within the field of AI in soil liquefaction. Several key aspects are examined to gain insights into the influential works, their impact, and the underlying research clusters.

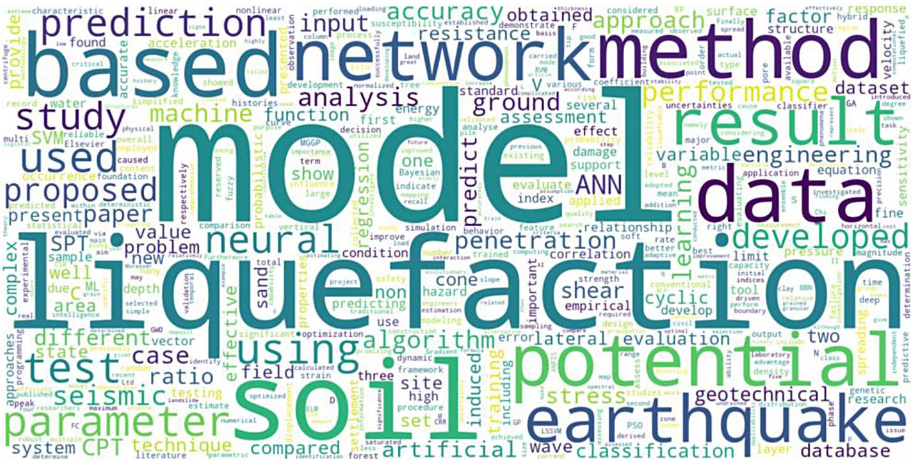

Fig. 10 Keyword cloud

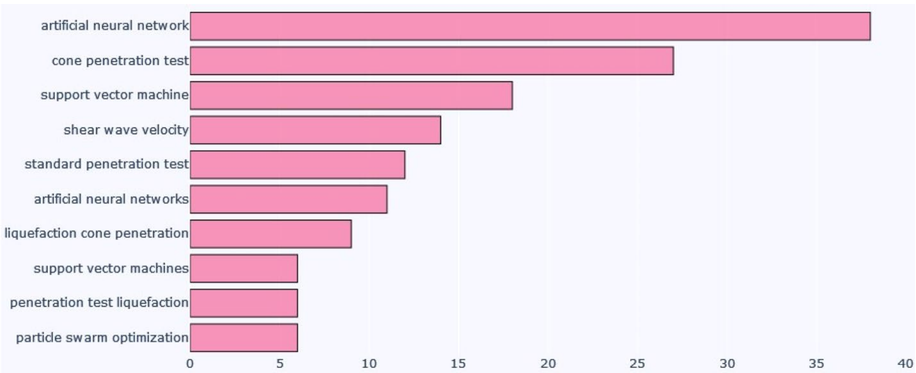

Fig. 11 Top ten keywords

3.5.1 Most cited articles in the field

The section begins by identifying and presenting the most cited articles in AI for soil liquefaction prediction. These articles have received significant attention and recognition within the research community, indicating their importance and impact on advancing knowledge in this domain.

Among the top globally cited papers, "GOH ATC 1994; J GEOTECH ENG-ASCE" stands out with the highest total citation count of 275, equating to an average of 9.17 citations per year and a normalized TC value of 1.00. Following closely are "CHO SE 2009; COMPUT GEOTECH" and "ALAVI AH, 2011, ENG COMPUTATION," with total citation counts of 197 and 195, respectively. They exhibit higher average citation rates per year compared to the top-cited papers. "XIE YZ, 2020, EARTHQ SPECTRA" emerges with the highest TC per year value of 34.25, indicating significant impact and sustained interest in

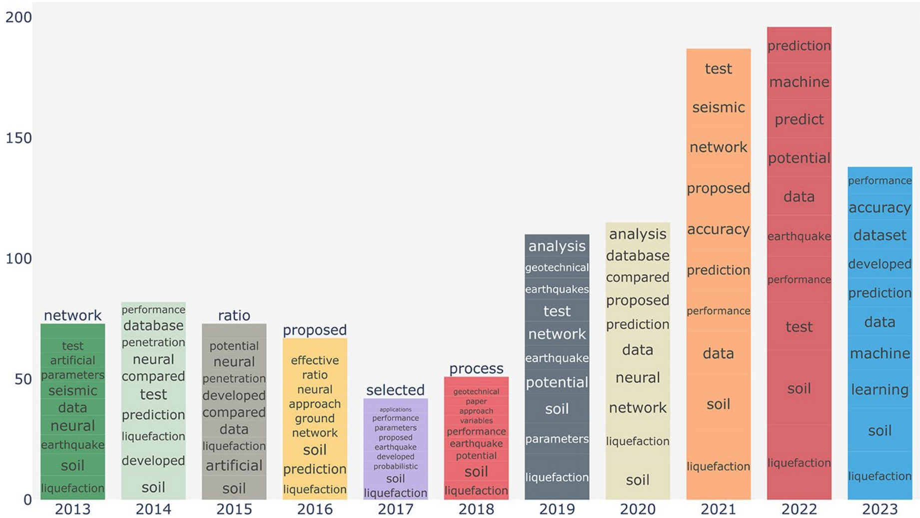

Fig. 12 Change in the abstracts in the last decade

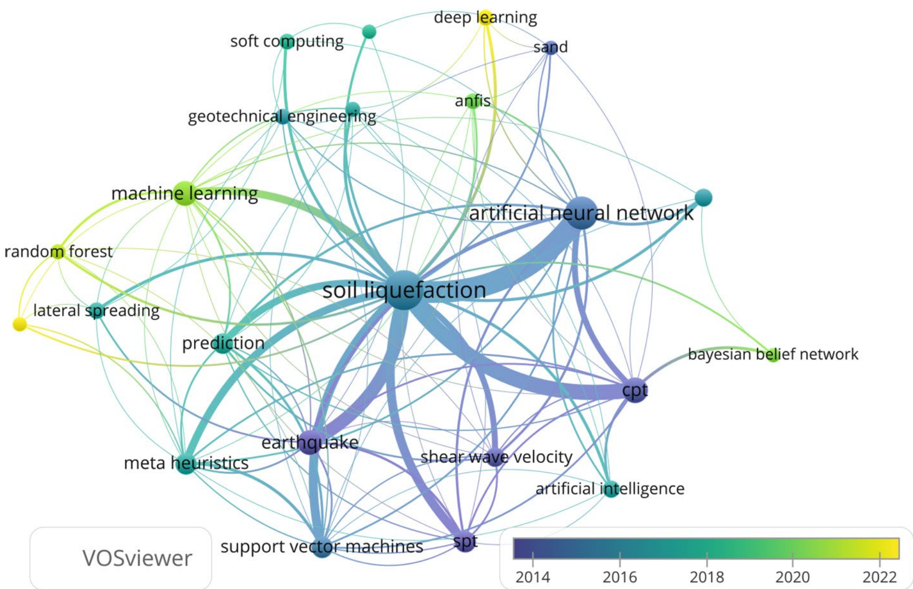

Fig. 13 Network of author keywords

the field. Figure 14 provides data on the most globally cited documents and their total yearly citations.

Impactful Papers Noteworthy papers such as "GOH ATC, 2007, COMPUT GEOTECH" and "GANDOMI AH, 2011, INFORM SCIENCES" showcase substantial total citation counts of 182 and 174, respectively. They exhibit moderate average citation rates yearly and normalized TC values, signifying their influence within the research community. "GANDOMI AH, 2012, NEURAL COMPUT APPL" garners a total citation count of 127 and a higher average citation rate per year, suggesting its impact and ongoing relevance.

Historical significance The enduring significance of older papers is demonstrated by "GOH ATC, 1996, J GEOTECH ENG-ASCE" and "JUANG CH, 2003, JOURNAL OF GEOTECHNICAL and GEOENVIRONMENTAL ENGINEERING," with total citation counts of 111 and 137, respectively. Despite their age, they continue to receive citations, underscoring their historical importance and lasting relevance in the field.

Diverse paper sources The top-cited papers hail from various journals, including "J GEOTECH ENG-ASCE," "COMPUT GEOTECH," "ENG COMPUTATION," "INFORM SCIENCES," "EARTHQ SPECTRA," "JOURNAL OF GEOTECHNICAL and GEOENVIRONMENTAL ENGINEERING," "NEURAL COMPUT APPL," and "Canadian Geotechnical Journal." This diversity of sources underscores the variety and breadth of geotechnical and geological engineering research.

Local citations vs. global citations The study "GOH ATC 1994; J GEOTECH ENG-ASCE" receives the highest number of local citations, 90, indicating its impact within the local research community. In contrast, "GOH ATC, 2007, COMPUT GEOTECH" garners the highest number of global citations with 182, signifying its broader recognition and global influence. Notably, "GOH ATC, 2002, Canadian Geotechnical Journal" achieves a relatively high number of global citations (120) compared to its local citations (43), resulting in a higher LC/GC ratio of 35.83%, highlighting its significance outside the local research community. Figure 15 displays the most locally cited documents, including global and local citation counts.

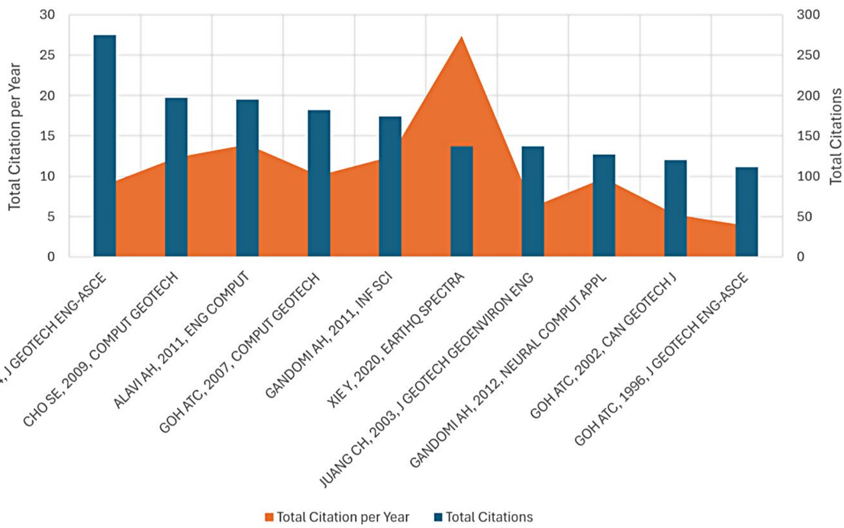

Fig. 14 Most globally cited documents

Normalized citations Several studies, such as "JUANG CH, 2003, JOURNAL OF GEOTECHNICAL and GEOENVIRONMENTAL ENGINEERING" and "JUANG CH, 1999, Canadian Geotechnical Journal," have normalized local citations of 1.00, indicating their impact within the local research community relative to other papers. Similarly, "GOH ATC 1994; J GEOTECH ENG-ASCE" and "GOH ATC, 1996, J GEOTECH ENG-ASCE" achieve normalized local citations of 1.00, emphasizing their local influence relative to other papers.

LC/GC ratio The study "GOH ATC, 1996, J GEOTECH ENG-ASCE" exhibits a higher LC/GC ratio of 64.86%, suggesting it receives more citations from the local research community than the global research community. Conversely, "JUANG CH, 2003, JOURNAL OF GEOTECHNICAL and GEOENVIRONMENTAL ENGINEERING" maintains a relatively balanced LC/GC ratio of 35.04%, indicating a similar level of recognition both locally and globally. The study "JUANG CH, 2003, JOURNAL OF GEOTECHNICAL and GEOENVIRONMENTAL ENGINEERING" has a relatively balanced LC/GC ratio of 35.04%, indicating a similar level of recognition both locally and globally.

Impactful documents The study "PAL M, 2006, INT J NUMER ANAL MET" garners a high number of local citations (46) and a relatively high number of global citations (107), indicating its impact both locally and globally. "SAMUI P, 2011, NAT HAZARD EARTH SYS" achieves a high LC/GC ratio of 49.37%, suggesting a strong local influence and potential regional significance.

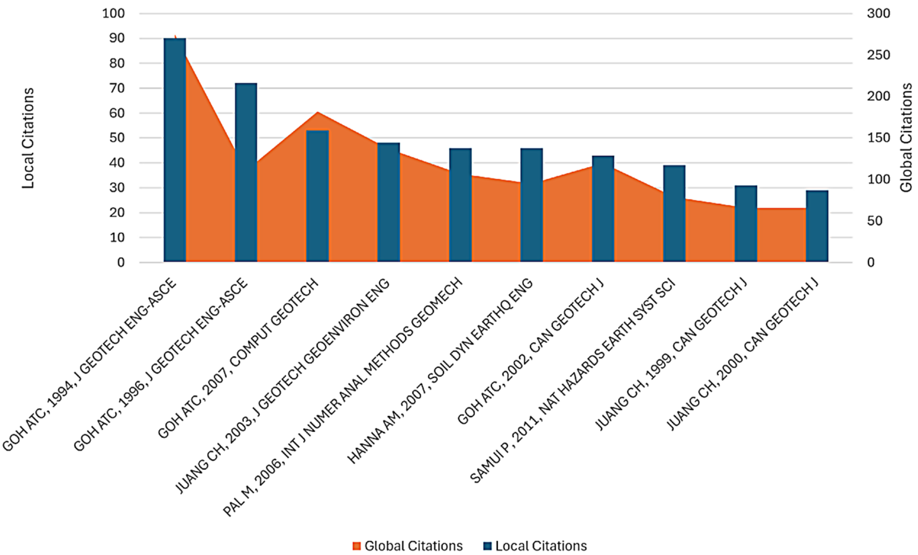

Fig. 15 Most locally cited documents

3.5.2 Influential works and their impact

Upon analyzing the most cited articles, this subsection delves deeper into the influential works identified in the previous section. It explores the impact of these works on the field, discussing how they have shaped research directions, methodologies, and theoretical frameworks. The subsection may highlight specific findings, breakthroughs, or innovative approaches introduced by these influential works.

Anthony Teck Chee Goh has the most locally cited papers, especially those published in 1994, 1996, and 2007. These studies highlight advanced computational techniques for modeling liquefaction potential based on seismic and soil parameters, such as neural networks and support vector machines. These methods offer promising alternatives to conventional approaches and show potential for improving our understanding and prediction of liquefaction phenomena.

On the other hand, Goh (1994), Cho (2009) and Alavi and Gandomi (2011) have the most globally cited papers. These studies also implement artificial neural networks and genetic programming variants in geotechnical engineering. These methods address the challenges posed by uncertainties, provide accurate predictions, and offer valuable tools for analyzing complex geotechnical systems.

3.5.3 Co-citation analysis and topic clusters

In this subsection, the article explores co-citation analysis and topic clusters to uncover the interconnectedness of ideas and research themes within the field. Identifying articles frequently cited together makes it possible to identify core topics and subdomains within AI in soil liquefaction. The analysis may reveal clusters of related research, indicating areas of active exploration and collaboration among researchers.

The thematic map of author keywords is presented in Fig. 16. Basic themes are more prominent compared to other themes. These basic themes can be divided into two clusters, primarily focusing on AI and soil liquefaction-related keywords. In contrast, geotechnical engineering and data mining keywords are associated with emerging or declining themes. Within the central motor themes for structuring research, we find two clusters. The first cluster comprises keywords like “xgboost,” “random,” and “correlation,” while the second cluster includes “regression” and “shallow foundation.” Niche themes, which have a limited connection to the main subject, form a single cluster, encompassing keywords such as “Monte Carlo,” “cohesionless soils,” and “simulation.”

3.6 Evaluation of journals with the MULTIMORA method

The first step in applying the MULTIMOORA method is the preparation of the decision matrix. Two hundred fifty-eight articles from each journal, published between 1994 and 2023 and defined in the Web of Science database, on the prediction of Soil Liquefaction with AI techniques were analyzed, and the decision matrix in Table 3 was created by extracting the data corresponding to the criteria specified in Sect. 3.4. In the first MULTIMOORA application, criterion weights were taken equally.

After creating the decision matrix, the equations in Eq. 2 were applied sequentially, and the Moora-Ratio ranking was obtained (Table 4).

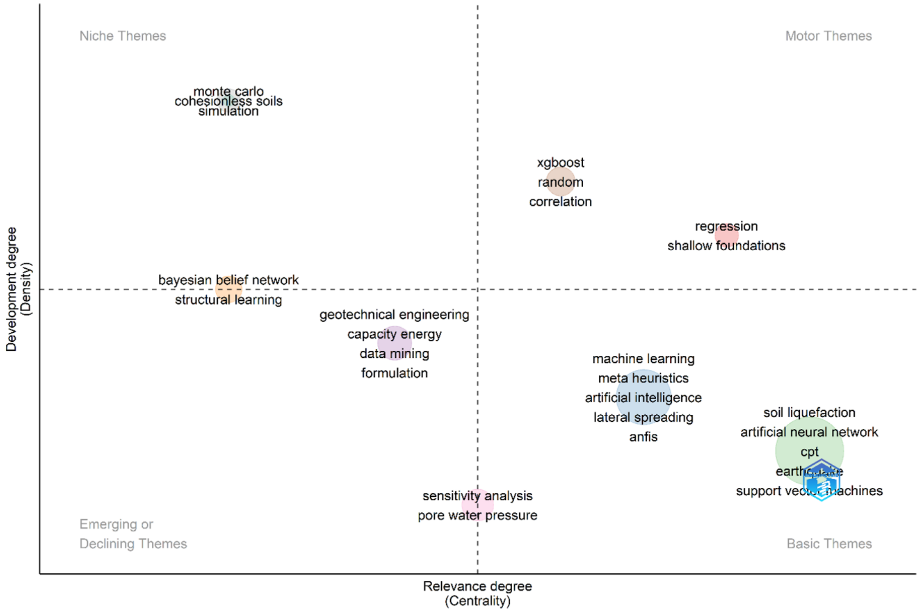

Fig. 16 Thematic map of author keywords

Table 3 Decision matrix

Objective	Max	Max	Max	Max	Max	Min
Publication	HI	GI	MI	TC	NP	PYS
B ENG GEOL ENVIRON	7	10	0.78	264	10	2015
CAN GEOTECH J	4	4	0.16	283	4	1999
COMPUT GEOTECH	5	6	0.26	497	6	2005
ENG COMPUT	4	4	1	147	4	2020
ENVIRON EARTH SCI	7	10	0.54	136	10	2011
INDIAN GEOTECH J	4	4	0.4	56	4	2014
INT J NUMER ANAL MET	5	5	0.21	236	5	2000
J GEOTECH GEOENVIRON	5	7	0.22	407	7	2001
NAT HAZARDS	5	8	0.39	167	8	2011
SOIL DYN EARTHQ ENG	11	20	0.5	528	20	2002

The following Reference Point Approach results were obtained when the normalized values obtained in Table 4 were processed in Eq. 3 (Table 5).

The decision matrix values in Eq. 1 were processed through Eq. 4 equations, the Full Multiplicative Form method was applied, and the following order was obtained (Table 6).

The ranking results obtained with Moora-Ratio, Reference Point Approach and Multiplicative Form method were evaluated through the Theory of Dominance Order to obtain the final MULTIMOORA ranking (Table 7).

When the performance of journals that publish studies on soil liquefaction prediction with AI techniques is evaluated in this field, the Soil Dynamics and Earthquake Engineering journal ranks first. It is followed by the Bulletin of Engineering Geology and the Environ-

Table 4 Moora-Ratio application results

Objective	Max	Max	Max	Max	Max	Min		
Publication	HI	GI	MI	TC	NP	PYS	∑max-∑min	Rank
B ENG GEOL ENVIRON	0.0609	0.0581	0.0798	0.0447	0.0581	0.0528	0.2488	2
CAN GEOTECH J	0.0348	0.0232	0.0163	0.0479	0.0232	0.0524	0.0931	9
COMPUT GEOTECH	0.0435	0.0348	0.0266	0.0841	0.0348	0.0526	0.1714	4
ENG COMPUT	0.0348	0.0232	0.1024	0.0249	0.0232	0.0530	0.1556	6
ENVIRON EARTH SCI	0.0609	0.0581	0.0553	0.0230	0.0581	0.0527	0.2027	3
INDIAN GEOTECH J	0.0348	0.0232	0.0409	0.0094	0.0232	0.0528	0.0788	10
INT J NUMER ANAL MET	0.0435	0.0290	0.0215	0.0399	0.0290	0.0524	0.1106	8
J GEOTECH GEOENVIRON	0.0435	0.0406	0.0225	0.0689	0.0406	0.0525	0.1638	5
NAT HAZARDS	0.0435	0.0465	0.0399	0.0282	0.0465	0.0527	0.1519	7
SOIL DYN EARTHQ ENG	0.0959	0.1162	0.0512	0.0894	0.1162	0.0525	0.4163	1

Table 5 Reference point approach results

	Max	Max	Max	Max	Max	Min		
Publication	HI	GI	MI	TC	NP	PYS	Max	Rank
B ENG GEOL ENVIRON	0.0348	0.0581	0.0225	0.0447	0.0581	0.0004	0.0581	2
CAN GEOTECH J	0.0609	0.0930	0.0860	0.0415	0.0930	0.0000	0.0930	8,9,10
COMPUT GEOTECH	0.0522	0.0814	0.0758	0.0053	0.0814	0.0002	0.0814	6
ENG COMPUT	0.0609	0.0930	0.0000	0.0645	0.0930	0.0006	0.0930	8,9,10
ENVIRON EARTH SCI	0.0348	0.0581	0.0471	0.0664	0.0581	0.0003	0.0664	3
INDIAN GEOTECH J	0.0609	0.0930	0.0615	0.0800	0.0930	0.0004	0.0930	8,9,10
INT J NUMER ANAL MET	0.0522	0.0872	0.0809	0.0495	0.0872	0.0000	0.0872	7
J GEOTECH GEOENVIRON	0.0522	0.0756	0.0799	0.0205	0.0756	0.0001	0.0799	5
NAT HAZARDS	0.0522	0.0698	0.0625	0.0612	0.0698	0.0003	0.0698	4
SOIL DYN EARTHQ ENG	0.0000	0.0000	0.0512	0.0000	0.0000	0.0001	0.0512	1

ment and Environmental Earth Sciences journals, respectively. It can be seen in Fig. 17 that the rest of the ranking consists of two clusters. The first cluster includes Computers and Geotechnics, Journal of Geotechnical and Geoenvironmental Engineering, and Natural Hazards journals. The second cluster includes Engineering with Computers, International Journal for Numerical and Analytical Methods in Geomechanics, Canadian Geotechnical Journal, and Indian Geotechnical journals. Although the journals in these two clusters were ranked differently in their clusters with the three techniques that make up MULTIMOORA, the final MULTIMOORA ranking obtained with the theory of dominance order is shown in Table 7; Fig. 17. It should be noted that when obtaining ranking results, the MULTIMOORA method is applied by giving equal weight to all criteria. When the criteria weights change, the place of some journals in the rankings will change. However, the results obtained with the MULTIMOORA application show that Soil Dynamics and Earthquake Engineering, Bulletin of Engineering Geology and the Environment and Environmental Earth Sciences journals contribute significantly to the creation of the scientific publication inventory for the prediction of soil liquefaction with AI techniques. The ranking results also give researchers who want to publish in this field an idea about the possibilities of publishing their work. The journal rankings they will choose during the submission process of the article will be similar

Table 6 Full multiplicative form results

	Max	Max	Max	Max	Max	Min		
Publication	**HI**	**GI**	**MI**	**TC**	**NP**	**PYS**	A_j / B_j	**Rank**
B ENG GEOL ENVIRON	1.3831	1.4678	0.9594	2.5328	1.4678	3.5540	2.0374	2
CAN GEOTECH J	1.2599	1.2599	0.7368	2.5623	1.2599	3.5492	1.0638	9
COMPUT GEOTECH	1.3077	1.3480	0.7989	2.8144	1.3480	3.5510	1.5046	4
ENG COMPUT	1.2599	1.2599	1.0000	2.2973	1.2599	3.5554	1.2923	7
ENVIRON EARTH SCI	1.3831	1.4678	0.9024	2.2677	1.4678	3.5528	1.7163	3
INDIAN GEOTECH J	1.2599	1.2599	0.8584	1.9560	1.2599	3.5537	0.9449	10
INT J NUMER ANAL MET	1.3077	1.3077	0.7710	2.4859	1.3077	3.5495	1.2074	8
J GEOTECH GEOENVIRON	1.3077	1.3831	0.7770	2.7223	1.3831	3.5498	1.4905	5
NAT HAZARDS	1.3077	1.4142	0.8548	2.3467	1.4142	3.5528	1.4766	6
SOIL DYN EARTHQ ENG	1.4913	1.6475	0.8909	2.8430	1.6475	3.5501	2.8880	1

Table 7 MULTIMOORA ranking obtained with the theory of dominance order

Publication	Moora-Ratio Ranking	Reference Point Ranking	Multiplicative Form Ranking	MULTI-MOORA Ranking
B ENG GEOL ENVIRON	2	2	2	2
CAN GEOTECH J	9	8,9,10	9	9
COMPUT GEOTECH	4	6	4	4
ENG COMPUT	6	8,9,10	7	7
ENVIRON EARTH SCI	3	3	3	3
INDIAN GEOTECH J	10	8,9,10	10	10
INT J NUMER ANAL MET	8	7	8	8
J GEOTECH GEOENVIRON	5	5	5	5
NAT HAZARDS	7	4	6	6
SOIL DYN EARTHQ ENG	1	1	1	1

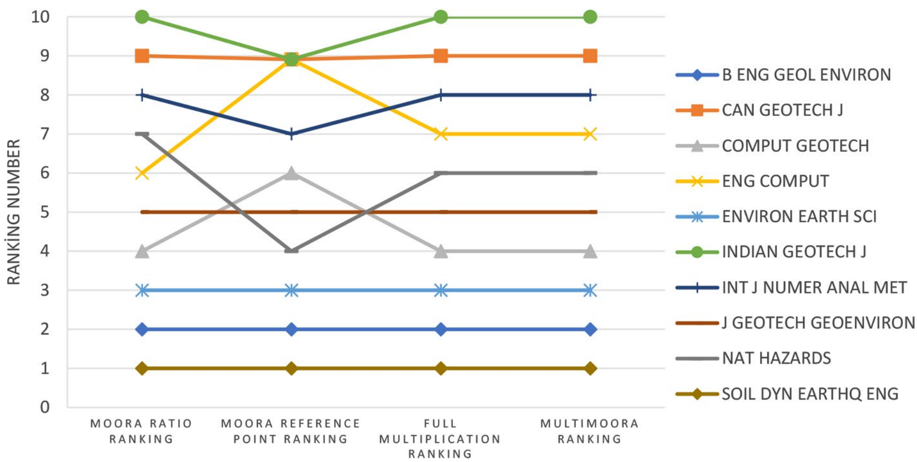

Fig. 17 Graphical representation of Moora-Ratio, Reference Point, Full Multiplicative Form and final MULTIMOORA ranking results

to the MULTIMOORA rankings and will guide the authors. The ranking results will also guide authors in creating the necessary reference works for books, articles, lecture notes and other works planned to be prepared in this field.

3.7 Discussion

Computer technology has become an indispensable part of our daily lives and has expanded its usage areas with the ability to learn and make decisions like humans. AI methods are increasingly used to solve difficult problems that cannot be expressed mathematically and are difficult for humans to solve. AI methods can learn from examples, experience and analogies to make decisions and produce solutions to events and problems. Various AI and ML models, such as ANNs, adaptive neuro-fuzzy inference systems (ANFIS), and support vector machines (SVM), are widely used to solve problems that traditional calculation methods cannot solve. AI methods have many advantages over traditional methods, such as non-linearity, learning, generalization, adaptation, data processing, error tolerance, parallelism, and working with incomplete data. Thus, AI methods have become a strong alternative to solving complex problems dominated by uncertainties.

Computer science is crucial in offering the computational frameworks and tools necessary for AI algorithms to process large datasets, enabling the practical application of machine learning models. The collaboration between geotechnical engineering, computer science, and machine learning creates a robust interdisciplinary framework that allows AI to emerge as a powerful alternative for solving complex and uncertain problems inherent in geotechnical engineering. Bibliometric analysis is a quantitative and statistical examination of publications in a specific category. It plays an important role in reflecting on a research field and identifying its strengths and weaknesses(Andrés 2009). Geotechnical engineering deals with many complex problems and bibliometric analyses can be used to determine trends and prominent elements related to research topics. This information can determine the productivity and effectiveness of researchers and research institutions, understand research networks and collaborations, list prominent sources, and identify keywords and their relationships related to the research topic.

This bibliometric analysis, which uses multiple-criteria decision-making (MCDM), has identified the top journals in soil liquefaction and artificial intelligence (AI). The analysis found that SOIL DYN EARTHQ ENG, B ENG GEOL ENVIRON, and ENVIRON EARTH SCI consistently ranked highest in all evaluation criteria, indicating their significant influence and contribution to the field. SOIL DYN EARTHQ ENG is the top-ranked journal, indexed in GEOSCIENCES, MULTIDISCIPLINARY - SCIE(Q2), and is a high-impact journal. It aims to promote the role of mechanics and related disciplines in earthquake engineering. It is a pivotal platform for publishing applied mathematical methods and AI applications in earthquake engineering analysis and design. B ENG GEOL ENVIRON is in the second position, indexed in ENGINEERING, GEOLOGICAL - SCIE(Q2). Although it does not explicitly mention AI in its objectives, the journal has shown acceptance of AI techniques, with 116 AI-related studies in its publications. ENVIRON EARTH SCI ranks third and has 83 years of publication history. It is indexed in GEOSCIENCES, MULTIDISCIPLINARY - SCIE(Q2), and its objectives explicitly include AI, indicating its commitment to publishing new, cutting-edge research in AI and earth science domains.

4 Conclusions

Soil liquefaction is a challenging issue in geotechnical engineering due to its uncertainties and the nonlinear behavior of soils. Many methods have been proposed in the literature to assess soil liquefaction potential, but they often need help with uncertainties and non-linear behavior. Recently, researchers have explored the potential of AI techniques as a robust alternative for predicting soil liquefaction. With their strong learning capabilities and non-linear fitting abilities, AI techniques offer promise in addressing this complex geotechnical issue.

A comprehensive bibliometric analysis examined 258 scientific research papers in this field. The analysis used Bibliometrix and pyBibX tools to assess publication trends, authorship patterns, affiliated institutions, publication sources, and citation patterns. The study provided valuable insights into the interdisciplinary nature of AI applications in liquefaction research. Furthermore, The analysis evaluated the contributions of journals that publish research on soil liquefaction using AI techniques. For the first time, the data obtained by bibliometric analysis were evaluated using the MULTIMOORA method. The results showed that the Soil Dynamics and Earthquake Engineering journal was at the top of the journals that publish studies on soil liquefaction prediction with AI techniques. It was followed by the Bulletin of Engineering Geology and the Environment and Environmental Earth Sciences journals, respectively.

To ensure objectivity, journal performance indicators were evaluated using equal criteria weights. Future research might investigate how ranking results vary with different criteria and weights through sensitivity analyses. MCDM techniques are pivotal in this stage, underscoring their adaptability and potential to expand future bibliometric analyses in geotechnical engineering and other fields.

The study also indicated increased AI techniques from the past to the present. The next trend is anticipated to shift from independently operated AI applications towards collaborative, network-based AI applications, where scientists from different countries come together through online interfaces. Additionally, there has been an observed movement toward adopting generative AI applications.

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Author contribution All authors contributed to the study conception and design. A. H. K. Methodology, Writing-original draft, Formal analysis, Visualization, Validation. C. E. Methodology, Writing-review & editing, Software, Data curation, Visualization, Validation A. S. D. Methodology, Writing-original draft, Supervision. T. F. K. Data collection, Conceptualization, Resources, Writing-original draft, Writing-review & editing, Supervision. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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