International Journal of Multidisciplinary and Current Educational Research (IJMCER)
ISSN: 2581-7027 ||Volume|| 5 ||Issue|| 6 ||Pages 50-63 ||2023||

Future skills in the Industry 4.0 study. A systematic review.

[1,]Luis Jose Gonzalez-Gomez, [2,]Julieta Noguez, [3,]Santiago Orozco Quintero, [4,]Eduardo Galindo Rojas Loa, [5,]Patricia Caratozzolo

[1,2,3,]School of Engineering and Science, Tecnologico de Monterrey. Calle del puente 222, Mexico City, 14380, CDMX, Mexico.

[4,]School of Engineering and Science, Tecnologico de Monterrey. Av Carlos Lazo 100, Santa Fe, La Loma, Álvaro Obregón, 01389, CDMX, Mexico.

[6,]Institute for the Future of Education, Tecnologico de Monterrey, Eugenio Garza Sada 2501, Monterrey, 64700, NL, Mexico.

ABSTRACT : Industry 4.0 comes with challenges. One of them is the alignment of employee's skills to those required in this new type of environment. Predictive future skills systems, framed in Industry 4.0, have been used to identify skills gaps and propose training and development programs for workers. In this paper we present a Systematic Literature Review to evaluate the latest research papers, journals, and studies to look for systems that predict future skills that employees will require in future jobs. We have a look into the existing landscape of predictive future skills systems, examining various frameworks that can enhance the precision of skills estimation and forecasting. This comprehensive review holds promise for categorizing and exploring the present knowledge and required skills in the frame of industry 4.0, while also shedding light on the emerging demands of the industry. By conducting this review, we uncover potential avenues for the advancement of skills prediction and forecasting systems. These systems have the capacity to assist organizations in creating better strategies for workforce development and elevating their competitiveness in the digital age.

KEYWORDS - Predictive future skills, Industry 4.0, Skill gaps, Artificial Intelligence techniques, Skills taxonomy.

I. INTRODUCTION

In today's rapidly evolving digital landscape, the alignment of employees' skills with the demands of Industry 4.0 presents a significant challenge. Predictive future skills systems have emerged as a promising approach to address this issue, enabling organizations to identify skill gaps and design effective training and development programs. However, the existing literature in this field exhibits certain gaps and limitations that need to be addressed. To bridge these gaps, our study aims to conduct a comprehensive review of recent research papers, journals, and studies. We evaluate current innovative systems that try to predict future skills and examine different frameworks to enhance skills estimation and forecasting accuracy. By accomplishing these objectives, our research can contribute to the advancement of predictive future skills systems within the context of Industry 4.0. In this review, we have analyzed various aspects of the topic, including research studies, techniques for identifying patterns in workforce open-data, and the use of Artificial Intelligence (AI) techniques to automate skill gap identification and guide skill development. The literature reveals that while some papers explore competency needs and skill anticipation, they often overlook the role of Industry 4.0 systems and AI techniques.

Moreover, there is a limited number of studies specifically addressing the automation of skill gap identification and the development of in-demand skill sets. These gaps present an opportunity for further research to explore new AI techniques for assessing and improving workers' skills. Study motivation arise from the recognition of the critical role that predictive future skills systems can play in enabling organizations to strategically develop their workforce and enhance their competitiveness in the digital era. By understanding and bridging the gap between existing employee skills and emerging industry needs, organizations can effectively allocate resources, design targeted training programs, and foster a workforce equipped with the most relevant and in-demand skills. Our research aims to contribute to the classification and exploration of Industry 4.0 knowledge and required skills while offering insights into emerging industry demands. The significance of our work lies in its potential to inform organizations and researchers about the capabilities and limitations of predictive future skills systems, guide the formulation of effective strategies for workforce development, and orient the way future studies explore new AI techniques that enhance the assessment and improvement of workers' skills.

DEFINITION OF TERMS: While Industry 4.0 Is A Term That Is Probably Well Known These Days. Here We Include Is A List Of The Most Important Terms Related To This Research As Well As A Brief Definition For Each One:

Future skills: competences that enable individuals to effectively address intricate problems in rapidly evolving contexts, while demonstrating self-organizational capabilities. These proficiencies are rooted in cognitive, motivational, volitional, and social resources, and are imbued with core values. Furthermore, they can be acquired through a deliberate process of learning. It is noteworthy that these Future Skills are intricately intertwined with the knowledge of emerging technologies [1].

Abilities: capability to do something the fact that someone or something is able to do something. A level of skill or intelligence [2].

Industry 4.0: refers to the fourth industrial revolution, characterized by the integration of digital technologies into manufacturing and production processes. It encompasses various advanced technologies such as the Internet of Things (IoT), AI, big data analytics, cloud computing, robotics, and cyber-physical systems [3].

Skills mismatch: refers to the sub-optimal use of an individual's skills in the activity they perform, i.e. an under-use of skills or, conversely, a situation where the skill level is below that required [4].

Skill gap: measure the extent to which workers lack the skills necessary to perform their current job. Refers to the disparity between the skills that employers seek in the workforce and the skills that job seekers or employees possess [5].

Knowledge skills: refer to a set of cognitive abilities and proficiencies that enable individuals to acquire, comprehend, retain, and apply knowledge effectively in various contexts.

PRISMA: set of guidelines for authors to improve the reporting of systematic reviews and meta-analyses. It includes a checklist and flow diagram to enhance the quality of reporting. It is applicable to different types of research, particularly intervention evaluations. It can also be used for evaluating published systematic reviews [6]. The PRISMA 2020 statement replaces the 2009 statement and includes new reporting guidance that reflects advances in methods to identify, select, appraise, and synthesize studies [7].

Taxonomy: structured classification system that allows for the organization and categorization of objects or information based on their shared characteristics or relationships.

II. RESEARCH METHODOLOGY

Objective of the review : The primary objective of this systematic review is to recognize and present a summary of the current state of predictive future skills systems. This includes the evaluation of various research papers, journals and other studies with the aim of identifying the most innovative systems for predicting future skills. Another purpose of the review is to find areas of opportunities for enhancing the accuracy of the forecast of such skills. This could both impact workers and employers in a positive way when thinking and planning strategies for the better alignment of the employee’s current knowledge and skills and the emerging needs of the industry.Employers could benefit from better predictions to design more effective training programs that align with the evolving needs of the industry. At the same time, workers could use this information to identify areas of opportunity to develop their skills and knowledge to remain competitive in the job market.

RESEARCH QUESTIONS

RQ1. How can predictive future skills Industry 4.0 systems be used to identify skills gaps /and propose training and development programs for workers?

RQ2. Which techniques are being used to identify patterns in workforce open data to decision making about the effective training and development programs?

RQ3. Which AI techniques can be used to automate the identification of employees’ skill gaps and to provide guidance in the development of new, most demanded skill sets?

III. INFORMATION SOURCES

In order to find recent and valid information regarding studies related to our research questions, we found the following databases to be ideal due to their vast amount of material and well-known prestige:

Web Of Science: Comprehensive database for scientific research, with a user-friendly interface and powerful tools for refining searches.

Scopus: Large abstract and citation database that covers research literature in various disciplines. Also allows users to refine their searches.

Google Scholar: Freely accessible search engine with a broad range of scholarly literature and various advanced search features to refine and customize search results.

The database search engines used include other specialized databases such as Science Direct, IEEE Xplore, Springer Link, among others. The keyword combinations in the searches should retrieve articles related to the research topic.

SEARCH STRATEGY :

Taking into consideration the research questions, we created a list of keywords including the most important terms. This list was further organized in three categories: Future skills, Skills in industry 4.0 and Skills mismatch. Then, for each category, we included a combination of different keywords related to the main subject of our research.

In total, we constructed 70 different search strings by combining different keywords of each category. **Table 1** summarizes the keywords by database and shows the number of records retrieved by each of the keyword combinations. Only search combinations that yielded more than 1 result are shown. Keyword search combinations that found thousands of results are also omitted.

Table 1
Keywords used in queries

Database	Category and subcategories	Keywords search combinations	Number of records
Web of Science	Future skills Higher education Labour market	(future skills)	125
		(future skills AND higher education)	27
		(future skills AND (labor market OR labour market))	9
		(future skills AND (labor market OR labour market) AND (higher education))	6
	Skills in industry 4.0 Workforce Future workforce Reskilling revolution	(skills AND industry 4.0)	60
		(skills AND industry 4.0 AND workforce)	2
	Skill mismatch Obsolescence skills Reskills Layoffs	(skill mismatch)	126
Scopus	Future skills Higher education Labour market	(future skills)	204
		(future skills AND higher education)	25
		(future skills AND (labor market OR labour market))	22

	Skills in industry 4.0 Workforce Future workforce Reskilling revolution	(skills AND industry 4.0) (skills AND industry 4.0 AND workforce) (skills AND industry 4.0 AND future)	89 4 6
	Skill mismatch Obsolescence skills Reskills Layoffs	(skill AND mismatch) AND (LIMIT-TO (SUBJAREA,"COMP")) (skill AND mismatch) AND (obsolescence AND skills) (skill AND mismatch) AND (layoffs)	92 3 3
Google Scholar	Future skills Higher education Labour market	(future skills AND (labor market OR labour market))	45
	Skills in industry 4.0 Workforce Future workforce Reskilling revolution	(skills AND industry 4.0 AND workforce)	37
	Skill mismatch Obsolescence skills Reskills	(skill mismatch AND computer science AND reskills)	162
Total			**1047**

Eligibility criteria : Once the searching phase was done, the resulting articles were added to a library using the software Zotero. During this phase we removed 218 duplicated entries, 7 articles were marked as ineligible by automation tools and 2 records were removed due to other reasons. After that, we ended with a list of 820 articles ready for the second phase: screening. Only papers published after 2017 were considered. For the screening round, the 820 articles were randomly split among the researchers as shown in **Table 2**. These articles were screened by reading the title and the abstract looking for information valuable to our research questions.

Table 2
Number of articles assigned by researcher.

Researcher 1	**Researcher 2**	**Researcher 3**
n = 274	n = 273	n = 273

This screening round was primarily focused on the scope of the study. Articles were excluded if they did not include any work related to the search of future skills, or if they did not propose an approach to either improve workers skills, search for skills mismatch or gaps, or somehow investigate the needs of new skills related to Industry 4.0 in the labor market. Review articles were not taken into consideration. At the end of the second screening round, 514 articles were excluded by the researchers after screening their title and abstract. That left us with 306 articles to search for.

Another screening round was conducted using the software Rayyan. The 306 article list was formatted to a suitable CSV file that was then loaded into Rayyan. In that process we removed 5 articles that were different versions of the same article, ending with a final list of 301 articles. Once Rayyan was ready, we conducted this second screening review in which the same three researchers read all the articles' abstracts thoroughly and voted to either include them, remove them, or leave them as "maybe". The voting was done in a 'blind' way where the other researchers cannot see what their colleagues voted for. Once the researchers were done with the voting, we conciliated the articles where there was conflict, for example, where one of the researchers voted to include it but other voted otherwise, or some researcher voted yes while others voted maybe. Differences were discussed and each researcher presented their thoughts, after a short discussion, an agreement was reached for each article to either be included or not in the final list. As a result of this second screening round, 243 articles were excluded to end up with 58 articles. The main reasons for the exclusions can be seen in **Table 3**. The sum of the total of articles excluded is greater than 243 because some articles triggered more than one exclusion criteria.

Table 3
Exclusion criteria

Exclude reason	Number of articles excluded
not related to industry 4.0	162
wrong population	127
background article	84
other	93
Total number of articles excluded	**243**

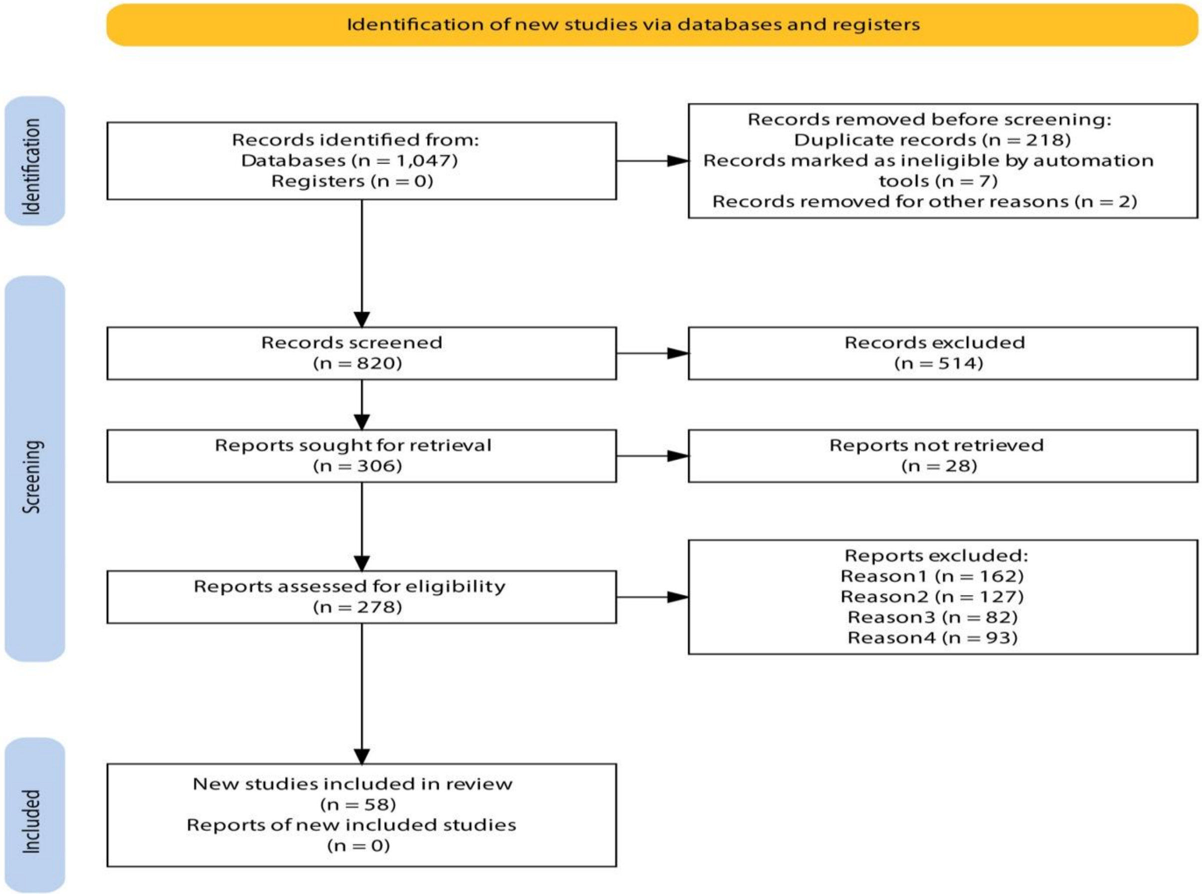

Figure 1
PRISMA flow diagram

Quality assessment: From the 58 sought articles, 3 were not available for download. After getting the full available 53 chosen articles, three parameters were identified, each one corresponding to a research question. The eligibility criteria consisted of three subgroups that were based on the degree to which the articles fulfilled them.

QA1. The study identifies skill gaps and proposes training or development programs.

QA1.1 The study does not identify skill gaps, or it does but without any training or development program suggestions.

QA1.2 The study contrasts the worker skills with the job skill requirements. or proposes training or development programs.

QA1.3 The study relates the skill gaps with development programs or training.

QA2. The article discusses or proposes techniques to identify patterns or skills that are either mismatched or outdated and inspects its effectiveness for improving training and development programs.

QA2.1 The article does not include techniques to identify workers skills.

QA2.2 The study identifies mismatched or outdated workers skills but does not further inspect how to overcome these mismatches.

QA2.3 The study relates the found skills to development programs or training to deal with mismatched or outdated skills.

QA3. The study uses AI techniques to automate the employee's skill gap identification and provide guidance for new skills development.

QA3.1 The study does not use any AI technique to automate the skill or skill gap identification.

QA3.2 The study uses some kind of AI to find the employees skills or skill gaps but does not use any AI technique to propose guidance for new skills development.

QA3.3 The study uses some AI techniques both to find employees skills or skill gaps and to propose guidance for new skills development.

IV. DATA EXTRACTION

For the data extraction phase, we first analyzed the papers looking for the level of depth in which they relate to each of the proposed research questions. Papers were assigned a subjective percentage based on the consideration of the researcher. This percentage, that can be seen in **Fig. 2**, reflects how strong the paper relates to each of the research questions depending on how they approach each subject in their study.

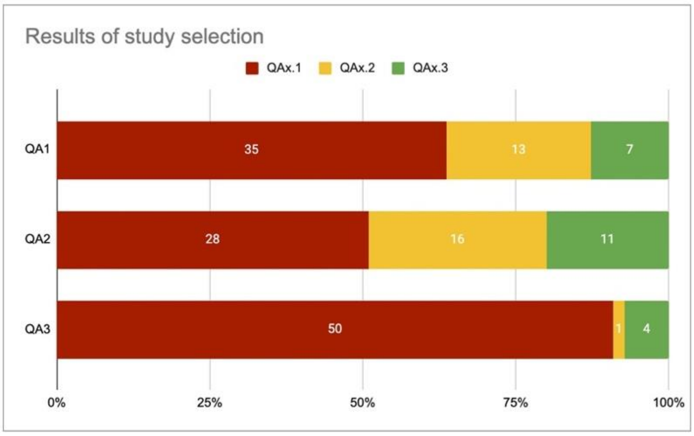

Figure 2.
Percentage of each subgroup in the quality assessment.

Fig. 2 shows the result of this measure. In color red we can find the papers that relate <=33% to each of the research questions. The yellow color reflects a relationship between 34% and 66%. Finally, the green bars count the papers that relate more than 66% to each of the research questions. By "relate" we mean that the paper discussed the proposed question or analyzed it in some way.

From the previous chart we can see that the research question 2 was more discussed in the papers, followed by question 1 and finally question 3. It is interesting that this question, that relates to how AI is being used to automate the identification of employee skill gaps and provide guidance in the development of new, most demanded skill sets, was the one with the lower relation percentage. This can be because AI is still making its way into the options for improving such tasks.

This also shows areas of opportunity for this and other new studies. The red bars in **Fig. 2** imply that there is still plenty of room for new research to explore the opportunities for computer systems to identify skills gaps and propose training and development programs for workers. Yellow bars also suggest that more work is expected to further investigate the techniques that are being used to identify patterns in workforce open-data to decision making about the effective training and development programs for workers. Finally, the green bars suggest that there is still little work related to the AI techniques that are being used to automate the identification of employee skill gaps and provide guidance in the development of new, most demanded skill sets.

Table IV
Summary of the article's features.

#	Reference	Propose framework or methodology	Framework	The method used to identify skills	Country	Data collection process	AI technique used	Programming language/package used	Gap identification	Proposes solution or mitigation
1	(Pater et al., 2022 [20])	Yes	N/A	Compare job requirements to declared skills	Poland	Web scraping and web surveys	N/A	Java	Yes	No
2	(Ada et al., 2021 [21])	Yes	N/A	Fuzzy ANP	Turkey	Pairwise comparisons	N/A	N/A	No	No
3	(Aljohani et al., 2022 [13])	No	N/A	Job-specific skills mapping	Saudi Arabia	Jobs lists Crawling + indexing	Word embedding in NLP	CBR with Python BM25	No	No
4	(Pellizzari & Fichen, 2017 [17])	Yes	N/A	PIAAC Survey of Adult Skills Analysis	Various (22)	PIAAC Survey of Adult Skills	N/A	N/A	Yes	Yes
5	(Maisiri et al., 2019 [19])	No	N/A	Systematic literature review	South Africa	Scopus search	N/A	N/A	Yes	No
6	(Phaphuangwittayakul et al., 2018 [14])	No	N/A	Word cloud	Thailand	Web scraping, keyword extraction	N/A	Python (BeautifulSoup & Scrapy)	No	No

7	(Khokhlova & Khokhlova, 2022 [18])	No	N/A	Naive forecasting, simple exponential smoothing, and ARIMA	International	Web-collected through lens.org	Predictive regression models	Python	No	No
8	(Telukdarie et al., 2021 [10])	No	N/A	Keyword analysis	International	Download and analysis of 700k papers	N/A	N/A	Yes	No
9	(Karakolis et al., 2022 [15])	Yes	N/A	Skill Extraction from Job Posts using web crawling	Greece	Scrapy Python framework	N/A	Python	Yes	Yes
10	(Caratozzolo et al., 2022 [22])	Yes	Education 4.0 Framework	Curriculum review, survey, literature review	México, USA	The survey, literature review, and review of university courses	N/A	N/A	Yes	Yes
11	(Maisiri et al., 2021 [23])	No	N/A	Delphi method	N/A	Delphi method with experts	N/A	N/A	Yes	Yes
12	(Fareri et al., 2020 [9])	Yes	Text Mining techniques	Systematic literature review, job advertisements search	Italy	Text Mining	Decision tree algorithm to classify job advertisements	R	Yes	Yes
13	(Breugel, 2017 [8])	Yes	https://www.cepal.org/en/projects/technical-and-vocational-education	Macro-level forecasts, sectoral studies, literature reviews, questionnaires to employers, and regional surveys of employment	Latin America and the Caribbean	Surveys, literature study, informed opinion, and specialist knowledge	N/A	N/A	Yes	Yes
14	(Stephany & Luckin, 2022 [11])	No	N/A	Systematic literature review, job-specific skills mapping	Europe	Jobs lists Crawling, data review, literature review	N/A	N/A	Yes	Yes

15	(Tommasi et al., 2022 [12])	No	N/A	A qualitative study of Interview		Interview	N/A	N/A	Yes	Yes
16	(McGuinness et al., 2018 [24])	No	N/A	Systematic literature review	Europe	Data from European skills and job surveys	N/A	N/A	Yes	No
17	(McGuinness et al., 2021 [25])	No	N/A	Systematic literature review	Europe	European international dataset	N/A	N/A	Yes	No

V. DISCUSSION AND FINDINGS

The 53 gathered papers were analyzed thoroughly against the three research questions. For better understanding and representation of the articles, we created a comparative table (**Fig. 3**) in which we compare the different characteristics of the studies, trying to find common patterns as well as future research opportunities. This table allows us to find and categorize the different contributions made by different researchers and studies.

A summary of the works contained in **Table 4** related to each topic is described below, adding a brief analysis of their contribution to the research questions. While some papers discussed subjects related to each of the three questions, some of them were more related to one question. In the next paragraphs we present a discussion noting the relation of each paper with the research questions.

Papers were grouped and analyzed according to the responses to the research questions, highlighting the contribution and limitations of each work. In this section, we discuss the different approaches taken in the reviewed papers and their contributions toward a better way of finding workers skills, skills mismatches, and skill gaps in order to propose distinct courses of actions to address these inconsistencies.

RQ1.- How can predictive future skills Industry 4.0 systems be used to identify skills gaps /and propose training and development programs for workers?

Our first research question tries to find systems that are being used to find current skill gaps and/or propose some kind of training or development program to reduce such a gap. In his paper Breugel [8] analyzes the mechanisms used by international organizations and developed countries to identify and anticipate the training, competency, or skill needs of businesses. It pays particular attention to the identification and anticipation of the competencies of people with technical and vocational education and training, both at the secondary and tertiary levels. Although the article offers a global overview of the methods used to identify competency needs, it does not directly address the role of Industry 4.0 future competency prediction systems or AI techniques in identifying competency gaps and proposing training and development programs.

The work done by Fareri [9] contributes to all three research questions. The study analyzes the impact of Industry 4.0 on job profiles and competencies and proposes a data-driven approach and text mining techniques to quantify the preparedness of employees belonging to a large company with respect to the industry 4.0 paradigm. The article provides a framework for estimating the preparedness for Industry 4.0 of a company's human capital and suggests that data mining and text mining techniques can help organizations identify competency gaps and develop training programs to improve their workforce's qualification. The article also addresses the importance of soft and cross-cutting skills in the current digital era and proposes a tool that HR managers can use to gather information on key professional skills and competencies in the company and automate the review and integration of job profiles.

Telukdarie [10] makes a relevant contribution to the first research question by analyzing data on the development of competencies over the last 21 years. The study uses a combination of qualitative, quantitative, and analytical techniques to monitor the growth in the number of qualifications requested and identify increases, novelties, and decreases in qualifications. However, the article does not directly address how to fill these competency gaps through training and development programs.

Stephany & Luckin article [11] analyzes current and future labor trends and identifies the competencies that will be in demand in the future. The report emphasizes the importance of data-driven competencies and forecasting training to ensure that the workforce is equipped with the necessary competencies to succeed in the future job market. Although the article provides a valuable overview of the competencies that will be in demand in the future, it does not provide specific techniques or approaches for identifying competency gaps or proposing training and development programs.

The work by Tommasi [12] provides valuable information on the competencies and skills needed for future workers in relation to Industry 4.0. Although it does not directly focus on identifying skill gaps or proposing training and development programs for workers.

Breuguel's article [8] provides a comprehensive overview of the methods employed for identifying competency needs, yet it does not directly address the role of Industry 4.0 future competency prediction systems or AI techniques in identifying competency gaps and recommending training and development programs. This absence of focus on AI techniques and new training programs is also evident in the studies conducted by Telukdarie [10], Stephany & Luckin [11] and Tommasi [12], as they predominantly employ surveys, literature reviews, or curricula reviews to obtain the requisite information. In contrast, Fareri's research [9] employs a data-driven approach and text mining techniques to acquire data and proposes frameworks that can be valuable in identifying desired competencies for Industry 4.0.

RQ2.- Which techniques are being used to identify patterns in workforce open-data to decision making about the effective training and development programs?

Research question number 2 deals with the techniques that are being used to identify patterns in workforce open-data to decision making about the effective training and development programs for employees. Studies related to this question contribute to the understanding of skills requirements in different labor markets and aim to bridge the gap between education and industry needs. While each study has its own unique approach and focus, there are some things in common that can be put together to better analyze and familiarize with the current techniques.

Several studies use data analysis techniques to extract relevant information from job posts found in internet websites and identify skill requirements. For example, Aljohani et al [13] employ artificial intelligence, deep learning and big data technologies to analyze job posts in Saudi Arabia to identify essential skills for digital transformation. Phaphuangwittayakul [14], use web scraping and keyword extraction algorithms to analyze job postings in the Thai labor market. Similarly, Karakolis et al. [15] develop services to gather job post data and extract skills from online sources for personalized recommendations.

Furthermore, many studies emphasize the importance of aligning education with industry needs. Aljohani et al. [13] aim to align business and industry with academia, while Karakolis et al. [15] recommend courses to bridge the gap between technological education and job market requirements. Kusmin et al. [16] develop a framework for collaboration between education and the labor market to address the skills needs of Industry 4.0. On the other hand, there are also differences in the methodologies and focus of the studies.

For example, Pellizzari and Fichen [17] propose a measure of skill mismatch based on worker data from the Programme for the International Assessment of Adult Competencies (PIAAC). They classify workers as under-skilled, well-matched, or over-skilled in literacy and numeracy domains. This differs from the other studies that primarily analyze job postings to identify skill requirements. Additionally, Khokhlova [18] analyzed time series data for patents to identify technological trends and predict skills in demand. Their approach focuses on analyzing patents and technological advancements rather than directly analyzing job postings.

Moreover, Maisiri [19] developed an Industry 4.0 Competency Maturity Model using the Delphi technique and expert consensus, which is different from the data-driven approaches of text mining and analysis used in other studies. Overall, these studies contribute to the understanding of skills requirements, skill mismatch, and the alignment of education with industry needs. They employ various methodologies, ranging from data analysis techniques to expert consensus, and provide insights into different labor markets and technological trends. While all these works mainly use data mining techniques. The details of how the method they use is implemented are not discussed in detail. Their focus lies more on where they got the information. Some of them use job offers as the source for their information [15] while other used job profiles [9]. Aside from these differences there seems to be no clear action plan to further innovate the techniques used for getting the data.

RQ3.- Which AI techniques can be used to automate the identification of employees' skill gaps and to provide guidance in the development of new, most demanded skill sets?

More related to question 3 is the work done by Fareri [9], while it also contributes to the other two research questions. The study analyzes the impact of Industry 4.0 on job profiles and competencies and proposes a data-driven approach and text mining techniques to quantify the preparedness of employees belonging to a large company with respect to the industry 4.0 paradigm. The article provides a framework for estimating the preparedness for Industry 4.0 of a company's human capital and suggests that data mining and text mining techniques can help organizations identify competency gaps and develop training programs to improve their workforce's qualification. The article also addresses the importance of soft and cross-cutting skills in the current digital era and proposes a tool that HR managers can use to gather information on key professional skills and competencies in the company and automate the review and integration of job profiles.

The study by Aljohani et al. [13] is especially relevant to the third question, as it uses artificial intelligence, deep learning, and big data technologies to analyze job posts in Saudi Arabia cyberspace and identify the essential skills required for digital transformation. The study aimed to improve student satisfaction, retention, and employability, align business and industry to academia, and promote the labor market's sustainable evolution towards technology-driven innovation. The methodology includes a semantic-based approach with three modules: a data layer, a word-embedding layer, and a mapping layer. The study used the Okapi BM25 matching formula to find similarities between different cases in a CBR system. The study supports the development of a machine learning-powered dashboard to analyze web data, prepares the young Saudi generation for the digital transformation under industry 4.0, and encourages the alignment of business and industrial sectors to academia.

The article from Karakolis [15] contributes to the third question, as it discusses the development of two services, JobCrawler and JobWatch, to gather job post data from online sources. JobCrawler crawls Greek job posting websites and extracts relevant information, while JobWatch uses APIs to gather data from well-known job posting websites in English. Over 1500 job posts were gathered for analysis. A Knowledge Extraction service was developed to extract skills from job posts, which were then classified as "Product", "Tool", or "Topic". The Skill and Course Recommendation service used this data to provide personalized recommendations to students and learners, with courses derived from the school's curriculum and presented in order of importance. The identified skills are clustered into specializations such as DevOps software engineer and Database software engineer. The service uses association rules mining to identify missing skills in a school's curriculum and recommend courses that are suitable to introduce those skills. The association rules are calculated and stored on a weekly basis. The text also provides examples of association rules identified with high probability in Greek job posts. The article presents a Multi-criteria Decision Support (MCDSS) service combined with a Skill and Course Recommender service and a Curriculum Designer service to facilitate optimal decision making.

In their work, Khokhlova [18] contributed to the third question by collecting and analyzing time series data for different classes of patents according to the International Patent Classification from 2010 to 2020, grouping patents into "dying," "promising," and "breakthrough" technologies. Predictive regression models of subsections/classes of patents were built using classical forecasting methods and the best model was the ARIMA model, with results presented in figures and tables. The study used Python and libraries such as OS, Requests, NumPy, Matplotlib, and Scikit-Learn. The developed algorithm for analyzing patents can determine the demand for specialists and skills in the labor market based on promising or "breakthrough" technological trends. This algorithm can process large patent data sets and build predictive regression models, helping researchers, educational institutions, employers, and job seekers make informed decisions about future professions and skills in the labor market.

Previous authors used text mining and AI techniques on existing data to generate a list of useful skills for a certain position. Such lists proved to be very useful for forecasting which skills are going to be required for workers in the future. However, the approach used by the authors is different and can be clustered based on the source of the data that was processed: Aljohani [13], Karakolis [15] and Fareri [9] obtained their data from existing job positions. On the other hand, Khokhova [18] obtained the data from the Patents made from 2010 to 2020. All of the previously mentioned authors processed the gathered data using AI and text mining procedures in order to obtain a list of useful skills, however each author used the information for a different purpose: Aljohani [13], Karakolis [15] and Khokhlova [18] use their data to give recommendations for educational courses that would cover the skills they found to be essential, making a connection between Academia and employers. Fareri [9] on the other hand suggests the creation of a tool to help HR managers get a better idea of the necessary skills for the future of their company.

Out of all the revised documents, the third question was the one with the least number of complementing documents, which limited the scope of the analysis as a wider variety of sources would give the review more information to work with. However, the lack of information creates an opportunity for future research to find new implementations of AI techniques that aim to improve the techniques to assess and improve workers skills.

VI. LIMITATIONS OF OUR WORK AND RESEARCH AREA OPPORTUNITIES

The study limitations are observed in the heterogeneity in the approaches taken when trying to extract the different skills from various sources as well as in the unique ways in which they analyze the data. Another significant limitation is the domains covered by the research. Not all domains were analyzed in this research which leaves space for more analysis. One final limitation is the number of authors analyzed in the review. This number was narrowed down to allow the researchers to focus on the works more relevant to our study and more related to the research questions proposed. More papers can be brought to the analysis.

Figures 3 and 4 show two radial charts representing the distribution of the papers based on the year published (**Fig. 3**) and the type of study carried out. For this last classification we identified three different types of research: first we found classical systematic literature reviews (SLR). Another group are the papers that present both a SLR plus another methodology or technique involved in the research or classification of the findings. The third group includes studies that aren't SLR but rather present original research works. As we can see, there seems to be an increasing number of studies related to expanding the current knowledge on subjects related to industry 4.0 and the necessary workers skills to fulfill these emerging needs. Most papers selected (28 out of 55) are from 2021 and 2022. We can expect this number to be higher in the upcoming years.

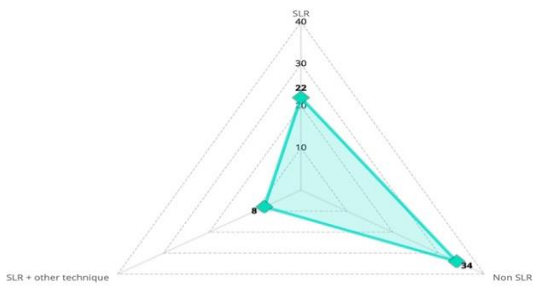

Figure 3.
Number of studies by research type

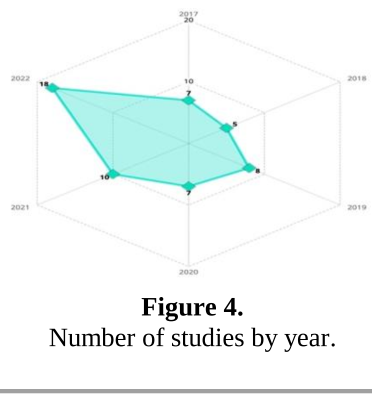

Figure 4.
Number of studies by year.

In the current digital era, identifying skills gaps and proposing training programs for workers has become crucial for organizations. One promising approach is developing an Industry 4.0 skills prediction system or AI techniques. These systems can identify competency gaps and recommend training and development programs for the workforce using data mining and text mining techniques. Soft and cross-cutting skills (such as teamwork and critical thinking) are also gaining importance in the digital age, and tools that HR managers can use to gather information on crucial professional skills and competencies in the company can be developed.

Another area of research is investigating specific techniques or approaches for identifying competency gaps and training, proposing, and developing programs for workers in the context of Industry 4.0. Organizations can make informed decisions about effective exercise and improve their development programs by analyzing the techniques used to identify patterns in workforce open data. Developing new data analysis techniques to extract relevant information from job posts on internet websites can help identify skill requirements. Artificial intelligence, deep learning, and big data technologies can also be explored to analyze job posts and better identify skill requirements.

VII. CONCLUSION AND FUTURE WORK

This paper presents a systematic literature review to assess recent research papers, journals, and studies to identify the most innovative systems for predicting future skills. We look at the current state of predictive future skills systems and different frameworks for enhancing the accuracy of skills estimation and forecasting. The review has potential positive impacts on the classification and exploration of industry 4.0 current knowledge and needed skills as well as the emerging needs of the industry. The study can help identify opportunities to develop prediction and forecasting systems skills. Such systems have the potential to help organizations develop better strategies for workforce development and improve their competitiveness in the digital era.

Investigating the skills requirements in different labor markets for bridging the gap between education and industry needs is an essential area of research. By doing so, organizations and Universities can develop better student and worker development strategies to improve their competitiveness in the digital era. In summary, these research areas can help organizations address the current challenges in identifying skills gaps and proposing training and development programs for workers, especially in the context of Industry 4.0. By investing in these research areas, organizations can improve their ability to attract and retain skilled workers and achieve a competitive advantage.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the financial support of Writing Lab, and the Challenge-Based Research Funding Program, Grant no. IJXT070-22EG51001, both of the Institute for the Future of Education, Tecnologico de Monterrey, Mexico, in the production of this work. We also thank the Vicerrectoría de Investigación y Posgrado, the Research Group of Advanced Artificial Intelligence, and the Cyber Learning and Data Science Laboratory of Tecnologico de Monterrey.

REFERENCES

[1] Ehlers, U.-D. (2020). Future Skills: The Future of Learning and Higher Education. BoD – Books on Demand.

[2] Oxford University Press. (2023). Oxford Learners Dictionaries. https://www.oxfordlearnersdictionaries.com/definition/american_english/ability_1

[3] Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

[4] Brun-Schammé, A. and Rey, M. (2021). A new approach to skills mismatch. OECD Productivity Working Papers, 2021–24.

[5] McGuinness, S., Pouliakas, K., & Redmond, P. (2018). SKILLS MISMATCH: CONCEPTS, MEASUREMENT AND POLICY APPROACHES (rayyan-958721453). 32(4), 985–1015. https://doi.org/10.1111/joes.12254

[6] Mohasses, M., Shukla, B., & Joshi, M. (2020). Industry 4.0 Core Skills: A Research Report. In K. S. Soliman (Ed.), Education Excellence and Innovation Management: A 2025 Vision to Sustain Economic Development During Global Challenges (pp. 695–707). Int Business Information Management Assoc-Ibima. https://www.webofscience.com/wos/woscc/full-record/WOS:000661127400062

[7] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson,

A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, n71. https://doi.org/10.1136/bmj.n71

[8] Breugel, G. van. (2017). Identification and anticipation of skill requirements: Instruments used by international institutions and developed countries. https://repositorio.cepal.org/handle/11362/42233

[9] Fareri, S., Fantoni, G., Chiarello, F., Coli, E., & Binda, A. (2020). Estimating Industry 4.0 impact on job profiles and skills using text mining. COMPUTERS IN INDUSTRY, 118. https://doi.org/10.1016/j.compind.2020.103222

[10] Telukdarie, A., Munsamy, M., & Gaula, M. (2021). Big Data Analysis for Predicting Future Skills. 2021 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 411–415. https://doi.org/10.1109/IEEM50564.2021.9673039

[11] Stephany, F., & Luckin, R. (2022). Is the Workforce Ready for the Jobs of the Future?: Data-informed Skills and Training Foresight. Bruegel.

[12] Tommasi, F., Perini, M., & Sartori, R. (2022). Multilevel comprehension for labor market inclusion: A qualitative study on experts' perspectives on Industry 4.0 competences. Education+ Training, 64(2), 177–189.

[13] Aljohani, N. R., Aslam, M. A., Khadidos, A. O., & Hassan, S.-U. (2022). A Methodological Framework to Predict Future Market Needs for Sustainable Skills Management Using AI and Big Data Technologies. In APPLIED SCIENCES-BASEL (Vol. 12, Issue 14). MDPI. https://doi.org/10.3390/app12146898

[14] Phaphuangwittayakul, A., Saranwong, S., Panyakaew, S., Inkeaw, P., & Chaijaruwanich, J. (2018). Analysis Of Skill Demand In Thai Labor Market From Online Jobs Recruitments Websites. 2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE), 1–5. https://doi.org/10.1109/JCSSE.2018.8457393

[15] Karakolis, E., Kapsalis, P., Skalidakis, S., Kontzinos, C., Kokkinakos, P., Markaki, O., & Askounis, D. (2022). Bridging the Gap between Technological Education and Job Market Requirements through Data Analytics and Decision Support Services. Applied Sciences (Switzerland), 12(14). Scopus. https://doi.org/10.3390/app12147139

[16] Kusmin, K.-L., Tammets, K., & Ley, T. (2018). University-industry Interoperability Framework for Developing the Future Competences of Industry 4.0. Interaction Design and Architectures, 38, 28–45.

[17] Pellizzari, M., & Fichen, A. (2017). A new measure of skill mismatch: Theory and evidence from PIAAC. IZA Journal of Labor Economics, 6(1). https://doi.org/10.1186/s40172-016-0051-y

[18] Khokhlova, O. A., & Khokhlova, A. N. (2022). Analysis of technological trends to identify skills that will be in demand in the labor market with open-source data using machine learning methods. Izvestiya of Saratov University. Mathematics. Mechanics. Informatics, 22(1), 123–129. Scopus. https://doi.org/10.18500/1816-9791-2022-22-1-123-129

[19] Maisiri, W., Darwish, H., & van Dyk, L. (2019). AN INVESTIGATION OF INDUSTRY 4.0 SKILLS REQUIREMENTS. SOUTH AFRICAN JOURNAL OF INDUSTRIAL ENGINEERING, 30(3), 90–105. https://doi.org/10.7166/30-3-2230

[20] Pater, R., Cherniaiev, H. and Kozak, M. (2022), "A dream job? Skill demand and skill mismatch in ICT", Journal of Education and Work, Routledge, Vol. 35 No. 6–7, pp. 641–665, doi: 10.1080/13639080.2022.2128187.

[21] Ada, N., Ilic, D. and Sagnak, M. (2021), "A Framework for New Workforce Skills in the Era of Industry 4.0", INTERNATIONAL JOURNAL OF MATHEMATICAL ENGINEERING AND MANAGEMENT SCIENCES, Vol. 6 No. 3, pp. 771–786, doi: 10.33889/IJMEMS.2021.6.3.046.

[22] Caratozzolo, P., Lara-Prieto, V., Martinez-Leon, C., Rodriguez-Ruiz, J., Ponce, R., Vazquez-Villegas, P. and Membrillo-Hernandez, J. (2022), "Developing Skills for Industry 4.0: Challenges and Opportunities in Engineering Education", Proceedings - Frontiers in Education Conference, FIE, Vol. 2022-October, doi: 10.1109/FIE56618.2022.9962444.

[23] Maisiri, W., van Dyk, L. and Coetzee, R. (2021), "Development of an Industry 4.0 Competency Maturity Model", Vol. 112 No. 4, pp. 189–197.

[24] McGuinness, S., Pouliakas, K. and Redmond, P. (2018), "SKILLS MISMATCH: CONCEPTS, MEASUREMENT AND POLICY APPROACHES", Vol. 32 No. 4, pp. 985–1015, doi: 10.1111/joes.12254.

[25] McGuinness, S., Pouliakas, K. and Redmond, P. (2021), "Skills-displacing technological change and its impact on jobs: challenging technological alarmism?", Economics of Innovation and New Technology, doi: 10.1080/10438599.2021.1919517.