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Exploring the Role of AI Literacy on Employability Skills of Students in Higher Education Institutions

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Abstract:

This research aims to provide a detailed bibliometric analysis around the concept of employability within the context of higher education and increased attention to the place of Artificial Intelligence (AI) literacy. The research aims to address the differences of being adaptive, problem solving, collaborative, digitally literate, and a continuous learner. The research maps the scholarly conversations on the intersection of AI competence and skill development on the themes of emerging technology. Using a mixed-method approach, the research attempts to map the intellectual landscape using bibliometric techniques, and the Theory, Context, Characteristics, and Methodology (TCCM) framework to interrogate AI literacy within employability, curriculum design, and organizational fit. The analysis suggests that traditional soft skills are a key element of employability, and the infusion of AI literacy creates a greater need for innovative instructional design and measures. The research advocates for higher education institutions and policy makers to integrate AI literacy into the curriculum and organization strategy, particularly in digitally transforming contexts such as India, to train and equip graduates to work in AI enhanced environments.

Keywords:- Employability Skills, AI-Literacy, Higher Education Institutions , Artificial Intelligence, TCCM framework, Digital Literacy.

Introduction

A host of Digital technologies and digital workforce have shaped the past 10 years and created a paradigm shift on how higher education institutions understand the education and training of graduates for employment. The transformation focuses on employability skills defined as a range of qualities and skills such as adaptability, problem-solving, teamwork, digital technology skills, and a proclivity for continuous learning, which assist students in overcoming challenges in dynamic and complex workplace environments. At the same time, the recent surge of artificial intelligence (AI) in workplace technologies, educational technologies, and in the automation of organizational decision making has highlighted the requirement for much more than digital skills. AI Literacy is defined as the ability to critically understand, ethically engage, and meaningfully interact with AI systems in complex socio-technical systems. Therefore, students who are AI literate are not merely technologically competent, but are also well equipped to assimilate changes in workflows and thus improve their employment prospects in the workforce of the future. When considering the dual phenomena of employability skills and the omnipresence of AI technologies, this study starts by conducting a bibliometric analysis to identify the major intellectual themes, the key contributions and the gaps in the literature on AI Literacy, skills, and employability in the context of higher education.

Bibliometric studies have helped analyze areas like digital literacy and digital literacy and employability by showcasing metrics like growth of publication over time, themes of literature, and where publication concentration is located. For example, Tinmaz et al., (2022) studied the explosion of digital literacy publications during the COVID-19 Pandemic. Solak Berigel and Silbir (2024) studied the gaps and the new clusters in AI literacy research in Education and Technology. This studies aims to map these clusters to AI literacy and employability. Thus, this is the first study to provide a comprehensive overview of the field and its evolution to identify gaps that are of interest for further research. This bibliometric study provides the basis for understanding the workshops and how field is situated and will help frame contextual focus for this study. Third, and building on the findings of bibliometric mapping, the study offers a TCCM framework as an original and comprehensive tool for understanding how AI literacy relates to the employability skills of students in higher education. In the Theory section, AI literacy and employability is located within various theories, such as socio-technical systems theory, employability theory, and digital competence theory. The Context section considers higher education institutions, the regulatory framework of the nation, curriculum and organizational preparedness for AI.

Defining the basic components of the constructs' dimension – AI literacy and employability skills – their mutual relationships, and their possible mediators (student attitudes, institutional support, and previous AI exposure) are the main focus of the "Construct" dimension. Moreover, the "Measurement" dimension supplies a salient point about the need for valid and reliable tools and empirical measures to advance research. Recent bibliometric studies indicated that the measurable framework was often absent in numerous digital literacy studies, which confirmed the importance of this dimension. Therefore, the TCCM framework provides a way to combine existing research, provided by the bibliometric analysis, with new empirical research, like this one. This study also covers a number of important gaps in the literature by underscoring AI literacy as an essential facet of employability. To begin with, employability skills literature review reveals a significant amount of research in areas like business, engineering, and vocational education. Less focus, however, has been given to examining how new AI skills interact with employability primary components.

To begin with, research on the adoption of AI in education is more focused on the AI literacy and employment readiness of graduates; for example, more recent studies on the use of AI in education advocate for the definition of AI to be more precise for specific teaching-learning contexts rather than teaching-learning tools. Next, there are digital literacy frameworks available, but there has been no systematic study on AI literacy, and even fewer studies have concerned themselves with the measurement of AI literacy vis-a-vis employability; this has been noted in bibliometric reviews across domains. This study, through the combination of bibliometric analysis and the TCCM approach aims not only at the synthesis of the knowledge but also at the provision of actionable pathways in the domains of higher education, especially policy, curriculum reform, and the preparation of students for an AI-enabled world. The scope of this study is considerable. Should the link between AI literacy and employability be evidenced, higher education systems will need to reframe curriculum design, co-curricula, and strategies to embed AI literacy. Changes in the recruitment and training of employees are also anticipated. Policymakers will have to harmonize their frameworks, funding, and accreditation to support employability for graduates. This research holds particular importance in the Indian context in the intersection of digital transformation, the growing number of youth entering the workforce, the national focus on AI and Skilling. This work has notable scholarly and real-world significance, presenting current research in the field and shaping an academic, conceptual framework and evidence-based research.

This research investigates the extent to which understanding, applying, and engaging with AI impacts students' preparedness for the job market. Students' preparedness for the job market impacts their problem-solving, communication, flexibility, collaborative work, technological adaptability, and digital skills. These skills are critical for students in the context of the growing AI systems which are transforming the work of almost all industries. Students' preparedness for the job market is critical in the integration of AI, digital tools, and other teaching innovations in the teaching processes of Higher Education Institutions. AI literacy supports students in thinking critically and ethically. Digital literacy advances students' essential ability to process and communicate information and to use a variety of technologies. The TCCM approach stands for Theory, Context, Characteristics, and Methodology, and it connects these variables and offers a coherent way to map out theories, pinpoint the academic context, detail the AI-employability constructs, and analyze the techniques used to investigate these relations, which helps to put the TCCM approach to. It synthesizes and details the ways in which the study demonstrates the ability to develop AI literacy and the impact it will have on students' educational prospects.

Literature Review

Hussain (2013) quantified employability skills in engineering stream students in Malaysian higher education, concentrating on a single set of employers. An assessment of 171 employers uncovered the imbalances in training

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and expectations of the employers. This widening gap also indicated the necessity of instilling traditional skills along with AI to meet the educational needs of the workforce.

Rahim Bakar (2013) investigated 850 final year trainees of Malaysian Industrial Training Institutes and Indigenous Peoples Trust Council Skills Institutes for employability skills. This study with a 40 item SCANS oriented questionnaire determined the contribution of skills training on employability and highlighted the training of technical fields with the inclusion of AI competencies.

Dania (2014) used the SCANS model to examine employability skills of 214 vocational students from Malaysia. The results showed a mean score equal to 3.81 (SD = 0, 34), indicating a moderate level of proficiency. This suggested the importance of further improving the education offered, in particular, the employability education so it aligns with and enhances the level of technology used and AI competencies.

Poon (2014) analyzed the extent to which RICS-accredited real estate courses in the UK prepare graduates for the job market. Using a combination of qualitative and quantitative techniques aimed at collecting information from employers, HR managers, graduates, and course directors, the study identified various skill deficiencies and gaps and proposed several educational intervention strategies to include other digital and AI competencies.

Collet (2015) assessed skills for employability among graduates of the UK's knowledge-intensive industries from the perspective of a survey of CEOs and other senior managers. The study recognized a gap between the skills employers expected and those that academics believed the graduates offered, highlighting an enduring gap, and suggested that educational institutions develop skills to facilitate the attainment of data and AI literacy for the industry.

Misra (2017) studied the skills perceived as necessary for employability in information technology. The study pointed out a considerable gap between the academic training provided and the expected industry training in dealing with critical thinking and interpersonal skills. The findings proposed that educational programs in the institutions of higher education be remodeled to embrace the needed technology as well as the other soft skills for employability.

Chan (2018) identified crucial soft skills, such as effective communication, teamwork, and problem-solving as the main gap in self-employability skills in the manufacturing sector in Malaysia based on a survey of employers. The research findings centered on the importance of enhancing certain competencies to increase graduates' industry-related competencies.

Subekti's (2018) researched on the employability communication, collaboration, and problem-solving skills gained and developed while doing teaching practices in vocational high schools in Indonesia, and how these teaching practices in factories offer a solution to SMK Negeri 1 Cibadak's problem of students' abilities to face a flexible and constantly changing labor market by training students to be adaptable and acquire relevant skills. The research pointed out the importance of teaching factories in equipping the primary employability skills needed in a workplace characterized by artificial intelligence.

Hadromi (2019) focused on the employability competencies from the perspective of the vocational school. The mandatory abilities were communication, knowledge on the use of information, problem-solving, collaboration, and flexibility. The competencies were classified into three strata namely basic, self-management, and collaboration skills, which led to the conclusion that vocational educators are supposed to be trained in a composite manner to be suited to the industrial and educational needs.

Sumarno (2019) presented the findings on the promotion of employability skills to the students to the degree of a three-year diploma in mechanica engineering, Medan State University. The results showed that while the students were performed to be reasonable acceptable in the technical knowledge in the concerned engineering work, the students' soft skills of collaboration, flexibility, and communication remained generally low to be educationally employed.

Soares et al., (2019) investigated the impact and importance of social media marketing communication on the loyalty of customers and the image of the brand. Their work emphasized the interactive communication and digitally-based methods in promoting consumer trust and the value of digital skills in marketing and employability.

Shatimwene et al., (2020) investigated the experiences of nursing students during their clinical training in the utilization of e-learning platforms. It was noted that digital learning environments positively impacted the self-efficacy, adaptability, and preparedness of graduates in the healthcare sector.

Dyki (2020) integrated employability skills into the assessment practices framework in higher education. The study, based on feedback from students, concluded that the integration of employability skills in the assessment practices framework provided students with the opportunity to demonstrate job readiness and provided instructors with the opportunity to conduct meaningful assessments. This enhanced the employability-education gap along the dimensions of employability, focusing on the new education practices in the context of AI.

Garrido-Yserte and Gallo-Rivera (2020) focused on the contribution of the different actors to the advancement of the framework of sustainability in higher education institutions. The findings showed that joint governance and cross sector collaboration improve both the efficiency of the institutions and the employability of graduates through the learning of inter-institutional projects.

Suarta (2021) proposed a conceptual model on employability skills in the digital business world. The review of the academic and policy documents showed that digital skills, flexibility, and AI literacy are required of graduates to be compatible with the current world. The model provided a basis on which the transformation of employability skills resulting from technology was established.

Deutsch et al., (2021) reviewed the e-government requirements for digital governance in the educational management of higher education institutions. The introduction of digital governance in education management brought about improvements in transparency, increased digital competencies of employees and students, and enhanced digital literacy in the domains of employability.

Khuziakhmetov (2022) described the transition from employment to employability in the educational system focusing on the enhancement of students employability skills in higher education. The study describes the actions of master's and doctoral students in the enhancement of employability, where the students are described as having the necessary competencies in communication, actions and self-organization for productivity and the control of skills development for the labor market.

Froese (2022) discussed the construction and validation of an employability scale in the context of China and examines the influence of some socioeconomic variables, e.g. parents' education and occupation, income etc., on the employability of 1,146 vocational school students. The analysis is concluded with the statement that educational and employment opportunities are intertwined with some socioeconomic variables. This indicates that there are fundamental inequities in the system that affect the acquisition of skills.

Abdullah (2022) analyzed the employability skills training program from the perspective of Competency and the Readiness of Technical and Vocational Education and Training (TVET) instructors. The study showed that there is a high level of preparedness of experienced and novice trainers to assume the roles of facilitators of employability skills acquisition. The study demonstrates the importance of the interrelationship of the three variables: trainer competency, employability development, and AI literacy for the design of skills training programs.

Bueno et al., (2022) compiled a dataset on the environmental and social footprints of organizations.Sustainability metrics, along with other forms of data-driven decision-making, shape value proposition elements tied to motivation and job abilities related to ecological literacy and ethics, as noted by their study.

Herawati and Ermakov (2022) studied the integration of human rights education in Indonesian universities and found that the inclusion of civic and ethical education in the curricula increased the moral reasoning of students and the social accountability competencies needed for global labor market employability.

Halili (2022) studied employability skills 4.0 and their relevance to students' preparedness for work-based learning in Malaysia. The study, with a 633 students' survey from 5 research universities, found communication, adaptability, and digital fluency as fundamental skills in the context of Industry 4.0. The findings underscore the necessity of AI literacy and lifelong learning in the preparation of graduates for contemporary work settings.

Teoh (2023) analyzed employer views in Malaysia on the importance of graduates' employability skills and their satisfaction. The study, which surveyed 63 employers, revealed a significant difference between perceived importance and satisfaction and hence a dire need for educational transformations to meet employers' needs.

Widarto (2023) studied the implementation of employability skills within the context of the vocational education diplomas (VED) in Indonesia. Due to inconsistent definitions of skill standardization as well as misalignment of academic programs and industry expectations, a unified framework is required for the provision of vocational curricula, as indicated by the semi-structured interviews of the five VED lecturers of the study.

According to Southworth et al., (2023) AI has the potential to augment education across curricula. AI embedded within general education helps to improve students' data literacy and critical thinking, which is a vital skill needed in today's digital world.

Rashidi (2023) evaluated the evaluation of the Personal Record Building (PRB) system, as a means of developing skills for employment within technical tertiary levels of education, indicated that, as with ePortfolios, the PRB system was able to foster learner self-regulation and the documentation of achievements.

Segbenya (2023) analyzed the impact of some demographic factors on graduates' perception of employment skills in Ghana, particularly in the areas of Gender, Education Level, and National Service Sector concerning the nine employment skills. The study was based on pragmatism, explanatory sequential design, with a sample of 2,269 participants of the National Service and 363 Employers from a total sampling frame of 77,962.

Hornberger (2023) determined university students' AI literacy levels which then could be used to improve one of the components within the curriculum. The study examined AI literacy frameworks and acknowledged issues such as over-reliance on self-reports and some concerns about the psychometrics of the instruments. Advocating for the development of measurement frameworks is becoming crucial since Hornberger suggests the need for an evidence-based relationship construction between AI literacy and employability.

Gafni (2023) examined how the information systems undergraduates' employability skills developed in the course of working on capstone projects. The research confirmed that collaborative work in projects developed the students' ability to work and communicate efficiently and to learn independently which meets the expectations and requirements of the industries. The study confirmed the need for experiential learning for employability in continually advancing digital environments.

Nasreen (2024) investigated the skills needed for employability in Industry 4.0 and emphasized the disconnect between what is taught and what is practiced in the industries. The study showed that students in the technological industries do not have the ability to work on specialized tasks, thus the need to strengthen the gap between educational institutions and the industries.

Bisschoff (2024) offered a soft skills competency framework that is projected to improve graduate intern employability by creating employability capital. Based on theoretical analysis and Delphi techniques, the study reached a consensus on mainstreaming core employability competencies in internship programs.

Mustaffa (2024) undertook a systematic review of the employability skills of surveying graduates. The study determined various competencies employers expect, including digital literacy, teamwork, and the ability to manage projects. It reached the conclusion that surveying education needs to advance to satisfy the requirements of the construction industry through curriculum innovation.

Modran et al., (2024) examined the convergence of theoretical and experiential learning in technical education. They discovered that such models developed creativity and innovation, as well as critical thinking, which are the core employability skills needed in the context of Industry 4.0.

Moon et al., (2024) examined the development of AI education programs incorporated in the national curriculum. Their study showed that training integrated with AI encouraged the development of skills such as computational thinking, and innovation, as well as creativity which are highly employable in the digital era.

Farhat (2024) evaluated the embedding of employability skills in educational programs concerning the International Labour Organization (ILO) 2022–2030 strategic plan. The findings underscored the importance of frameworking the curriculum in a way that addresses the needs of the labour market to prepare students to the anticipated demands of work, especially in areas that involve AI.

Otermans (2024) overviewed employability skills in higher education on the pedagogy for the teaching of employability skills. The synthesis recognized the experiential, interdisciplinary, and AI-supported approaches as effective in bridging the skills gaps and improving students' preparation for the changing labor market.

Yim (2024) examined the education of AI literacy at the primary school level and concerned the absence of a theoretical framework and pedagogy for younger learners. The study argued that teaching AI at an appropriate age is important for closing the gaps and for the early attainment of work-related skills in digital economies.

Preiksaitis et al., (2024) examined the potential of large language models (LLMs) in education. The study argued that AI-enabled teaching systems offer considerable support for tailored education and the acquisition of skills, thereby transforming the access and pathways of the workforce through automation and personalized feedback.

Kanar and Heinrich (2024) studied the influence of university co-curricular activities on students' employability skill development. The study showed that participation in structured extracurricular activities improved teamwork, communication, and leadership competencies that are in high demand by the labor market.

Kovačević et al., (2024) studied employability development in undergraduate students in different European programs. Their study revealed that the alignment of the curriculum with the labor market needs and the provision of internships increased the employability of graduates.

Aditiyawarman (2025) studied the influence of interpersonal, intrapersonal, and suprapersonal skills, career adaptability on employability skills of Airlines Polytech cadets in Indonesia. From February 25, 2021, to February 25, 2022, the research stretched over twelve months. The Aviation Personnel Development Center within the Indonesian Institute of Aeronautics conducted a research project in collaboration with the Indonesian Institute of Aviation Medicine over the course of twelve months across seven official schools. The study focused on 300 students through the use of purposive sampling, and the results highlighted the effectiveness of the interrelationships of the student and the inner self, and flexibility as variables that predict the level of employability aviation education to a positive extent.

Richmond and Nicholls (2025) analyzed the use of generative AI and its potential to enhance the psychological and cognitive benefits in learning environments. The results of the research demonstrated a positive influence of students using AI on the development of their critical thinking, creativity, and advanced problem-solving ability.

Avsec and Rupnik (2025) presented the concept of transformative agency and AI literacy. They argued that the development of AI literacy in students fosters the employability skills of complex and reflective thinking and the ability to adapt in the technology-dominated field.

Carrasco-Sáez et al., (2025) studied the usage of generative AI tools by students in higher education. The results of the study demonstrated that the educational value of self-directed learning and problem-solving skills were strengthened through frameworks that fostered effective prompt design.

Dringó-Horváth et al., (2025) investigated the AI literacy and digital skills of university teachers. The study focused on the training teachers need to develop skills in students that are employable in digital environments as well as the need for the support of a learning institution.

Biloshchytskyi et al., (2025) focused on assurance of quality in higher education systems. The research is focused on education systems in the Ukrainian higher education system, which has been faced with challenges due to war.

The authors connected strong evaluation frameworks with skill-based learning outcomes and proposed quality assurance as a means of increasing employability.

Xie (2025) examined AI literacy and emotional responses of English teachers at Chinese universities. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examined four domains of AI literacy knowledge, application, evaluation, and ethics and showed they significantly shaped teachers' enjoyment, anger, and anxiety. The study contributed to the understanding of the emotional and cognitive aspects of AI-assisted learning and employability.

Pamungkas (2025) examined the understanding of AI literacy, as a component of digital literacy within the framework of Society 5.0. . The study called attention to the provision of validated tools for measuring AI literacy in adolescents as it will be critical for employability, and learning science as well.

Lan (2025) examined the connection between mindfulness and AI literacy in the context of media education and how metacognitive awareness might improve students' willingness to use AI tools. The study positioned AI literacy at the heart of the digital revolution and argued that mindfulness enhances cognitive flexibility and self-regulation, thus providing educational opportunities in AI-enabled workforce.

Pantaruk (2025) used PLS-SEM to study the associations between soft skills, internship experiences, and employability of graduate students in hospitality and tourism. The study demonstrated how internships bridged the gaps between theory and expected knowledge in AI-augmented hospitality environments and how communication, and, problem-solving, and teamwork skills positively affected employability outcomes.

Chee (2025) developed AI literacy competency framework through systematic review by PRISMA. The study served as a reference for inclusive AI curriculum design in relation to employability by segregating the primary competencies and sub-competencies by educational stage.

Karaduman (2025) demonstrated the distinction that AI literacy is the understanding and evaluation, whereas, AI competency is the practical application of the technology. This distinction offered new pedagogical avenues in the integration of AI employability skills in teacher education.

Cheng (2025) referred to the UNESCO report stating 70 countries have embraced AI strategies and reported global challenges in AI literacy and gender equity. Cheng (2025) found limited fundamental AI literacy coupled with a persistent gender gap as critical. Early inclusive education has been advocated, ensuring the equitable use of rapidly advanced AI as a fundamental tool for employability.

Wu (2025) examined AI literacy training for librarians in leading Chinese and global universities. The study highlighted the gaps in UI policies and implementations, training content, and librarian participation. Incorporating AI ethics, systematizing workshop activities, and upskilling librarians to make job-focused AI education better were the eight proposed improvements.

Kasinidou (2025) reviewed Cypriot teachers' attitudes towards AI, digital functionalities, and AI competencies. Kasinidou examined the adapted tools scaling to Greek, registered an AI literacy considerable, and underlined the demand for AI proficient teachers' training coursework to sustain the educational system's leverage for the employability of the students.

Bibliometric Analysis

Bibliometric analysis is a means of measuring and analyzing published work, looking to assess patterns of literature evaluation across different fields, or sub-fields analyzing the dynamics and evolution of a given field. It includes the collection of quantitative data from profile pages of published work, such as the author, where they published, how many times it was cited, and what they wrote about (Donthu et al., 2021). It aims to identify the key scholars of a given sub-field based on the volume of their cross field collaboration, through the bibliometric analysis of core themes, focusing on selected sub-discipline. VOS Viewer and other similar tools are designed to identify these emerging relationships in a specific sub-field in the domain of interest and across many fields of study.

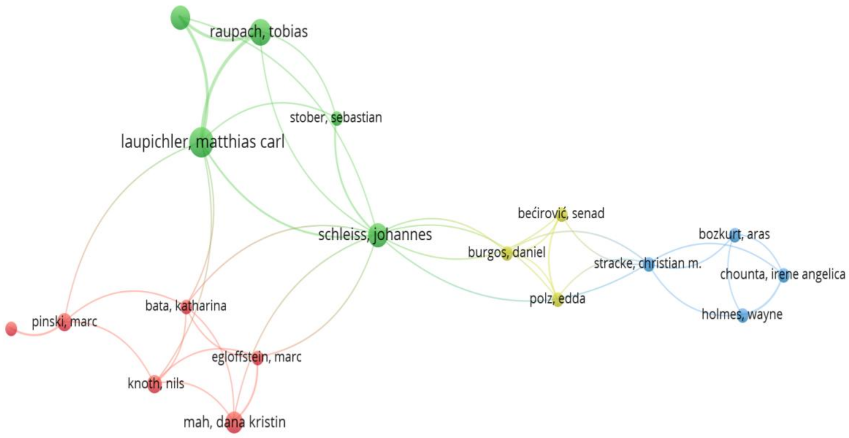

Figure 1: Co- Authorship of authors

Figure 1 illustrates the structural characteristics and levels of academic collaboration of 18 researchers. The network consists of thirty-nine relationships and 18 nodes which are grouped into 4 clusters. Each node indicates a researcher, while the lines between them represent collaborative relationships, such as co-publication of the paper. The thickness of the lines illustrates how much two researchers work together, and the colors of the lines showcase how there are many separate, but connected research groups. These results show that the green group is the most influential and sits at the center of the network. Within this group are many distinguished researchers, including Laupichler Matthias Carl, Raupach Tobias, Schleiss Johannes, Aster Alexandra, and Stober Sebastian, exemplifying a cohesive and successful research group that collaborates a lot. Within this network, the red group, which consists of Pinsl Marc, Egloffstein Marc, Mah Dana Kristin, Bata Katharina, and Knoth Nils, is a small, but highly integrated sub group that likely delves into more specialized research topics within the overarching concept of employability. The yellow cluster, which contains Polz Edda, Burgos Daniel, and Becirovic Senad, is a bridge between the central green group and the more outside blue group, suggesting that it facilitates the collaboration of more distinct or separate groups. The blue group, which contains Stracke Christian M. Chounta Irene Angelica, Bozkurt Aras, and Holmes Wayne, shows a different pattern of collaboration, leaning more towards being internally organized and cohesive, which suggests that they are a more focused research community.

The data shows that this is a moderately connected, but still very organized, collaboration network. Within the community of scholars, Schleiss Johannes acts as a pivotal connector, integrating various segments and improving the movement of information and collaboration between the various research fields. With a cumulative link strength of 58, the network demonstrates a well-balanced arrangement of collaboration, blending robust intra-cluster collaboration with a degree of inter-cluster ties that are low but of high strategic value. This arrangement indicates the balance of both a highly differentiated and a highly integrated research system, and therefore both the depth and the breadth of activity in the research of employability.

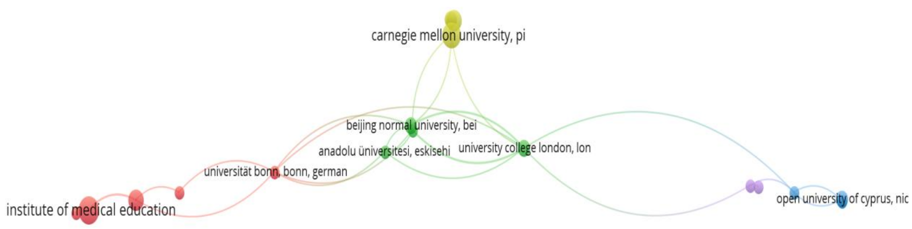

Figure 2: Co- Authorship of Organizations

This figure 2 presents the relationships between co-authoring academic institutions. This analysis revealed 17 elements (institutions), which are grouped into five clusters that are colored differently, to denote the higher degree of collaboration or thematic cohesion within the cluster of institutions. This illustration conveys 27 connections for these elements, which indicates partnerships or collaboration between the institutions. The total link strength of the network is 32, indicating the overall power and density of these relationships. Among the institutions, the nodes of Carnegie Mellon University (Pittsburgh), University College London, and Open University of Cyprus are noticeably located at the center, which indicates a higher degree of collaboration and centrality within the clusters, as well.

The clustering pattern indicates regional and institutional collaborations. For example, there is a tight-knit subgroup of the Institute of Medical Education and Universität Bonn, while there is a bridging of Beijing Normal University and Anadolu Üniversitesi toward connections with universities in Europe and the United States. In general, the network is characterized by a moderate degree of global academic collaboration in the area of employability-related research, with distinct cluster-based linkages demonstrating mutual research interests and cooperative engagement among the different institutions.

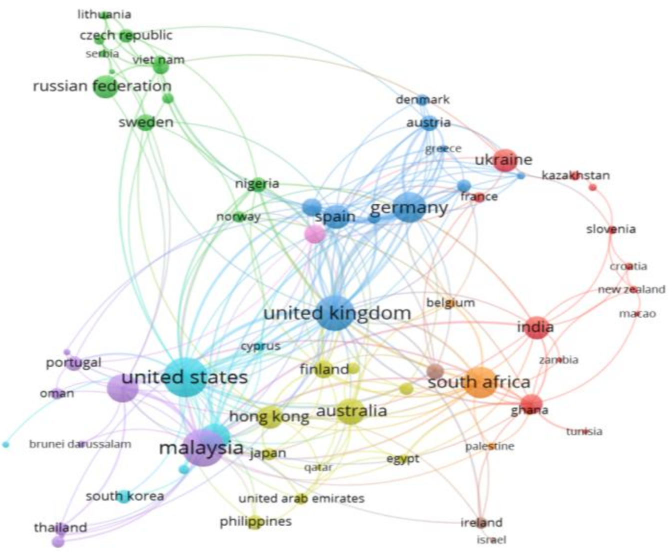

Figure 3: Co- Authorship of Countries

Figure 3 presents the most extensive example of worldwide collaboration regarding the area of employability-related research. In the visualization, there is a total of 67 items (countries) and 9 clusters (groups) represented in different colors that show diversified research linkages and regional collaboration networks. The figure shows there are 249 links with co-authorship in the countries, represented by a total link strength of 406, and a moderate level of collaboration in the field. Top nodes in the figure include the United Kingdom, United States, India, Germany, South Africa, and Malaysia, indicating these countries are among those that most significantly contribute to the fostering of worldwide academic collaboration regarding employability studies. The United Kingdom and United States serve as co-centric strong hubs that connect disparate clusters and are primary conduits of cross-continental collaboration for research. The regional cluster around countries like Germany, Spain, Sweden, and Poland is quite cohesive, whereas, between Africa and Asia, India and South Africa serve as key points for cooperation.

The pattern of clustering shows the extent of the geographic and scientific cooperation. European and North American countries are at the center of the most densely collaborative clusters. In contrast, a number of countries in Asia and Africa are on the fringe of clusters, exhibiting strong but nascent ties. Overall, this network shows the worldwide integration of research on the employability, signifying a good balance between well-established points of academic concentration and the emerging countries making a strong contribution to the collaborative research and the exchange of ideas.

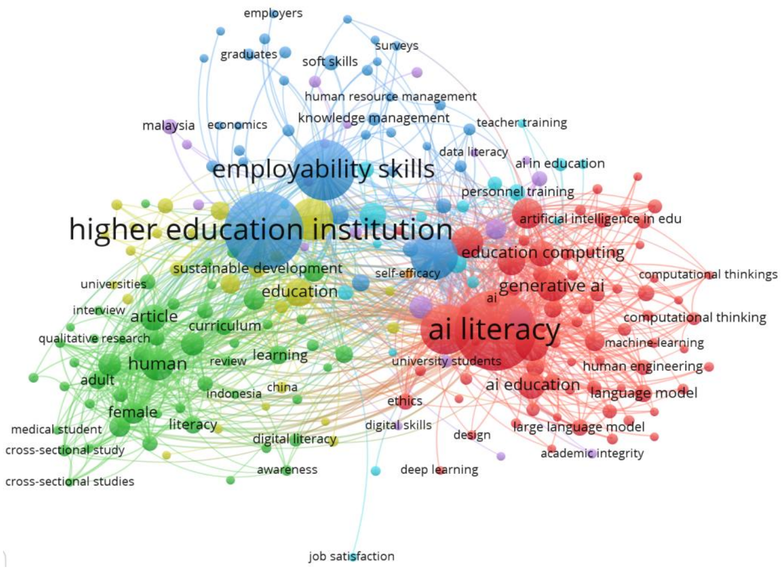

Figure 4: Co- Occurrence of all keywords

The co-occurrence of keywords in employability-related research is shown in Figure 4. The visualization shows seven clusters, each representing a distinct key theme of the existing literature. The network has 4,666 connections, indicative of a literature base in which themes are interlinked with significant collaboration and overlap, as denoted by a total link strength of 11,357. The largest keywords, "higher education institution," "employability skills," "AI literacy," and "generative AI," in the visualization, indicate the most prominent concepts in the field and the most used keywords. The pattern suggests a strong co-existence of themes in traditional employability with themes in emerging technology.

In particular, the red cluster highlights the importance of the increasing influence of AI on educational settings with a focus on AI literacy, generative AI and computational thinking. The green cluster highlights the focus on education, human development, digital literacy, and the integration of technology which demonstrates the importance of human-centered approaches on employability. The blue cluster highlights employability skills, soft skills, and knowledge management which ties to the themes of traditional higher education and workforce readiness. As a whole, the network suggests that employability research focuses on a multidisciplinary integration of higher education, digital transformation, and AI. The strong connections across the clusters illustrate the merging of pedagogical innovation, digital skills, and competency-based education as the dominant research frontiers shaping employability discourse in the post digital age.

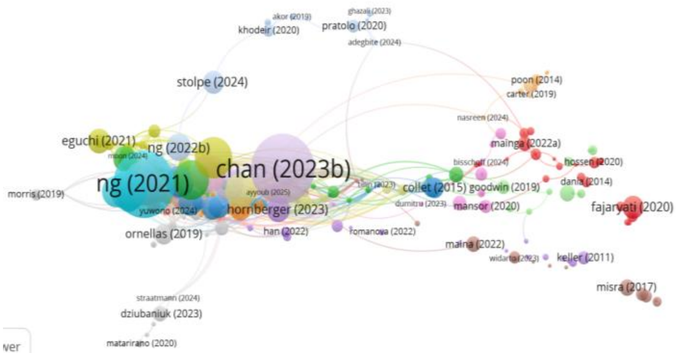

Figure 5: Bibliographic coupling of documents

Figure 5 provides the visualization of documents related to employability research, detailing bibliographic coupling and citation relationships. The visualization illustrates a multi-dimensional structure comprised of 317 items (authors/documents) that are well connected and divided into 21 clusters, which demonstrates a rich diversity of themes and collaboration in the employability literature. The network exhibits a total of 1,272 links, representing the interconnections and co-occurrence strength among authors, with an overall total link strength of 1,377, signifying a strong degree of intellectual connectivity and citation impact across research work.

Ng (2021), Chan (2023b), Hornberger (2023), Eguchi (2021), and Stolpe (2024) are examples of primary and major contributors to the network, which are signified by larger nodes representing their high citation counts and a strong link to their nodes. These primary major contributors are authors of works that have recently made a sizeable impact in the employability scholarship. The visualization of the interconnections shows a spatial distribution of the clusters illustrating diversity in area of skills, higher education, employability teaching frameworks, digital literacy, and competencies for the future workforce. The clusters are color-coded to show the trends and the collaborations among scholars that have emerged during 2011 to 2024, highlighting the active interdisciplinary work in the area of employability research.

According to the map produced by VOSviewer, employability research has become a specialized area, with employability studies as a highly interconnected area, and with the period 2021 to 2024 being marked by an increase in collaboration and the formation of new research areas related to employability skills, technology, and education.

The TCCM Framework

The TCCM Framework, an abbreviation for Theory, Context, Characteristics, and Methodology, is an integrative and systematic approach applied primarily to bibliometric analyses and literature reviews in the fields of research synthesis, evaluation, and organization. In Paul and Rosado-Serrano's 2019 study, the authors attempted to produce a framework that strengthens and improves the transparency and rigor of systematic literature reviews in the literature of management and social sciences. This framework was designed to assist researchers in finding and organizing knowledge while proposing comprehensive and theoretically sound future research.

In the past, the TCCM framework was designed for addressing the lack of review processes. For example, the narrative review and the descriptive reviews suffered from the same problems, which were a lack of rigorous coherent analytical frameworks. Paul and Rosado-Serrano develop TCCM from the principles of evidence-based research synthesis, which aim to ensure that reviews do more than provide a highly informative overview of the literature. As for the theories in TCCM, they aim to find all the conceptual premises, frameworks, and theories that have been used in the literature. The context looks at the different geographies, industries, cultures, and situations where the respective research was done. The characteristics look at the key variables, the relationships, and constructs that have been reviewed. Lastly, the methodology looks at the research design, the methods of analysis, and the methods of data collection of the reviewed studies.

In various fields, including management, marketing, education, sustainability, and information systems, the TCCM framework has been used to structure literature reviews, meta-analyses, and conceptual papers. The order of information makes it easy to find theoretical perspectives that are less researched, contextual areas that are ignored, and methodological weaknesses, which helps to formulate future research plans. With the TCCM model, research conducts within the certain area are more scholarly, rigorous, replicable, and can build on each other.

Integrating Bibliometric Findings with the TCCM Framework

This part of the research wants to combine the bibliometrics data enabled by the VOSviewer maps with one of the TCCM to organize the literature, show the gaps in the literature, and suggest future research. The bibliometric maps that show co-authorship (Authors: 18 items, 40 links, TLS=58; Organizations: 17 items, 27 links, TLS=32; Countries: 67 items, 249 links, TLS=406; keyword co-occurrence: 224 items, 4666 links, TLS=11,357; bibliographic coupling: 317 items, 1,272 links, TLS=1, 377) are the basis of empirical evidence of each component of TCCM.

Theory

The keyword co-occurrence network and bibliographic coupling identified the leading conceptual foundations in employability research. What this means is this prioritezed central location is demonstrating to us where our scholarship is currently located in and according to the two dominant streams of theory. These are: first the educational and human capital approaches to skill formation and graduate preparedness. Second is the technology-focused perspective which emphasize the digital competencies, AI literacy, and socio-technical dimensions of automation and its effect on employability. The bibliographic coupling map, which also encompasses 317 resources dispersed across 21 different clusters corroborates the presence of a plethora of theoretical subfields, including but not limited to, curriculum and pedagogy, foundational digital literacy and workforce analytics. This means that employability is best understood and conceived as a multi-dimensional and multi-theoretical domain. Theorist are, therefore, encouraged to advance comprehensive conceptual frameworks that would combine and integrate human capital and capability approaches with sociology to explain the phenomena of skill formation and the disruptive nature of technology.

Table 1: Theoretical frameworks used in the literature

Theory	Key idea	Representative citations
Socio-technical / Socio-technical systems theory	Understands AI literacy as interaction of people, tools, and institutional routines.	Several studies emphasize AI in educational systems and socio-technical implications (e.g., Hornberger, Suarta, Dringó-Horváth).
Technology Acceptance Model (TAM) / Diffusion & TPB	Predictors of adoption: perceived usefulness/ease, attitudes, norms used for AI tool uptake and student/teacher adoption.	Used to explain adoption of AI/learning tech and prompting behaviours (Hornberger, Carrasco-Sáez; references to TAM-style constructs).
Competency / Skill frameworks (Digital literacy → AI literacy)	AI literacy treated as an extension of digital literacy and competency taxonomies (knowledge, application, evaluation, ethics).	Chee (2025), Pamungkas (2025), Hornberger (2023) and competency syntheses (Chee systematic review).
Experiential & Constructivist learning theories	Emphasize project-based, capstone, internships to build employability & AI skills.	Gafni (2023), Pantaruk (2025) show capstones/internships increase employability and AI-related skills.
Resource-based / Dynamic capabilities	Institutions' capacity (resources, analytics, faculty skill) determine ability to integrate AI into curriculum → influence employability outcomes.	Institutional readiness and organizational capability discussions (Biloshchytskyi et al., institutional QA links).
Ethical / Critical frameworks (AI ethics, equity)	Focus on ethical literacy, equity, gender gaps and inclusive AI education.	Cheng (2025) highlights gender and inclusion concerns; numerous papers call for ethics in AI literacy measurement.

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

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Theory Dimension

The bibliometric sample clusters around applied technology-adoption and competency frameworks, with growing attention to ethical and equity theories. Theoretical work is often multi-level: individual (TAM/TPB), curricular (experiential/constructivist), and institutional (RBV/dynamic capabilities). However, the review shows limited integration of critical socio-political theories (e.g., labour market/justice perspectives) in studies linking AI literacy directly to employability. This imbalance suggests a theoretical gap: stronger multi-theory syntheses are needed to explain how AI literacy translates into employability across contexts (student background, discipline, institutional capacity).

Context

Geographic and institutional patterns from the co-authorship (organizations) and country maps point to a geographically uneven research base. The country map (67 items; 9 clusters; TLS=406) highlights concentration in Anglophone and European hubs (United Kingdom, United States, Germany) while showing increasing connectivity with regions such as India, South Africa, and Malaysia. Organizational clustering (17 items; 5 clusters; TLS=32) indicates that specific universities act as regional or thematic anchors. These findings imply that research contexts are biased toward higher-resourced educational systems and that contextual variables (e.g., national labour market structure, regional digital infrastructure, higher education governance) are under-represented in cross-national comparative work. Future empirical work can explicitly incorporate contextual moderators policy regimes, industry composition, and digital readiness so that theory testing moves beyond single-country generalisations.

Table 2: Context (Sectors, geographies, and institutional settings in the mapped literature)

Context category	**Key idea**	**Representative citations**
Higher education programs (disciplinary spread)	Engineering, IT, health sciences, teacher education; both undergraduate and vocational programs	Studies from China, India, Indonesia focusing on university and vocational contexts (Xie 2025; Kasinidou 2025; Aditiyawarman 2025).
Geographical concentration	Strong representation: India, Indonesia, China; also UK, Malaysia, Ghana, Thailand	Distribution shows India leading, with notable contributions across Asia and developing contexts.
Institutional readiness & policy context	National AI strategies, curriculum reforms, institutional PD for faculty	References to national strategies, calls for institutional embedding of AI literacy and faculty upskilling (Cheng 2025; Dringó-Horváth 2025).
Learning settings & pedagogies	Capstone projects, e-portfolios/PRB systems, MOOCs, internships, co-curricular activities	Gafni (capstones), Rashidi (PRB), Southworth et al. (AI modules) experiential modes emphasized.
Employer / labour-market interface	Employer perceptions, internship outcomes, skills mismatch	Teoh (2023) employer perceptions; Aditiyawarman (2025) and Pantaruk (2025) link internships and soft skills to employability.

Context dimension

The literature is concentrated in higher-education settings with a geographic skew toward Asia (notably India and Indonesia), reflecting policy interest and rapid digital adoption in those regions. Contextual analyses often report institutional and sectoral variability: healthcare and engineering show domain-specific AI literacy needs, while teacher education emphasizes faculty capacity-building. A notable gap concerns the longitudinal validation of workplace outcomes: only a limited number of studies empirically link institutionally assessed AI literacy with employer-verified indicators of employability. Furthermore, attention to policy mechanisms remains uneven; although many studies advocate curriculum reform, systematic evaluations of policy-driven curricular implementations are comparatively scarce.

Key constructs and relationships

The keyword network (224 items; 7 clusters; TLS=11,357) identifies recurring constructs (employability skills, digital literacy, curricula, AI literacy, generative AI, soft skills, work-integrated learning) and their co-occurrence patterns. Clusters reveal three broad characteristic domains: (a) skills and pedagogical design (soft skills, curriculum, higher education institution), (b) digital and AI competencies (AI literacy, generative AI, data literacy), and (c) institutional/organisational processes (knowledge management, work-integrated learning). The dense interlinkages (4,666 links) suggest that relationships among these constructs are highly interconnected, but bibliographic coupling indicates fragmentation into thematic subgroups. Thus, future research should prioritise clarifying construct definitions (e.g., operationalising “AI literacy” vs “digital literacy”), specifying directional relationships (how curricula interventions affect specific employability outcomes), and testing mediators/moderators (e.g., industry placement intensity, socio-economic status).

Table 3: Construct (How AI literacy & Employability skills are conceptualized)

Construct	Operational Elements	Examples from the mapping
AI Literacy (multi-dimensional)	Knowledge of AI concepts, technical application, critical evaluation, ethical understanding, prompting strategies	Hornberger (2023), Chee (2025), Carrasco-Sáez et al. (2025) many studies parse AI literacy into knowledge, application, evaluation, ethics.
Employability skills (core & soft)	Communication, teamwork, problem-solving, adaptability, digital competence, reflective practice	Repeated across sample (Halili 2022; Subekti 2018; Pantaruk 2025). Soft skills remain central to employability.
Interaction / Pathway constructs	AI literacy → enhanced problem-solving, self-directed learning, prompt design → employability outcomes	Studies linking prompting, generative AI use to self-directed learning and problem solving (Carrasco-Sáez; Richmond & Nicholls 2025).
Moderators / mediators	Prior digital skills, socio-economic background, internships, institutional support, attitudes	Froese (2022), Segbenya (2023) indicate demographic and socioeconomic moderators; institutional support emerges as a strong mediator.
Outcomes (employability metrics)	Self-reported readiness, employer satisfaction, internship placement, employment rates, domain competency tests	Teoh (2023) employer satisfaction gap studies; many use self-report scales rather than employer-verified outcomes.

Minnesota Journal of Business Law and Entrepreneurship

Volume 2026, No. 3

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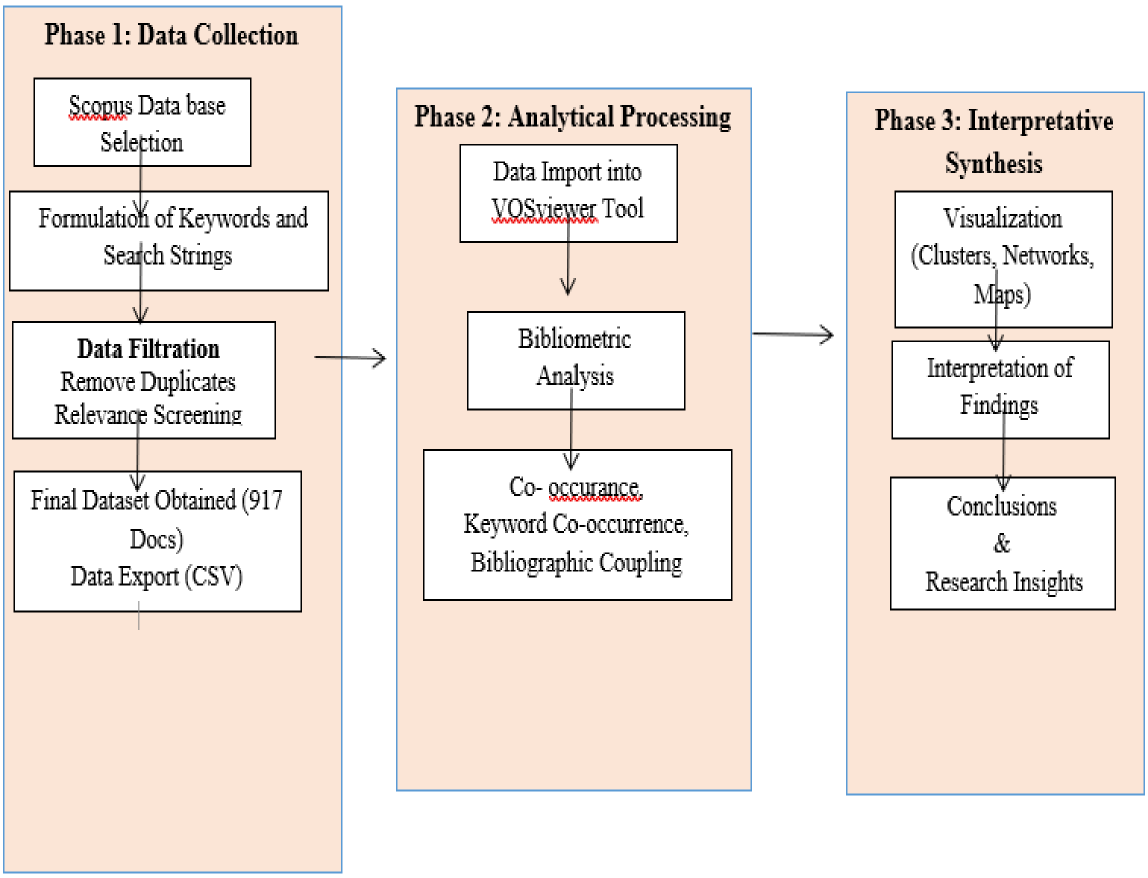
Construct dimension

AI literacy is consistently presented as multidimensional combining technical, evaluative, and ethical elements and is frequently hypothesized to bolster classical employability skills (problem-solving, adaptability). Most studies use theoretical pathways where AI literacy improves learning processes (e.g., prompting leads to better self-directed learning), which in turn increases employability. Critical gaps: (1) inconsistent construct definitions across studies (some equate AI literacy with basic digital skills), (2) over-reliance on self-report measures for both AI literacy and employability, and (3) limited causal/longitudinal tests connecting AI literacy improvements to actual employment outcomes. A standardized construct taxonomy (knowledge / application / evaluation / ethics) and agreed-upon core employability indicators would improve comparability.

Methodology

The study inculcated bibliometric analysis to examine global scholarly contributions related to AI literacy and employability skills in higher education. Scopus, recognized for its comprehensive coverage of peer-reviewed literature, served as the primary data source. A structured search strategy using targeted keywords and Boolean operators retrieved relevant publications, followed by systematic filtration involving duplicate removal, English-language selection, and relevance screening. This process resulted in a final dataset of 917 documents. Metadata were exported in CSV formats and analyzed using VOSviewer to perform descriptive and network-based bibliometric techniques, including co-authorship, keyword co-occurrence, and bibliographic coupling analyses. The resulting visual maps and thematic clusters enabled interpretation of research trends, conceptual structures, and emerging directions linking AI literacy with employability skills. The methodology ensures rigor, transparency, and replicability, relying solely on publicly available data and adhering to established ethical standards.

Figure 6: Methodological Flowchart



Minnesota Journal of Business Law and Entrepreneurship

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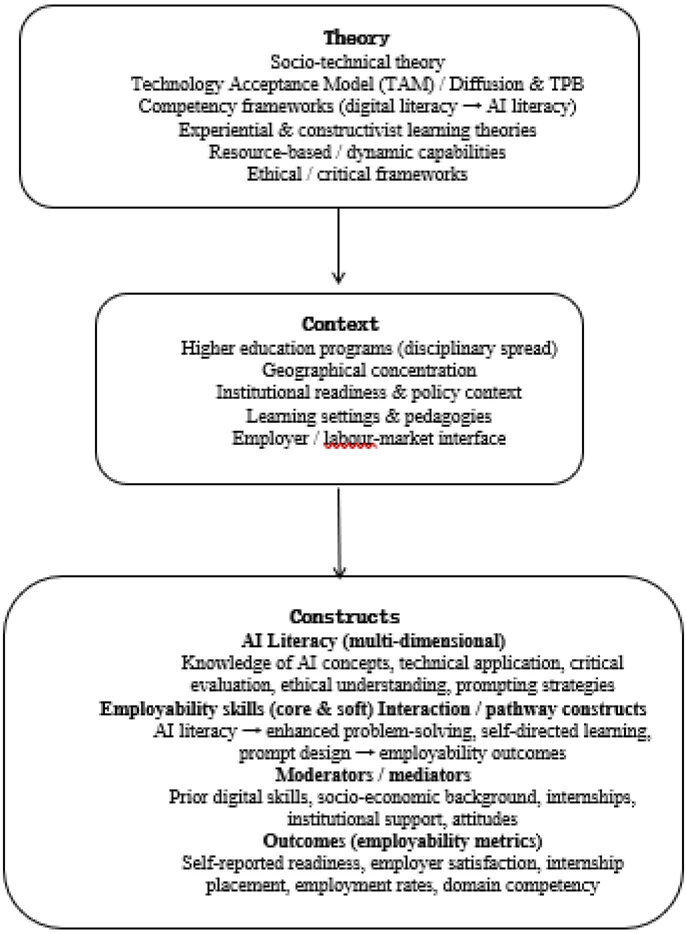

Figure 1: Exploring the Role of AI Literacy on Employability Skills of Students in Higher Education Institutions

The TCCM framework provides a systematic lens for mapping and evaluating the intellectual structure of research on AI literacy and employability skills within higher education. In the Theory dimension, the field draws upon a diverse set of conceptual foundations, including socio-technical theory, the Technology Acceptance Model (TAM), Diffusion of Innovations, and Theory of Planned Behavior. These are complemented by competency-based frameworks, experiential and constructivist learning theories, resource-based and dynamic capability perspectives, as well as ethical and critical frameworks that position AI literacy within broader debates on responsible technology use.

The Context dimension highlights the situational environments in which AI literacy and employability research is situated. Current studies predominantly examine higher education programs across various disciplinary domains, with notable geographical clustering. The literature also considers institutional readiness, policy landscapes, pedagogical settings, and the interface between employers and the labour market. These contextual factors shape how AI literacy initiatives are implemented and how employability outcomes are interpreted across institutions and regions.

The Constructs dimension reflects the conceptual variables that anchor scholarly inquiry. AI literacy is treated as a multidimensional construct encompassing technical knowledge, conceptual understanding, ethical evaluation, critical application, and prompting strategies. It is often linked to core and soft employability skills such as problem-solving, creativity, communication, and self-directed learning. Additional constructs include moderating and mediating factors such as prior digital skills, socio-economic background, internships, institutional support, and student attitudes. Outcomes are typically measured through employability indicators such as self-reported readiness, employer satisfaction, internship placement, employment rates, and domain-specific competencies.

Taken together, this TCCM mapping illustrates the theoretical breadth, contextual diversity, and construct complexity of the field, while simultaneously revealing methodological patterns and gaps that shape future research trajectories.

Implications and Future Research

Future researchers can formulate comprehensive theoretical models that integrate human capital, capability, and sociotechnical perspectives to elucidate the mechanisms through which AI and digital transformation shape and mediate employability outcomes. Expansion of contextual diversity by prioritising multi-country studies and including lower-resource contexts to correct the geographic concentration shown in the country map could be done. They can standardise constructs and measures (AI literacy, employability skills, work-integrated learning) to permit meta-analysis and reduce thematic fragmentation identified in keyword and bibliographic coupling maps. They can adopt longitudinal and intervention designs to move beyond cross-sectional snapshots and test causality of curricular and training innovations. They can facilitate the formation of collaborative consortia across institutions and countries to enhance intellectual linkages and generate large-scale, high-quality datasets, thereby addressing the limited institutional total link strength observed in co-authorship networks. Investigate equity implications how digital divides and labour market inequalities shape access to AI literacy and its returns in employment drawing on underexplored clusters and nations.

Conclusion

The comprehensive bibliometric review and TCCM analysis presented in this study illuminate the dynamic reconfiguration of employability skills in higher education under the pervasive influence of digital technologies and AI. Central to this transformation is the evolving conceptualisation of employability, which now encompasses not just core soft skills like communication, teamwork, problem-solving, and adaptability, but also robust digital competences and AI-related literacies. The systematic mapping of intellectual structures across author, institutional, and country collaborations reflects an increasingly interdisciplinary and globally coordinated research agenda, though notable geographic and thematic disparities persist. Scholarship is currently anchored in multifaceted theoretical paradigms: educational and human capital perspectives are being augmented with technology-driven frameworks, with socio-technical, competency, and ethical models gaining prominence. However, the analysis identifies critical gaps in the integration of justice and equity theories, as well as limitations in empirical generalisability due to the dominance of cross-sectional and self-reported methodologies.

Methodologically, the field is rich in survey-based and qualitative inquiries, yet suffers from a lack of validated, longitudinal outcome measures and limited employer-verified data. Most empirical work is concentrated in higher education contexts, with a particular emphasis on Asian regions where digital transformation is accelerated and national AI policies are highly influential. Despite these advances, there remains insufficient attention to longitudinal validation of employability outcomes in workplace settings, as well as to sector-specific needs and policy interventions that transcend institutional boundaries.

The TCCM framework proposed and applied here underscores the necessity of standardising key constructs such as AI literacy (knowledge, application, evaluation, ethics) and employability metrics to enable comparative studies and future meta-analyses. The study recommends a paradigm shift toward integrated theoretical models capable of capturing how AI and digital transformation mediate employability outcomes across diverse contexts including student background, institutional capacity, and labour market structures. Furthermore, enhanced methodologies are advocated, comprising longitudinal and intervention designs, multi-country comparative studies, and collaborative consortia that can develop large-scale datasets aligned with reproducible research standards.

Practically, the implications are substantial: higher education institutions must systematically embed AI literacy within curricular frameworks, faculty professional development, and strategic initiatives. Employers are urged to reconsider recruitment and professional development strategies to better align with AI-driven skill requirements, and policymakers should adapt regulatory frameworks, funding mechanisms, and accreditation standards to support AI-ready graduates. Promoting equity and digital inclusion, especially across gender and socioeconomic divides, is critical for broadening access to and benefits from AI literacy and employability enhancement.

This research not only synthesises current knowledge but charts actionable future directions. It calls for greater empirical rigor, theoretical integration, and contextual sensitivity within employability research, laying the groundwork for student competencies, institutional strategies, and policy reforms that are aligned with the future of work in AI-rich environments. The study's conclusive message is clear: stakeholder collaboration, innovative pedagogy, and robust measurement tools are indispensable in preparing graduates for the complexities of tomorrow's labour market.

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