A scientometric analysis and systematic review of scientific literature on the validation of computer science graduate employability factors and predictive models

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Abstract

Promoting student employability stands as a central objective for educational institutions, often serving as a barometer of their effectiveness. However, the landscape of the job market is undergoing rapid transformation, driven by forces such as globalization, automation, and the rise of artificial intelligence (AI). Understanding the pivotal determinants of employability and constructing predictive models can yield substantial benefits for all stakeholders. This knowledge empowers students to make more enlightened career choices by discerning their strengths and areas that require development. In this study, we use scientometric analysis and a systematic literature review (SLR) to delve into recent trends and future trajectories within the realm of identifying, validating, and constructing predictive models for employability factors about computer science (CS) graduates. Our research encompasses 592 pertinent studies published between 2010 and 2023, sourced from Scopus, a pivotal academic database. Through keyword co-occurrence and author co-citation analyses using VOSviewer and CiteSpace software, we scrutinize network parameters and vital data. This review primarily strives to chart the progression of research within the field of employability, pinpoint knowledge gaps, and chart a course for future investigations. The scientometric analysis uncovers four notable clusters in the cited articles, encompassing subjects such as factors influencing the employability of CS graduates, models for validating these factors, predictive models for employability, and the impact of employability matrices. Our SLR offers invaluable insights into the prevailing validation and predictive models for employability among CS graduates. Guided by our SLR, we propose that forthcoming research should explore the potential of innovative AI techniques to pinpoint key factors and elevate the precision of predictive models geared toward computer science graduates' employability.

Keywords: CS graduate, prime factors, factor identification, factor validation, employability prediction, scientometric analysis, SLR

1. Introduction

Ensuring that graduates find employment is a priority, for institutions as unemployment can hurt the economy [1]. Educational institutions annually increase the number of students graduating [2]. However, a major challenge arises from the mismatch between education productivity and labor market demands. This flawed system poses threats such as growth setbacks, high unemployment rates, and migration of graduates seeking job opportunities elsewhere [3]. The main cause of this gap stems from collaboration between the labor market and higher education sectors. Insufficient communication leads to labor shortages. Fixing these gaps comes at a cost [4]. To address this problem effectively higher education institutions must proactively take measures to enhance employability [5]. Graduates should possess a range of accomplishments that include skills, knowledge, and various attributes. With skill sets, in place they can secure gainful employment while excelling in their respective roles. This not benefits individuals as well as contributes to the success of organizations they are part of and ultimately bolsters the entire country's economy [6]. Moreover, a considerable number of university-arranged internships and placements are highly competitive. As a result, interested candidates may not take advantage of these opportunities, and some individuals may not fully understand their potential benefits [7]. There is currently limited understanding and insight into how students' backgrounds and personal circumstances influence their willingness to participate in these internships, and more research is needed.

Computer science (CS) graduates face a slow transition in the workplace, according to research in India [8]. The research clearly shows that 15.98% of CS graduates are unemployed one year after graduation, which is higher than the overall average of 6.1%. Looking back, data up to 40 months after graduation show that in 2021-2022 in the cohort, 7.96% of CS graduates are unemployed [9]. While this represents an improvement on last year's figures, it remains the highest unemployment rate of any sector surveyed. CS graduates need to concern a range of skills, knowledge and abilities in the process of securing their jobs and roles [10]. Capacity and demand in the technology industry change from time to time, and multinational companies increase or decrease their global workforce based on demand and labor costs. Although job security in the information technology (IT) sector may seem uncertain at times, there is evidence that it offers positive opportunities for social progress.

In recent years, several artificial intelligence (AI) techniques, including machine learning (ML), deep learning (DL), and reinforcement learning [11]-[13], have become influential employability prediction tools. However, these studies often cover specific dimensions of the employability prediction domain, from predicting student behavior, soft skills to identifying key factors, validating these factors, and developing predictive models [14]. These studies in some cases lack the interdisciplinary approach necessary to explain the heterogeneity of employability. Furthermore, only a limited subset of studies have addressed the complex landscape of AI methods and their relationship to employability prediction, literature dissemination, keyword co-occurrence, and evolutionary trends in these disciplines [15][16]. A clear void remains for comprehensive surveys that could provide a comprehensive review of the literature on the use of employability prediction models. To fill these gaps, this paper provides not only an up-to-date systematic review of the literature on the main factors affecting employability and employability prediction models but also a quantitative conceptualization of the existing research [17]. Specifically, the use of scientific quantitative analysis in this study is multifaceted: (a) it improves our understanding of the cognitive domain of factors affecting employability and employability prediction models, (b) it provides a greater degree of objectivity than traditional assessments, and (c) it provides a quantitative visualization of the research landscape. This study is fundamentally driven by the pursuit of answers to the following pivotal research questions (RQs):

- RQ1: To what extent has research explored the use of AI techniques in employability predictive models?
- RQ2: How have developments in this field evolved over recent years?
- RQ3: What prevailing themes define factors that influence employability and predictive models for graduate employability?
- RQ4: Which multidisciplinary knowledge areas are involved in applying AI techniques to employability predictive models?
- RQ5: What are the current research hotspots and future directions for the application of AI techniques in employability predictive models?

The following sections of this paper are structured into five primary segments. In Section 2, we present the research methodology and detail the process by which we retrieved relevant literature for this study. Section 3 describes the results with bibliometric and scientometric analysis of SLR on the employability prediction. Section 4 presents the detailed literature on the state-of-art studies on the field of employability prediction. The detailed discussion of SLR is explained in Section 5. Finally, the conclusion and future direction are given in Section 6.

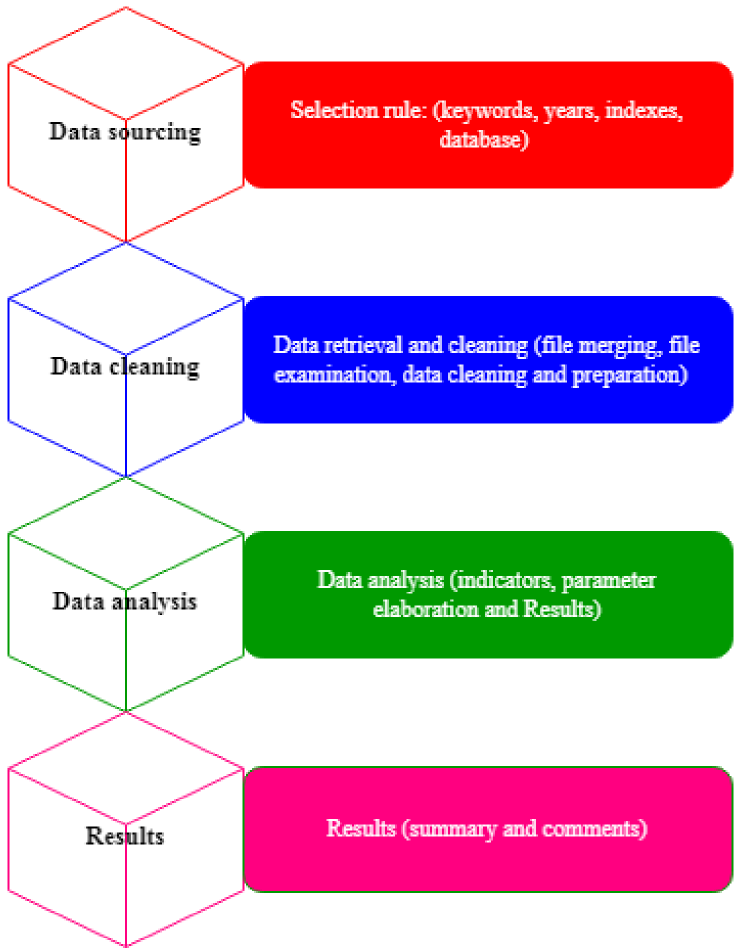

Fig. 1 Methodology used in this SLR

2. Methodology

In this study, we conducted a quantitative study with bibliometric and scientometric analysis to identify and evaluate SLR on the use of AI techniques for employability prediction. The initial phase of our research included activity analysis and scientific/bibliographic mapping [18]. It is a visual view of the relationships between different fields, subjects, specialties, individual scientific works, and authors. To achieve this, scientific quantitative analysis was used to create detailed maps that allowed us to gain insights into research themes and structural dynamics in our data set. Fig. 1 shows the methodology used in our SLR, including data cleaning, application of inclusion criteria, and relevance, to help organize and classify different subjects according to their importance and studies [19].

2.1 Bibliometric analysis

2.1.1 Data sources

As shown in Table 1, the data collection was limited to journal articles that are part of the Scopus, Web of science, and Lens core collection. The choice of this database was guided by three specific criteria:

1. Database comprises a substantial repository of highly indexed research papers.
2. The database has an extensive publication history spanning over a decade.
3. They offer straightforward and convenient accessibility for our research purposes.

2.1.2 Data cleaning

Our search was conducted to ensure that a comprehensive set of employment forecasting papers was included. Table 2 provides an overview of the original data set obtained from specific search strings. According to the inclusion criteria, we selected only articles published between 2010 and 2023. Exclusion criteria were designed to exclude articles not related to the area of predicting student outcomes [20][21].

2.1.3 Data analysis

The corpus of articles for this analysis, which involved a thorough manual review process, included 289 relevant articles from Web of Science, 523 articles from SCOPUS, and 185 from LENS. To ensure the integrity of the data set, we carefully removed 419 duplicate articles and matched author names and journal titles, resulting in a set of 578 articles that were judiciously grouped into a single file. Detailed results and discussion arising from this SLR are described in Section 3.

Table 1 Database Description

Database	Search string	Results
Scopus	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Article, language: English, publication year: 2010-2023	523
Web of science	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Article, language: English, publication year: 2010-2023	289
Lens	(("employability" or "CS employability") and ("prediction" or "predictive model") and ("AI" or "ML" or "DL")) Type: Journal article, language: English, publication year: 2010-2023	185

2.4 Scientometric analysis

Scientometric analysis [22][23], an invaluable methodology, helps to measure research impact and discover citation relationships by using insights from academic databases to link specific academic fields. This review paper conducted a comprehensive bibliographic search examining titles, abstracts, and keywords that provided the basis for a comprehensive survey of employability prediction in the literature. To provide multivariate analysis, this study used several analyses including keyword co-occurrence, author co-citation, journal co-citation, document co-citation, and clustering [24]. This progressive approach begins with keyword covariance and author covariance analysis, which provides a more complete picture of the research landscape. Citation analysis [25] then takes center stage in the paper, using clustering techniques and tagging of abstract terms to define different areas of research in the field of employability prediction. Fig. 2 shows the overall structure of bibliometric and scientometric analysis.

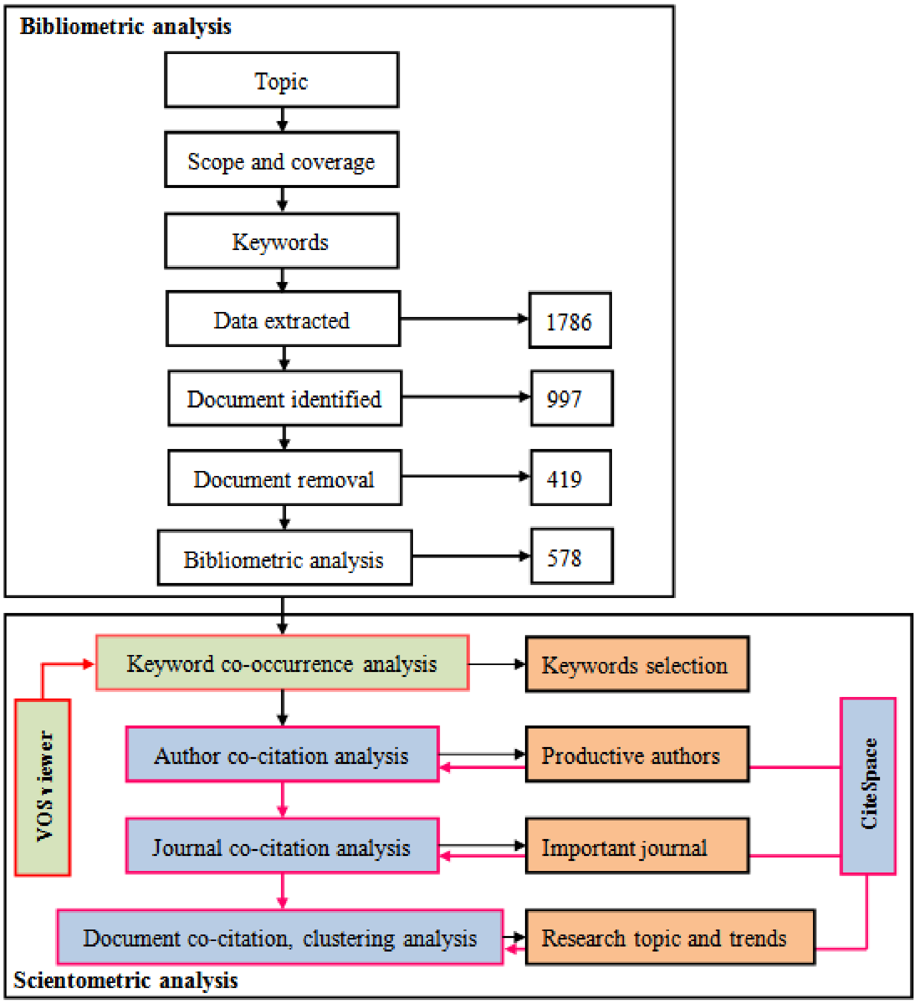

Fig. 2 Detailed methodology of this SLR with bibliometric and scientometric analysis

3. Results of bibliometric and scientometric analysis

In this section, this study presents SLR results with detailed bibliometric and scientometric analysis. Our comprehensive research includes keyword co-occurrence, author co-citation, journal co-citation, document co-citation, and clustering analysis, providing a comprehensive overview of the research landscape.

Table 2 Key findings from SLR

Description	Value
Duration	2010-2023
Main sources	103

Number of Articles	578
Number of Journals	71
Citations per documents	1003
Citations per year	2489
Number of References	1245
Keywords	1047
Authors keywords	1568
Number of Authors	1875
Single-author documents	64
Multi-author documents	986
Authors per document	334
Co-authors per documents	87

3.1 Data Acquisition

Insights from the data analysis are summarized in the descriptive statistics presented in Table 2. Academic resources, including scientific articles, journal articles, and conference papers [26][27] dealing with the issue of construction planning, were systematically collected using a targeted keyword search of the Web of Science, Scopus, and LENS databases [28]. As shown in Fig. 3, the Scopus database, which provides extensive categorization and sorting capabilities, found that 50.122% of the papers were in the engineering field and 12.569% in the social sciences. The highest publication years were 2010 and 2018, with 89 and 75 entries, respectively.

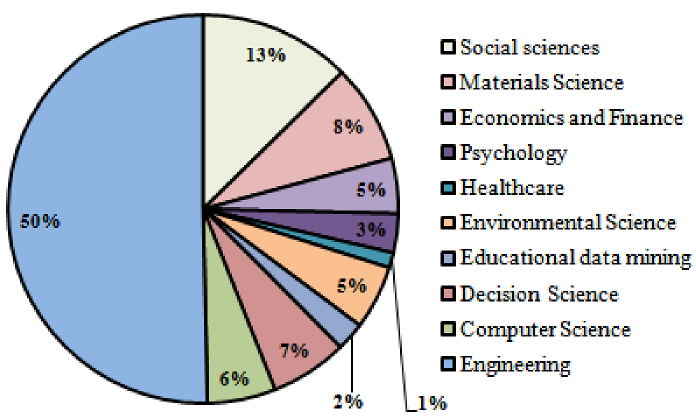

Fig. 3 Data acquisition from database

3.2 Keyword co-occurrence analysis

Keyword co-occurrence analysis [29][30] is powerful technique used in bibliometric and scientometric to understand dominant themes, emerging trends, and the overall structure of a particular field of knowledge. When performing basic co-occurrence analysis using software tools such as VOSviewer [31], the process collects a dataset of documents related to research area, including titles, abstracts, and keywords. VOSviewer offers a wide range of analysis and visualization options. Co-occurrence analysis remains the main option. We can adjust the parameters that determine the proximity of hidden co-occurrences to refine the analysis. Then identify keywords that appear together in the same document by revealing co-occurring patterns

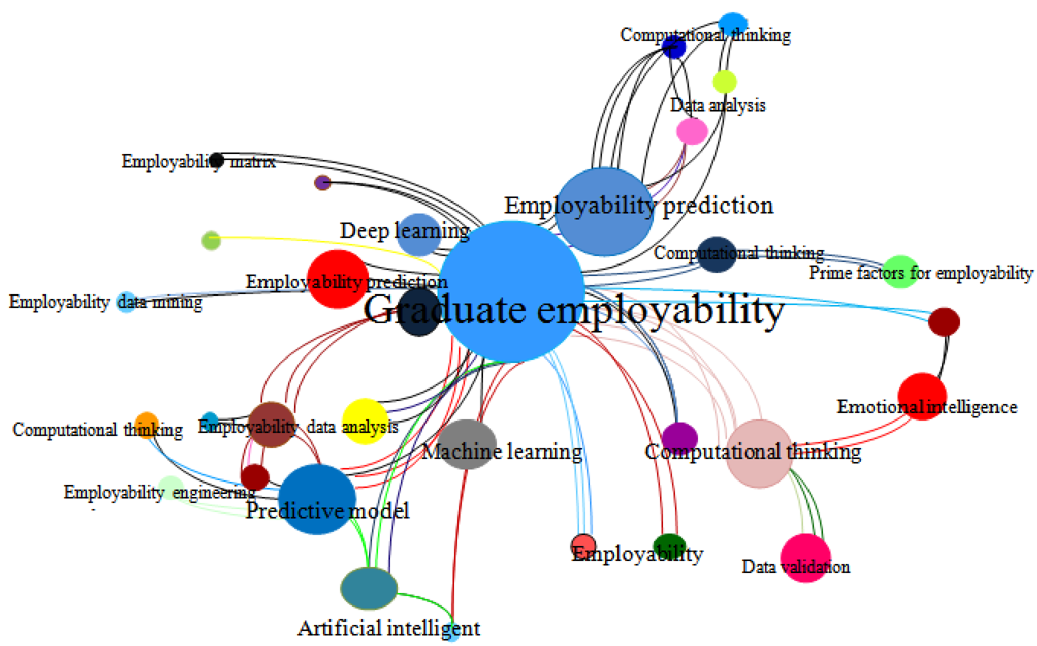

Fig. 4 Network from keyword co-occurrence analysis

VOSviewer creates data visualizations in the form of a network diagram. Identify keywords that act as key drivers of the research area. Emerging trends that ensure further investigation were identified [32]. It is a versatile and widely used method that facilitates knowledge mapping and trend analysis in various academic and research fields. Fig. 4 shows the basic co-occurrence network with 42 nodes, 46 links and 39 total connection strengths. Table 3 summarizes the most common keywords, their occurrences, the average annual number of links published, and total link strength. Based on the VOSviewer statistical technique, the keyword (employability prediction) is mentioned implicitly in different phrases such as graduate employability, predictive model for employability prediction, ML-based techniques for employability prediction and DL-based techniques for employability prediction. Combining the frequencies of these items results in 85 cases for employability prediction. Therefore, the keyword (predictive model for employability) can be considered the most cited keyword in the literature, while the keyword (prime factors affecting employability) would come in second place.

3.3 Author co-citation analysis

Author co-citation analysis [33][34] is bibliographic method that plays an important role in understanding author interactions and relationships in the context of educational research. To perform co-origin examination, analysts utilize specific programming devices, for example, CiteSpace [35]. In this, scientists gather a dataset of significant scholarly articles. Information is pre-handled to guarantee the data cleaning, expulsion of duplicates and normalization [36]. The dataset is then brought into CiteSpace where different boundaries are changed. The subsequent organization maps give bits of knowledge into the structure of the research field, influential authors, research groups, major areas of study, and the extent of scholarly collaboration. [37].

Figure 5 presents a gathering of references in the field of employability, featuring the researchers, distribution years, strength of reference, and the time spans in which these blasts happened [38]. The citation burst with the maximum strength is associated with the authors Christian Merkl and Thijs van Rens, with the strength of 31. This suggests that their work has been highly influential, signifying its impact on the field of employability as shown in figure 5.

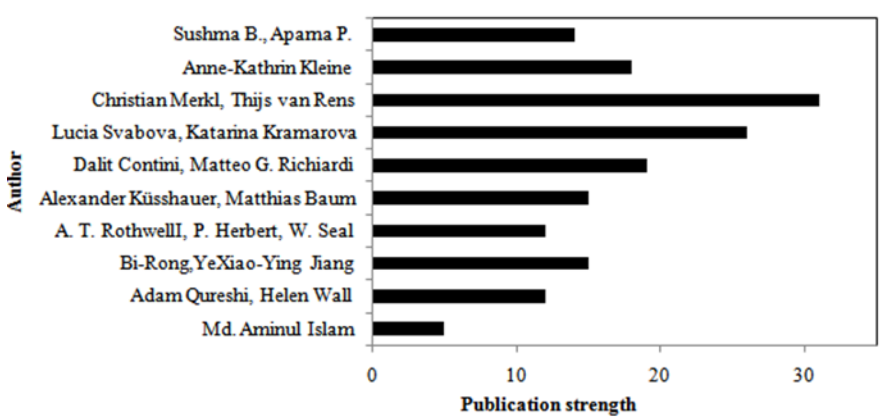

Fig. 5 Publication strength of authors in the “Employability”

Table 3 Network from keyword co-occurrence analysis using VOSviewer

Keyword	Occurrences	Published year (mean)	Links	Link strength
Employability prediction	42	2020	46	39
Predictive model	39	2018	32	30
Graduate employability	11	2019	18	15
Student performance	19	2015	26	21
Performance detection	15	2016	19	15
Student soft skill detection	86	2017	56	50
Computational thinking	7	2023	10	5
Emotional intelligence	6	2022	8	9
Factors affecting employability	4	2021	5	1
Data analysis for employability	3	2020	4	3
Employability	121	2018	6	5
Employability prediction using AI	15	2021	15	17
Machine learning-based predictive	26	2020	16	8
Deep learning-based predictive	31	2021	9	5
Employability matrix	7	2023	2	1
Feature optimization	5	2014	1	1
Data validation in employability	6	2015	3	2

3.4 Journal co-citation analysis

Journal co-citation analysis [39][40] is a bibliometric method that focuses on identifying connections between academic journals based on the co-citation of articles. For co-citation analysis, CiteSpace was loaded with the data, and boundaries were set. Table 4 describes the most refereed journal from the past prediction. Studies in educational evaluation, with its 21 related publications, have made significant contributions to the field.

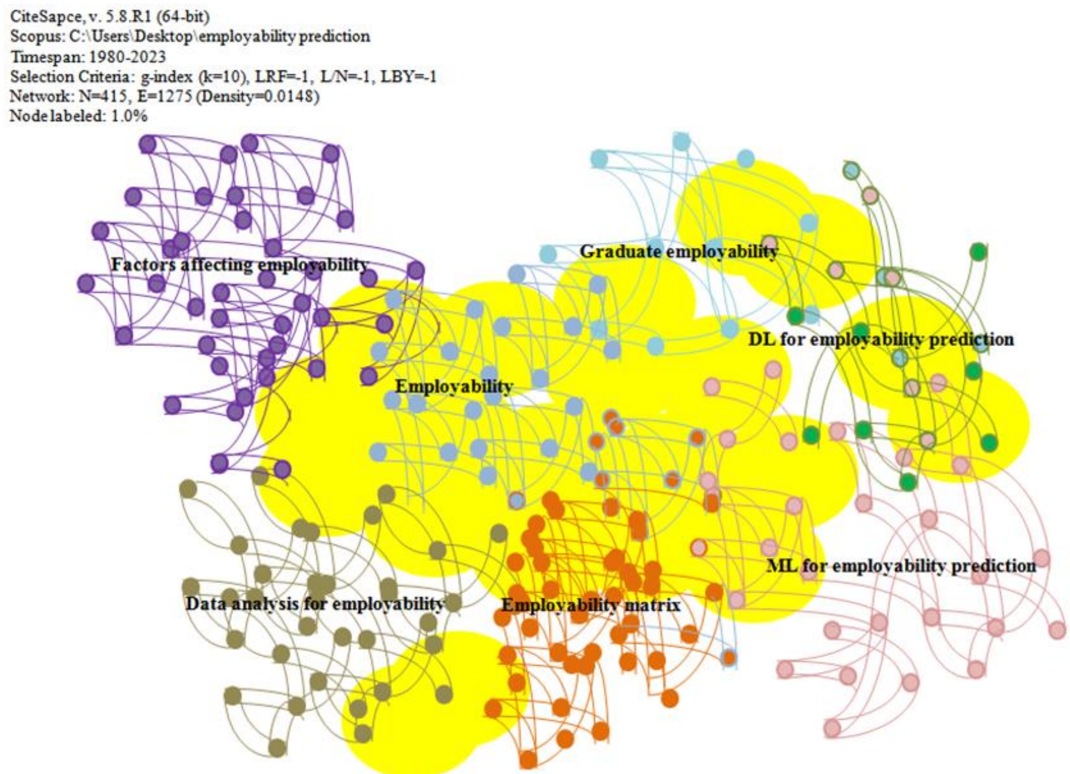

Fig. 6 Network of document co-citations analysis

Table 4 Top sources of journal articles of Employability

Name	Relevant publication	Total publication (%)
Journal		
International Journal of Educational Research	18	10.000
The International Journal of Management Education	15	8.333
Studies in Educational Evaluation	21	11.667
International Journal for Educational and Vocational Guidance	15	8.333
Social Sciences & Humanities Open	5	2.778
The International Journal of Management Education	4	2.222
Thinking Skills and Creativity	5	2.778
Journal of Vocational Behavior	6	3.333
Project Leadership and Society	4	2.222
Innovative Technologies and Learning	6	3.333
Employability Management 5.0	12	6.667
International Journal of Educational Technology in Higher Education	5	2.778
Vocations and Learning	15	8.333
Journal of International Migration and Integration	5	2.778
Higher Education	6	3.333
Education and Information Technologies	4	2.222
Employee Responsibilities and Rights Journal	15	8.333
Higher Education Policy	2	1.111
Science & Justice	1	0.556
Early Childhood Research Quarterly	2	1.111
World Development Sustainability	2	1.111
Conferences		
Procedia Computer Science	18	20.225
Materials Today: Proceedings	7	7.865
Social and Behavioral Sciences	12	13.483
Data-Driven Approaches in Digital Education	8	8.989
The Language of Employability	6	6.742
Entrepreneurship–Professionalism–Leadership	11	12.360
International Student Employability	29	32.584
Recent Advancements in Mechanical Engineering	4	4.494
Graduate Employability in Context	22	24.719
The Engineering-Business Nexus	4	4.494
Language Investment and Employability	13	14.607

3.5 Document co-citation analysis

Document co-citation analysis is bibliometric technique used in academic and scientific research to understand the relationships between scholarly documents based on how often they are cited together in other publications. CiteSpace identifies the same and visualizes the results in the form of a network or graph. A network of document co-citation has been constructed, consisting of 312 nodes and 1056 links. Each node within the network corresponds to an individual document, and the size of the nodes is indicative of the frequency of co-citations. The links connecting the nodes represent the co-citation relationships that exist between these publications. Furthermore, it's worth noting that the modularity score exceeds 0.3, and the silhouette score surpasses 0.5 for this specific network, as depicted in Fig. 6.

3.6 Clustering analysis

Following the document co-citation analysis, the subsequent phase involves clustering the research documents in the field of graduate employability. Form SLR we leverage latent semantic indexing (LSI) and log-likelihood ratio (LLR) technique implemented using CiteSpace, to create a total of 7 distinct clusters. Table 5 provides information about these clusters. Notably, we observed that the "employability" cluster exhibits the largest size, identified through LSI, while the "predictive model for employability" cluster, identified through LLR, also boasts a substantial cluster size.

4. Existing work in graduate employability

In this section, we will delve into the clusters as outlined in Table 6 and provide an in-depth review of the highly cited documents within each cluster. Furthermore, we will perform an analysis of the research topics prevalent in these clusters, prioritizing them based on the relevance and the quantity of publications within the graduate employability research areas. This comprehensive SLR aims to shed light on the existing research on graduate employability and its various focal points.

4.1 Factors affecting employability

The SLR concerning employability and predictive models for employability prediction in the context of CS graduates is extensive and multifaceted. Clustering analysis has unveiled the interconnected nature of Cluster #1, #3, and #4 within the network.

Table 5 Clustering analysis on graduate employability filed

Cluster-ID	Cluster size	Mean year	Most used items		Most cited
			LSI	LLR	
1	38	2016	Employability	Predictive model for employability	[49]
3	29	2014	Graduate employability	Computer science graduate	[50]
4	27	2019	Factors affecting employability	Prime factors	[51]
6	15	2021	Data analysis for employability	Data mining tools	[52]
7	12	2022	Employability matrix	Confusion matrix	[53]
9	7	2019	Machine learning-based prediction	ML for employability prediction	[54]
12	6	2020	Deep learning-based prediction	DL for employability prediction	[55]

These clusters, through the application of LSI and LLR, reveal distinct thematic areas. Cluster #1, #3, and #4 collectively represent the underlying factors influencing the employability of CS graduates. The specific areas illuminated by these clusters are described as follows.

- Cluster #1: This cluster pertains to the concept of "Employability." It encompasses the fundamental ideas and practices associated with employability, offering a comprehensive view of the topic.
- Cluster #3: "Graduate employability" emerges as a key theme within this cluster. It delves into the employability prospects and challenges faced by CS graduates, addressing their transition from academia to the professional world.
- Cluster #4: "Factors affecting employability" constitutes a significant subject matter within this cluster. It focuses on various elements that impact the employability of CS graduates. These factors use wide range of considerations, from educational quality to industry demands.

In this SLR, we place a particular focus on two pivotal factors that play a significant role in influencing the employability of CS graduates: computational thinking (CT) and emotional intelligence (EI). These factors are essential components of the employability landscape, and their impact on the career prospects and success of CS graduates cannot be underestimated.

4.1.1 State-of-art studies on computational thinking

This factor examines the basic cognitive and problem-solving skills that are central to computer science. Computational thinking (CT) involves a structured and analytical approach to solving complex problems and designing mechanisms. In terms of employment, CT is very important for CS graduates, to create innovative solutions and solve challenges. The review will delve into how the development of CT skills can enhance the employability of CS graduates and prepare them for a dynamic job market. The following existing studies have concentrated on CT with employability. Gonzalez et al. [58] have presented evidence of the reliability and criterion validity of a novel assessment tool designed to measure CT. They identified the expected positive, albeit modest to moderate, significant correlations between CT and three of the four primary mental abilities within the intelligence model. Yagci et al. [59] have developed to assess the CT skills of high school students, and its validity and reliability were evaluated using data from 785 student participants.

Gonzalez et al. [60] have addressed the issue by examining the connections between CT and fundamental cognitive variables, including primary mental abilities and problem-solving skills. Korucu et al. [61] have investigated the computational thinking skills of secondary school students while considering various variables. They utilized the CT consisting of 22 items on a 5-point Likert scale, for data collection. Doleck et al. [62] have explored the connection between CT and academic performance. To investigate this relationship, they employed a structural model utilizing the partial least squares approach.

Durak et al. [63] have investigated the extent to which various variables can account for students' CT skills. They aimed to construct a model that elucidates and forecasts the relationships between computational thinking skills and these diverse variables. Tsai et al. [64] have utilized an impactful tool to assess all CT processes of students in various problem-solving contexts. An exploratory factor analysis using the principal axis method with optimal rotation to extract 19 items organized into five specific dimensions explained 64.03% of the total variance and presented an overall reliability of 0.91. Gong et al. [65] proposed an SEM analysis to investigate the main factors that influence students' learning and students' CT. Souto et al. [66] suggested assessing CT skills. They used CFA to test the hypothesis that the CT competencies are competitively evaluated. PCA is used to extract the required number of factors from the data. Table 6 describes the tools used for factor analysis of CT from existing state-of-art works.

Table 6 Tools used for factor analysis of CT [58]-[66]

Ref.	Techniques	Tools used	Findings
[58]	Cattel-Horn-Carroll CHC)	R	Spatial ability, reasoning ability, problem solving ability
[59]	KMO and Bartlett tests	SPSS	Internal consistency level
[60]	BFQ-C	SPSS	CTs score
[61]	ANOVA	SPSS	Thinking skill ratio
[62]	Structural model-partial least squares	WarpPLS	Composite reliability, Average variance extracted
[63]	Structural equation model	SPSS	RMSEA, NFI
[64]	EFA, PCA with Oblimin rotation	MATLAB	MSE, RMSE, R2
[65]	EFA, CFA	SPSS	Absolute and incremental fit
[66]	CFA, PCA	R	RMSE, MAE

4.1.2 State-of-art studies on emotional intelligence

Emotional intelligence (EI) pertains to the capacity to recognize, understand, manage, and effectively use emotions in various aspects of life, including in professional settings. For CS graduates, EI plays a pivotal role in interpersonal interactions, teamwork, leadership, and overall career success. The review will explore how the cultivation of emotional intelligence can positively impact employability by facilitating effective communication, collaboration, and adaptability within the workplace. Hendon et al. [67] have proposed an examination of soft skills utilized by IT experts with the connection between EI and correspondence versatility. Afeez et al. [68] have proposed the impact of EI capacity level. The information for the study was obtained using a questionnaire that evoked data on the understudies' capacity to understand individuals on a profound level. Chand et al. [69] have proposed to comprehend the job of employability and EI toward manager fulfillment in enrolling new data innovation designing alumni from foundations of higher learning.

Pappas et al. [70] proposed a subjective relative study of fuzzy synthesis in an information test of 344 undergraduate students. This exploratory study contributes to the literature by providing new knowledge about the relationship between computer science undergraduate students' goal achievement indicators and develops a theoretical basis to further integrate students' learning outcomes, motivation, and performance of graduation. Davis et al. [71] proposed the validation of a self-report measure of EI based on phenomenology and conceptualization. Meyer et al. [72] suggested that sensory experts converge on correct answers on tests and are more reliable than individuals from a general sample. Pathak et al. [73] have analyzed the IE concepts and aspects of the exams are the ultimate function of legal proof and prospective recruitment of new and active IT professionals. Fukuda et al. [74] contrasted Wong's 16-item Korean Interpretation and Discipline of Deep Understanding (WLEIS) with a sample of 161 Korean college students. Table 7 describes the tools used for factor analysis of EI form existing state-of-art works.

Table 7 Tools used for factor analysis of EI [67]-[74]

Ref.	Techniques	Tools used	Findings
[67]	SSEIT and CAS	R	Accuracy, RMSE and MAE
[68]	Cohen’s d and single and multiple regression	SPSS	SSREIS, AMS and ASS

[69]	CFA, PCA	R	RMSE and MAE
[70]	fsQCA	MATLAB	Accuracy, precision
[71]	SEM,CFA	SPSS	Absolute and incremental fit
[72]	Multiple regression	R	Goodness-of-fit index
[73]	LAL and NHS	SPSS	RMSE and MAE
[74]	CFA, PCA	R	NNFI, CFI, RMSEA
[67]	SSEIT and CAS	R	Accuracy, RMSE and MAE

4.2 State-of-art studies on validate model for prime factors

In employability prediction, the confirmation of the identified factors holds utmost importance, primarily because of its profound influence on prediction accuracy. Our clustering analysis has revealed that Cluster #6 is indicative of the validation model for prime factors. Gregorio et al. [75] have analyzed how advanced change has disturbed the showcasing vocation way by breaking down the most popular promoting abilities and recognizing open doors for future advertising experts. Serim et al. [76] have investigated the connections between representatives' view of ability models and employability results as well as the relationship with the authoritative citizenship conduct. Mehreen et al. [77] have proposed the Fuzzy based validation model for analyzing the key objective and the functional length of optimal size.

Priyadarshini et al. [78] proposed the hereditary calculation-based approval model to perceive thoroughness and employability. Unwavering quality and legitimacy scores were utilized to guarantee psychometric dependability for 14 of the 16 things initially accommodated survey. Nghia et al. [79] have proposed a vital part of numerous advanced education projects and temporary positions. The method involved with building and approving a scale is utilized to assess understudies' temporary job-related learning results. Caputo et al. [80] have proposed the dynamic career scale (DCS), which estimates four unique methods of working in confronting professional disappointments and difficulties as per Klein's item relations hypothesis.

Arora et al. [81] have proposed that fundamental data has accumulated through India from the students who have done live endeavors from 2018 to 2019. The fundamental data processed together concentrated to responses accumulated from 444 students using a coordinated survey. Fundamental condition showing using analysis of moment structures (AMOS) reasonable from SPSS used for data examination and it has found that students getting additional capacities during live endeavors are more associated with employability. Unguren et al. [82] have explored to extracurricular understudy club enrollment status of the travel industry understudies influence vocation expectations and post-graduation employability. Bozionelos et al. [83] have proposed a quasi-experimental arrangement with assessment and attempted a model whose variables tended to key parts of the practical calling process as trapped in outstanding thinking. Zhong et al. [84] have proposed a control structure-based validation model for the employability of postgraduate students. They utilized the different prime factors such as student skill sets and technical sets from the academic engagement. Audenaert et al. [85] have investigated how spreading out clear suspicions, developmental invitation, and various socially leveled targets can develop the employability capacities of feeble workers.

4.3 Employability Prediction Using Predictive Models

Employability prediction is the process of evaluating a person's ability to successfully perform a certain job or profession. The need for employability prediction stems from an increasingly complex job market where employers are looking for candidates who not only have the right qualifications, but also the soft skills and attributes needed to thrive in their organization. Predictive models are used to predict employment by analyzing an individual's education, skills, personality traits, social, professional networks, social, professional networks, and job opportunities.

Casuat et al. [86] have analyzed the student's employability prediction using different ML techniques. Here, they utilized the well-known three learning models such as decision tree (DT), random forest (RF), and support vector machine (SVM) for student employability prediction. Among other ML techniques, the SVM perform very well on the student's employability prediction which achieved the maximum detection accuracy of 91.22%. Bhagavan et al. [87] have proposed educational data mining (EDM) with the help of efficient data analytics tools. EDM utilizes the HLVQ for the prediction of student academic performance and employability chances which enhances the detection rate. Here, the data mining technique also incorporates to handling the missing value prediction in the student dataset. Moumen et al. [88] have proposed the ML technique for the student employability prediction model by using linear regression. The model utilizes the seven-layer design with systematic rules to formulate the prediction module. The functional verification is performed through the two-fold process which shows the maximum accuracy is 72.56%. Saini et al. [89] analyzed the employability opportunities after completion of the course by using different ML techniques. Those are also called data mining techniques, mainly decision tree, random forest, Navie Bayes, and k-nearest neighbor. Here, the decision tree achieved the maximum performance which is 89% for forecasting job opportunities.

Aderka et al. [90] have analyzed the occurrence of sudden gain and their job opportunities towards that. Here, the author utilizes the very well-known learning model called random forest which is based on the fuzzy-based rule formation layer. They also utilize adaptive boosting for data mismatch analysis which solves the training loss. Li et al. [91] have proposed a modified version of support vector machine (SVM) for employment prediction. They utilize the prime factor as the student entrepreneurship indexes for prediction along with the different activities of students. The maximum accuracy of this SVM model is 92.35% which is best among previous studies. Kumar et al. [92] have analyzed the MBA student placement performance using the Random forest model with the help of different factors such as skill impact, subject knowledge, and demographic characteristics. Here, they treat random forest as the recommended system to provide suitable options for students based on their performance. El-Sharkawy et al. [93] have proposed the hybrid technique called GNB and random forest for graduates' employability prediction. They focused on enhancing the student performance on their placement. In this work, they utilized the prime feature as the demand and knowledge. Here, they achieved a better prediction rate of 94.56% which is 12.34% higher than the SVM model. Saidani et al. [94] have proposed gradient gradient-boosting classifier for student employability prediction using the context-aware information of students. They first concentrate on identifying the most impacted features on student employability and verify through the random forest model. The model utilizes the extra ruling layer to formulate the internship context and formulate the effective employability prediction. Fallucchi et al. [95] have proposed a prediction model for employee attrition using an SVM. They analyzed the employee's current performance using the skill test to validate the employee attrition. The summary of review of the ML technique for employability detection is described in Table 8.

Table 8 Review summary of ML based predictive models for employability prediction

Ref.	Predictive model	Data collection	Performance measure (%)		
			Accuracy	Sensitivity	Specificity
[86]	Support vector machine	OJT course of School	91.220	89.562	85.978
[87]	HLVQ	Hindu college, Punjab	92.600	87.563	86.235
[88]	Linear regression	CSE-MUJ college	72.560	91.235	85.123
[89]	Decision tree	IT graduates from Egypt	89.000	88.025	79.568
[90]	Random forest	HRM dataset-US data	75.890	75.260	77.125
[91]	Support vector machine	CCIS-PNU 2019-2021	92.350	74.265	69.856
[92]	Random forest	IIT-Chennai	88.000	81.459	80.235
[93]	GNB and random forest	CSE-MUJ college	94.560	86.380	77.358
[94]	XGBoost, CatBoost, LGBM	MDU-CSR college	92.568	84.363	74.468
[95]	Support vector machine	OJT course of School	54.000	82.222	78.365

Table 9 Review summary of DL based predictive models for employability prediction

Ref.	Predictive model	Data collection	Performance measure (%)		
			Accuracy	Sensitivity	Specificity
[96]	JD-R model	Secondary data	78.780	68.526	72.056
[97]	XGBOOST	Smart card data of 4634 students	85.630	75.124	78.986
[98]	Recurrent network	Kaggle website	98.000	70.152	82.545
[99]	DNN-LSTM	Metallurgical Engineering major	86.330	81.245	78.502
[100]	Linear regression	Kaggle website	65.890	56.234	59.875
[101]	Optimal NN	Tecnológico de Monterrey	79.660	71.478	72.487
[102]	SRl-TCL	MOOC1 and MOOC2	85.360	72.659	75.632
[103]	Multivariate logistic	QS, Auezov University	78.990	69.895	67.489
[104]	Artificial intelligence	Kaggle website	92.000	75.485	81.025
[105]	CNN-LSTM	Pakistan’s online education	98.800	79.989	83.647

Roczniewska et al. [96] have investigated the availability of resources for job providers by using JD-R model which utilizes clustering information for prediction. The finding denotes the accuracy of predictive model is 78.78% for the binary classification. Nie et al. [97] have proposed the adaptive cluster based XGBOOST model for students' career choice prediction by using information such as student programming skill, technical knowledge, and extra activities. The cluster control process uses the XGBOOST model to perform prediction process to compute the gap between clusters and real-world examples. Naz et al. [98] have proposed the predictive model for employee churn count prediction using the recurrent network with multiple layers. The results highlight this model achieves the maximum accuracy of prediction is 98%. Tao et al. [99] have proposed the DL based predictive model for the student learning prediction using the clustering process. They utilized the deep neural network with long short-term memory (DNN-LSTM) for prediction model along with the back-propagation network for past progress computation. The DNN-LSTM achieves a steady enhancement of 12.5% accuracy in the student learning prediction. Ots et al. [100] have analyzed the employability factors on paid employment service by using the linear regression. The solution benefits to job seekers need along with the skill-based verification process. Anyway, the model insists that when workers remained employed rather than when workers exited paid employment. The summary of review of techniques for employability prediction is described in Table 9.

5. Discussion

In this section, we examine the analysis and interpretation of SLR results. Here, we describe the identified employability factors in the context of employability prediction and discuss their implications. We analyze the relationship between these factors and how they affect the labor market and the employment prospects of individuals. In describing our findings, we aim to better understand the dynamics of employability prediction.

5.1 Analysis and interpretation of findings

SLR is a valuable tool for assessing performance and trends in a particular field of study through rigorous analysis. It can reveal key factors that contribute to the development of research in a particular field and provide important insights to help researchers search for more fruitful areas of study. In our SLR, we examine a dataset consisting of 578 articles from 71 different journals that focus on predicting graduate employment. After limiting our search to 1980 to 2023, we pulled this data from three primary sources: Web of Science, Scopes, and Lens. Our results show that most records were related to approximately 50.122%. In engineering, the remaining 12.569% are related to social sciences. In addition, in 2010 we noticed the highest publication activity 89 articles. Our comprehensive SLR sought to address specific research questions and thus provided valuable insights into the field.

1. Regarding **RQ1**, our SLR shows that research in employability predictive models has significantly explored the application of AI methods. Several studies show that the combination of AI techniques such as ML, DL, and NLP improves the accuracy and efficiency of employability prediction [86]-[100]. AI models play an important role in capturing the complexity and nuances of employment factors, enabling the development of powerful predictive systems that provide valuable insights to job seekers and employers. This growing adoption of artificial intelligence techniques highlights their potential to transform employability forecasting and provide data-driven, personalized, and efficient solutions.
2. In response to **RQ2**, recent developments in employability prediction have shown significant developments over the years. The use of AI techniques has gained significant momentum, making forecasting models more accurate and sophisticated. ML models, especially those based on DL, have become increasingly popular due to their ability to analyze large amounts of data, and identify complex patterns.
3. Regarding **RQ3**, the SLR analysis reveals several themes that explain the expected employment patterns of graduates, such as educational factors, skills and abilities, work experience, personal characteristics, economic and labor market factors, and demographic and social factors.
4. Response to **RQ4**, generally employability prediction covers different academic fields, reflecting the complexity and interdisciplinary nature of the field. Data science includes skills related to data collection, cleaning, analysis, and interpretation. Data scientists play major role in pre-processing and preparing data for employability prediction. Educational researchers provide insights into curriculum design, teaching methods, and learning outcomes. The CS provides knowledge of computational techniques used in algorithm,

software development, and predictive modeling. Economic literacy is essential to understanding market dynamics, labor demand, and economic trends. Statisticians and mathematicians ensure the reliability of forecasting models.

5. Response to **RQ5**, the identification of suitable factors for employability prediction remains a challenge, as does the development of effective validation tools for the selected prime factors. Additionally, the creation of a suitable predictive model for employability prediction presents its own set of challenges. In our future research, we will focus on addressing these issues.

5.2 Limitations of the Study

Most previous studies have focused on the employability of engineering and management students. Although there are several employability opportunities for CSE graduates, they often do not cover all the factors that affect the predictability of employability. These studies use different algorithms to predict occupancy, and the performance of these models, especially in terms of accuracy, varies by algorithm and data set. Additionally, differences in students' skill sets may account for differences in research findings across socio-demographic variables. This study focuses on the discipline of computer science engineering, which is at the heart of the academic field. It considers important factors of all stakeholders and aims to develop a predictive model that can improve the employability of computer engineering graduates.

6. Conclusions and future work

6.1 Summary of key findings

Enrollment in computer science engineering programs across the country has increased as a result of the proliferation of engineering and technology institutions, reflecting a broader trend. However, many of these young graduates lack essential job skills. Previous survey data shows that engineer unemployment in the Indian IT sector is: 18.43% in software services and 3.21% in software product development and business process outsourcing. The main issue is the selection of different types of universities, but the main goal is to secure employment that would continuously increase the country's GDP. This is an important motivation for identifying recruitment factors. Despite the current employment challenges faced by recent cs graduates in India, there is little research in this area, particularly in the Indian context. Some studies examine the relationship between emotional intelligence and employability, others link technical skills to employability, and there are few studies examining emotional intelligence, technical skills, and employability. This study is a unique attempt to determine the relationship between emotional intelligence, computational thinking skills, and employability of computer science graduates.

6.2 Contributions to the field

The current SLR has uncovered many important areas, including data mining, employment, computational thinking, sentiment measurement, and employment forecasting. In the past, research has mainly focused on examining the isolated effects of emotional intelligence (EQ) or computational thinking (CT). However, these studies are often employer-based or international, and sometimes both. To address this research gap, there is a clear and urgent need for a study that comprehensively examines the three constructs of EQ, CT, and unemployment, particularly from the perspective of students in the specific context of India. Although several prediction models have been developed to predict the employability factors of engineering students, these models mainly use different supervised and unsupervised ML algorithms. Supervised learning such as decision trees and random forests and unsupervised learning such as k-nearest neighbors and neural networks are widely used. However, despite existing work, no predictive model has yet been developed that successfully integrates the combined effects of EQ and CT. This research gap highlights the need for predictive models that effectively integrate EQ and CT. The existing literature does not address whether EQ and CT are related or influence each other. This is a promising direction for future research that may provide valuable insights into the dynamic interactions of these constructs.

6.3 Future research directions

The SLR conducted in this study revealed several gaps and areas for further research. This research gap ranges from identifying factors influencing employment to developing composite employment indicators for employment forecasting. Based on the findings of SLR, the following areas are important for further research.

- To improve employability prediction models, future research should go deeper to identify the factors that have a significant impact on employment. An in-depth study of these factors will lead to more accurate and comprehensive forecasting models.
- It is important to develop evaluation models for selected work components. Developing robust tools to measure the employability impact of these factors will increase the reliability and accuracy of employability prediction models.
- The field of employability prediction will benefit from the development of forecasting models that incorporate multiple factors, including EQ and CT. These models aim to provide a comprehensive view of employability and its determinants.
- To fully understand employability and its dynamics, important to create an employment matrix. Future research should focus on developing and improving this policy and decision-making matrix.

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