A Matrix Taxonomy of Knowledge, Skills, and Abilities (KSA) Shaping 2030 Labor Market

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***Abstract*—This paper proposes a dynamic Knowledge, Skills, and Abilities (KSA) matrix-based taxonomy for the Industry 4.0 workforce. The study methodology consisted firstly of identifying the KSAs through a literature review and secondly of a KSA relevance analysis using information from World Economic Forum (WEF) global reports and the Organization for Economic Cooperation and Development (OECD). Finally, we identified the correlation coefficients of the KSA matrix elements concerning the data on jobs and occupations using information from the European Skills, Competencies, and Occupations (ESCO), Occupational Information Network (O*NET), and the strategic intelligence platform of the World Economic Forum. One of the goals was to make the taxonomy compatible with existing and future machine learning methods (i.e., AI-ready) that will enable efficient and effective use of AI in mining and explaining existing and potentially proposing novel trends and strategies. Preliminary results show that the KSA Industry 4.0 Taxonomy can serve as an international reference guide for designing 2030 educational approaches to active and experiential learning in Higher Education Institutions.**

Keywords— Educational Innovation, Higher Education, Labor Market, Future Skills, Knowledge, Skills, and Abilities (KSA), Industry 4.0.

I. Introduction

The high demand for workers and recent graduates trained in the so-called *Future Skills* is partly due to the pressure to meet, by 2030, the labor market requirements related to Industry 4.0 Knowledge, Skills and Abilities (KSA) taxonomy [1]. The combination of two phenomena, the high demand for skilled workers and the skills gap, requires a disruptive comprehensive solution: not only must the teaching-learning experience of young people in their Higher Education years be made more flexible, but also a culture of continuing education in recently graduated professionals must be implemented [2], [3].

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Traditional KSA taxonomies are static sets of Knowledge, Skills, and Abilities classified into ordered categories that follow a hierarchical sequence or format [4]. Before the pandemic, the traditional KSA taxonomies had continued to be used to design curricular plans in Higher Education Institutions (HEIs) and describe worker profiles in the companies' Human Resources Departments (HRD) [5]. These taxonomies were valid for many years and underwent few modifications, with the occasional addition of different combinations of soft skills, digital literacy skills, and communication skills. Generally, the changes were justified by the new incorporations of KSA that emerged from the Top Ten List of international studies [6].

However, we can find a turning point with the reports released in February 2020. The 2020 international reports by the World Economic Forum (WEF) and the Organization for Economic Cooperation and Development (OECD) began to suggest that mismatches will emerge, not only between current supply and demand considering the current KSA taxonomy but also mismatches would arise between those contemporary KSAs and those that would be required in the future due to the appearance of new occupations and jobs related to other phenomena such as the Twin Transition [7], [8]. In the following months, the reports included the risks associated with new global crises similar to the ones experienced with COVID-19 [9], [10]. Finally, new concepts related to improving a job appeared; the first is upskilling, which implies that, based on required changes in skills or adding skills to the personal profile, workers must learn new skills to remain in the position with the current role, the second, *Reskilling*, where looking to transition to a new complementary role, a new set of competencies must be understood [11]–[13].

A relatively low reduction in existing jobs is expected, around 3% [14]. However, as we get closer to 2030, the demand for labor could mean the automation of around 30% of employment, accompanied by an increase in the number of new professions [15]. Additionally, the increasing role of automation and Artificial Intelligence (AI) will create new opportunities and threats, making the labor market very sensitive and the traditional static KAS taxonomies obsolete [16]. This study aims to establish the basis for the design of a dynamic taxonomy of KSA. For this, it was first necessary to identify and understand the challenges associated with aligning employee skills with the requirements of the labor market environment by 2030. Given the speed of technological change and the threat of global risks for the labor market, we decided that machine learning tools would drive the taxonomy and that it would be based on future study strategies to forecast labor market requirements, using information from ESCO (European Skills, Competences, and Occupations); O*NET Frameworks (Occupational Information Network); and the Strategic Intelligence Platform by the World Economic Forum [17]–[19]. Consistent with the findings of those international reports, we stated the following research question:

RQ: What is the most appropriate design for a dynamic matrix-based taxonomy based on Knowledge, Skills, and Abilities (KSA) sets?

II. Literature Review

Understanding the development of knowledge, skills, and abilities-based taxonomy involves exploring the literature on taxonomies encompassing these types of competencies to grasp better the process of creating such a taxonomy and analyze the results. So, below, we present various skill taxonomies found in the literature.

A group of researchers from various universities based in the McKinsey Global Institute research and analysis and consulting organization around the world defined the future competencies in 2018 for the automation industry based on interviews with companies, where the model created established a categorization of skills based on physical, manual, basic cognitive, higher cognitive, socio-emotional, and technological skills [20]. Using this taxonomy, the researchers showed the changing patterns of skill requirements for their industries in a heat map where basic physical, manual, and cognitive skills were less in demand. In contrast, the other three industries were expected to increase in demand in the next three years [20].

The England charity Jyl Djumalieva and Cath Sleeman led the proposal for the 2018 NESTA taxonomy. It is based on a review of UK job advertisements in 2012-2017, applying Machine Learning to define and organize skills [21]. As a result of their clustering, A list of essential sectors emerged, where each sector is subdivided into skill groups, and the skill groups linked the skills in demand with the jobs [21]. Furthermore, this taxonomy classifies skill groups according to the potential growth of their needs and the associated density of wages [22]. Then, in 2019, Khaouja et al. They proposed a taxonomy based on soft skills and a series of alternative labels related to each skill. For the construction of this taxonomy, the data was obtained by extracting soft skills from job advertisements using a combination of techniques based on DBpedia and word embedding [23]. The same year, the Leadership Competition Development [2], as a three-dimensional model, explicitly focused on teaching leadership and was structured under the principles of Bloom's taxonomy and the Delphi technique. This taxonomy was structured mainly under categories by competencies and complexities related to these competencies, all under a domain or main competency level [4].

In 2020, Kiesler proposed a Competency Model for beginning Computer Science and Programming students based on Bloom's taxonomy for the first three semesters [24]. This classification divided the competencies into cognitive and non-cognitive, where each had dimensions based on knowledge, and knowledge had sub-dimensions based on processes [24]. The work of Xu et al. presented an exciting framework for looking at the competency profiles for different occupations and the possible effects on China's economic growth. They collected their data with machine learning tools based on the O*NET taxonomy. As a result, different occupations presented recompiled competency derivations in clustering mode [25]. In addition, there is a group view of all available skills and the main occupation related to any chosen skill. Skills taxonomy, where they were based on skills applicable to Higher Education STEM students in the UK. The taxonomy arose from data collected from accredited programs at Institutions of Higher Education based on Bloom's taxonomy. This taxonomy is divided into topics equivalent to what is learned in the levels of Bloom's taxonomy. Subsequently, skills, or descriptors, were distinguished as transferable or subject-specific skills [26].

In the case of the World Economic Forum, they built a robust framework under a membership system for complete access, in which you can learn about employability strategies for the industry 4.0 of the future, Reskilling for the jobs of the future, map opportunities for the economy of the future, and definitions in search of creating a global taxonomy based on occupations and skills, their data is obtained mainly through surveys of the leading employers worldwide, and they are organized through clusters, having various functionalities, they present multiple taxonomies based on the data they collect. Even so, all of these are based primarily on granular dimensions based on skills and occupations [7], [11], [15], [27], [28].

One of the open-source taxonomies is the global learning landscape. This taxonomy was made for education and innovation and is based on two data analysis and design procedures involving tiered machine learning and clustering [29]. Deloitte conducted a study on how organizations are changing how they define their jobs according to a model based on a collection of skills [30]. To obtain their data, they surveyed over a thousand workers and found a trend towards a model based on skills; however, less than 20% of the organizations in the study showed a systematic implementation of this model. Furthermore, among various obstacles identified for the performance of the skills-based model, 26% of the respondents mentioned the lack of a skills taxonomy as one of these difficulties. Therefore, it seems that there is a need for the industry to have such a taxonomy. Finally, it is mentioned that taxonomies are also fundamental in the industry [31].

In the framework presented by the Singapore government called SkillsFuture, which is mainly used for designing and updating occupational profiles, we can find a taxonomy created from data obtained from surveys of the country's active population. The surveys made it possible to organize the results by grouping them into domain areas, then into occupations, and then into knowledge, skills, and abilities. Finally, a professional level of detail should cover these knowledge, skills, and abilities [32]. Bi et al. mention the creation of a taxonomy based on occupations and skills from surveys and groups to obtain and order the data, which was used in the Singapore government's SkillsFuture framework mentioned above [33].

Skills–Future Learning and Future Higher research initiative Education decided to analyze the changes in organizations related to the workplace, define Future Skills, and, consequently, establish a possible path that Higher Education Institutions should follow to achieve them. Using the Delphi technique, they developed their taxonomy by asking experts from the European education sector to reason and evaluate the scenarios of future Higher Education [34], [35]. This Delphi Survey led to a set of future skills called the Future Skill Three Triple Helix Model (FSTTHM) and a collection of profiles based on future skills. The FSTTHM expressed that skills acquire meaning from the relationships between the subject, the specific, and the social [34], [36]. As a consequence of the developed taxonomy, four pillars or influential factors for Universities are: focus on future skills, multi-institutional study paths, personalization of academic learning, and lifelong learning.

ESCO (European Skills, Competences, Qualifications, and Occupations) is a database where it is possible to find the description of the multilingual European classification of Skills, Competences, and Occupations. The first version of the full ESCO was published in 2017, and the latest one was uploaded in 2022. This platform describes occupations and skills becoming essential for the EU education and labor market [17]. The ESCO occupational database is based on the ISCO-08 taxonomy, where the ISCO-08 taxonomy is an official document of the European Union based on main groups of occupations that include main subgroups and minor groups of these. In addition, ESCO is the result of how big data is affecting the Labor Market by having the possibility of efficiently discerning the skills, knowledge, and abilities that are required in the labor market [37]. For example, in Italy, the public administration has applied ESCO to "improve the match between labor demand and job seekers." In addition, in the field of the Ministry of Economy, consider that the list of skills is relevant to envision the following steps when seeking to create innovative profiles [38].

Another of the large databases on occupations is O*NET (Occupational Information Network), which contains a list of occupations involved in the US labor market [18]. The O*NET occupational database is based on the SOC taxonomy. The SOC (Standard Occupational Classification) taxonomy lists occupations and was published in 2018 by the Executive Office of the President of the United States as an official document. The importance of the O*NET database is reflected in examples such as its relevance to obtaining information on the psychosocial exposure of employees of three Massachusetts Health institutions [39]. Likewise, in 2010, Manuel Cifuentes and his colleagues compiled studies that used O*NET as a source of occupational exposure to organize an occupational exposure matrix [40].

III. Methodology

This work was developed under a methodological system where an initial review of the state of the art was carried out to identify the taxonomies based on existing competencies that have been developed in the last ten years under the recommendations described by Page et al. [41], the guidelines of Kitchenham and Charters [42], Xiao and Watson [43], and Torres-Carriét al. [44]. Each of these taxonomies was analyzed by reviewing their taxonomy concepts, taxonomic structure, KSA-based competencies, as well as the method by which they obtained the data to complete their taxonomies, intending to find their strengths and weaknesses, and thus, create the background and identify the area of opportunity, then an analysis of the said state of the art was carried out where the area of opportunity was validated, and the contribution was perfected.

Subsequently, a KSA-based matrix taxonomy proposal is created based on the suggestions of Nickerson et al. [45], Vogelsang [46], and Horst & Prendergast [47], where the taxonomy will have a solid base where the categorical scale of domains, sub-domains, occupations, competencies (knowledge, skills, abilities) and other necessary data will be considered, which will allow having a functional dynamic matrix taxonomy that covers the required operational needs. Some dynamic aspects of taxonomy will be associated with the contents of each category according to the evolution of the occupations through machine learning techniques.

Next, to obtain the initial data that are part of this KSA-based matrix taxonomy, the public data provided by the different taxonomies mentioned in the literature review were reviewed, where, due to the criteria discussed above, we chose to work with the data supplied by SkillsFuture [32], [33], the Standard Occupational Classification (SOC) [48] and NESTA [21]. In addition, it is considered that the taxonomy may be modified or updated through artificial intelligence techniques, such as machine learning and clustering, which would keep the taxonomy updated by applying this type of dynamism. Perhaps at some point, it may even lead to the simulation of future scenarios of occupational profiles based on knowledge, abilities, and skills.

Afterward, an analysis of the results is carried out where the contribution regarding the related works is put into perspective, the research question is answered, and the limitations of the work are shown. Finally, conclusions and future work emerge.

IV. Findings and Analysis

A. Analysis of existing taxonomies

After analyzing the existing skill taxonomies, Table I shows the taxonomies in the literature and the methodology or techniques used in their construction. Figure 1 presents the frequencies of the methods/techniques used. Surveys are the most used technique to obtain data, followed by Machine Learning techniques. Next, Delphi techniques, systematic reviews, and adaptations of the Bloom taxonomy have been used.

As seen in Figure 1, censuses and consultancy are used to a lesser extent, as well as systems based on neural networks such as World2vec and data banks such as DBpedia.

It can be seen in Table I and Section IV.B that the taxonomies presented are primarily used for occupation profiling; in some cases, they are used to design occupation training, and in a third case, these are used to offer resources related to Skills requested by employers. Academies have also used them to seek/predict the future of professional skills.

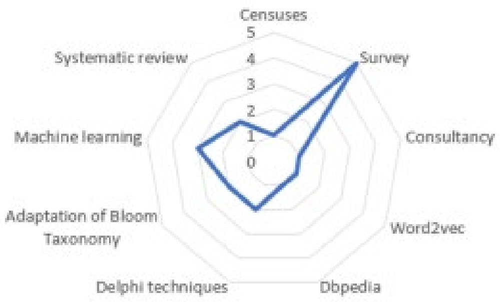

Fig. 1 Data techniques used on the reviewed taxonomies.

TABLE I. Review of existing taxonomies

Taxonomy	**Data Base and Methodology/Techniques Used**	**Reference**
Leadership Competence Development	Delphi technique and adaptation of Bloom Taxonomy	[4]
McKinsey Global Institute Workforce Skill Model	Consultancy	[20]
Nesta Taxonomy	Machine Learning	[22]
Soft Skill taxonomy	Word2vec and DBpedia	[23]
Competency Model for Programming Courses Bloom taxonomy	Adaptation of Bloom Taxonomy	[24]
Skill Space of China	Machine Learning	[25]
21st Century Skills Taxonomy	Systematic literature review	[26]
Report's research framework	Surveys	[27]
Global Learning Landscape	Machine Learning	[29]
Digital Skill taxonomy	Systematic literature review	[31]
SkillsFuture	Surveys	[32]
Critical core skills profiling	Surveys	[33]
Future Skill Three Triple Helix Model	Delphi technique	[35]
SOC	Surveys	[48]
ISCO-08	Censuses and surveys	[49]

Figure 2 shows the type of competencies that the fifteen taxonomies include. As observed, the skills are mentioned in the major frameworks, followed by knowledge. Abilities are scarcely mentioned in the taxonomies. Approximately a third of these taxonomies contemplate skills, knowledge, and abilities simultaneously, and the other two-thirds only attended one of these competencies.

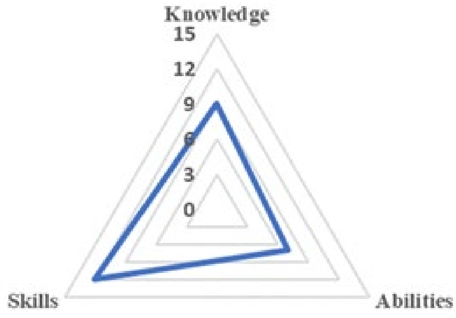

Fig. 2 Competencies state for the analyzed taxonomies.

Another aspect to explore in taxonomies is the domains. Figure 3 shows how taxonomies are typically developed for the Education field. The sectors with less developed taxonomies are the Construction Industry and Industry 4.0.

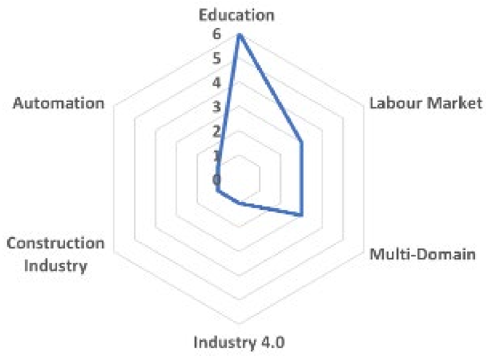

Fig. 3. Domains related to analyzed taxonomies and their results.

Suppose it is taken into consideration the access to the taxonomies. In that case, it can be added that most of these taxonomies are free to access, and few are not usually working through memberships.

Finally, after presenting the current analysis, we can summarize the opportunity areas of the existing taxonomies. One of these is in using techniques to obtain data, since until now, Artificial Intelligence techniques have not been considered, which might be beneficial in covering this task of collecting and ordering data. Therefore, as part of the contribution of this work, we will seek to work with techniques related to Artificial Intelligence for collecting, collecting, and possibly analyzing data. Considering the type of skills to attend, there is a need to involve abilities and knowledge. In domains, Industry 4.0 seems to be an opportunity area; moreover, currently, this is being a driver in the redefinition of occupations, roles, and, of course, the skills, abilities, and knowledge required. Also, mixt access to a taxonomy may be adequate to allow its diffusion while guaranteeing their funding, which would help with their constant maintenance and update. Hence, building a new taxonomy addressing these opportunity areas will address the detected gaps.

B. Proposal of a Dynamic Matrix KSA Taxonomy

Nowadays, comparing and analyzing the specific and diverse contexts of the industry to obtain an overview is still tricky. However, as some taxonomies show the dimensions and characteristics based on some context, researchers can understand, communicate, and apply these more completely [46]. When creating a taxonomy, we must consider different factors, such as knowledge, skills, and abilities, necessary to cover the functionality needs relating to the work to be evaluated [47]. In addition, we must be able to identify and analyze the different dimensions that can classify and explain the elements present in the taxonomy [46], seeking to create a categorical scale that allows generalization and a better understanding of the data.

Based on the work of Nickerson et al., it can be said that a helpful taxonomy must be concise, with a limited number of characteristics and dimensions, also robust, where the number of features and dimensions allow the differentiation of the objects of interest, in addition, it is comprehensive, where objects within a domain can be classified under specific considerations, along with this, it must be extensible, allowing the inclusion of new dimensions or characteristics, it is also explanatory, where they provide helpful information or explanations of the objects that are classified [45]. A taxonomy can be represented, according to Vogelsang et al., through the following steps[46]:

- Determine the meta-characteristics, where the implications must be identified, who it involves, and the next steps for the object
- The completion conditions must be determined, which can be established with the definition and application of iterative tasks
- The use of the taxonomy must be chosen, and it must be done empirically toward the conceptual
- The sub-elements of the objects must be identified, where possible, characteristics from previous literature
- The features and dimensions in common between the components must be identified through the review of the context of each one
- The elements must be grouped into dimensions
- The dimensions of each must be independently named and discussed with the work team
- Finally, it must be reviewed if the completion conditions have been met; if so, the process has ended

Along with the above, it can be said that modern machine learning (ML) methods are designed to work efficiently with various categories of classical computer science data structures, such as grids [50], meshes [51], or graphs [52]. One of the main goals of our new proposed taxonomy is to make it AI-ready [53], thus enabling existing and future ML algorithms to mine and extract information from it effectively.

Based on the guidelines and recommendations of Nickerson et al. [45], Vogelsang et al. [46], and Horst & Prendergast [47] mentioned above, we are working on a matrix taxonomic structure. It is focused mainly on supporting individuals, academies, and companies seeking to profile occupations and directing or providing academic support for developing skills, knowledge, and abilities to people who want to carry out a specific domain. Additionally, seeking to feed taxonomic data dynamically through the use of ML seeks to provide academies and companies with updates or perhaps in some future simulations on the behavior of the labor market of the future, where academies will be able to focus their courses on the development of skills, knowledge, and abilities for the occupations of the future. Companies will be able to seek to stay at the forefront by having collaborators who are updated with the development of their occupational work. In its structure, the taxonomy can be seen as a multidimensional temporal grid, a matrix. Each data point corresponds to a category, and the temporal features show the movement of the class over time. Each element of the array will store all the corresponding collected data. The matrix representation will allow reasoning about current states and predictions at various scales. Generative approaches will require a deep understanding of the internal coding of the data and making it compatible with AI-based techniques [54], [55].

Based on the ideas of the implications as mentioned earlier and utilities of the taxonomy, as well as the concepts of its structuring and the main taxonomies that provide us with public data and a taxonomic structure similar to the desired one (SkillsFuture [32], [33], SOC [48] and NESTA [21]), our taxonomy, as shown in Figure 4, was initially structured under the categorical scale of domains, sub-domains, occupations, and competencies (Knowledge, Skills, Abilities), and this will have its initial data by collecting and analyzing the public data provided by the taxonomies mentioned above, which will allow having a functional matrix taxonomy that covers the required operational needs.

Once all the base data is collected and analyzed to complete the initial data for the taxonomy, various ways of feeding the taxonomy with new data are proposed, giving it the necessary dynamism to seek to stay updated. Initially, we will work with AI methods that collect information through machine learning and natural language processing in selected documents. In addition, one could seek to simulate the current state of each domain, sub-domain, or occupation; the next state can be determined with a certain probability from the previous one. Also, domains, sub-domains, or occupations with similar characteristics could be grouped, and statistical distributions could be generated from their values. The AI model will be able to process and reason about state gradients and will be able to learn and establish present patterns.

Along with this, the option of seeking support from academies and companies could be analyzed to carry out surveys related to the occupations that they develop within them, either educationally or business-wise, to feed the taxonomy data. Finally, it is considered that having diverse data sources that provide the taxonomy will enable generative methods [54] to predict possible future scenarios.

V. Discussion

Based on the literature review findings, we can say that using taxonomies based on the three competencies of knowledge, skills, and abilities is not very common since most of these existing taxonomies mainly focus on one or two. However, in skills, as seen in Fig.1., creating a taxonomy based on the three competencies mentioned above can provide a better profile for the users who will use it. Furthermore, let's consider the domains used in the works found in the literature review.

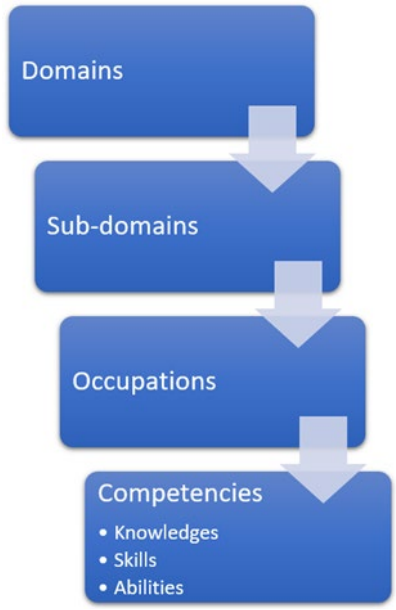

Fig. 4. Proposed structure of KSA matrix taxonomy.

We notice that very few taxonomies are focused on Industry 4.0, as seen in Fig.2. This taxonomy can reference knowledge, skills, and abilities in this domain. In addition, based on the data collection techniques of the taxonomies found in the literature review (Fig. 3.) and the proposal to use artificial intelligence to manage this taxonomy (Section IV), it can be glimpsed that the use of Artificial intelligence techniques such as machine learning is a benchmark for data collection and analysis, as well as the use of clusters to manage said data.

Therefore, to integrate our dynamic skills matrix-based taxonomy, we have already started a first approach to create such a classification based on sectors, subsectors, occupations, and SKA. The taxonomy will have a solid base where the categorical scale of domains, occupations, competencies (knowledge, skills, abilities), and other data are considered necessary. Some dynamic aspects of the taxonomy will be associated with the contents of the different categories according to the evolution of occupations in the labor market, using machine learning techniques. These will allow having a functional dynamic matrix taxonomy that covers the required operational needs. In addition, when using the profiles of individual and business users, the taxonomy can be modified or updated through the use of artificial intelligence techniques, as they could be the use of machine learning and clustering, which would maintain the current taxonomy when applying this type of dynamism, and perhaps at some point even be able to give rise to the simulation of future scenarios of occupational profiles based on knowledge, skills, and abilities. The research has potential impacts in the following fields:

1) Economic, by reducing the mismatch and gap in education systems that are hindering the effective redistribution of latent and underutilized talent at tremendous financial cost;

2) Educational, by allowing the personalized training of students in future skills;

3) Social, by reducing the global risks of unemployment, job insecurity, and economic stability of future workers; and

4) Machine Learning by proposing a novel AI-ready taxonomy.

VI. Conclusion and Future Work

This document proposes a Dynamic Knowledge, Skills and Abilities Matrix (KSA) taxonomy based on Artificial Intelligence techniques and according to the requirements of the Industry 4.0 workforce. First, the concepts of taxonomies definition were studied, and a literature review was carried out. As a result of this process, it was found that characterizing and attending to the gap skill is noteworthy. Secondly, the existing taxonomies frameworks presented in the last ten years were reviewed and analyzed, considering fifteen revised taxonomies, finding out that it is necessary to have a flexible KSA taxonomy. This implies balancing Knowledge, Skills, and Abilities in Machine Learning outcomes. We found that taxonomies are generally clustered in one of these competencies. We consider that this could not work for our taxonomy concerning Industry 4.0. Finally, these taxonomies were compared regarding the status of competencies, their application domains, and the data techniques used. With this background, the proposal of a dynamic taxonomy was made and considered a multidimensional temporal grid, including Artificial Intelligence techniques to improve the possibilities of getting a more suitable profile.

This work shows that now we are concentrating on creating a suitable taxonomy with AI aims. Also, this expands the range of possibilities related to Future Studies. Consequently, our subsequent research intention could be building a simulation of future scenarios of occupational profiles based on KSA.

In future work, Machine Learning algorithms for natural language processing will be developed that allow efficient and effective use in document mining to identify and explain existing and potentially proposed trends and novel strategies. Next, the classification algorithms, Markov chains, and those necessary to update and keep useful the KSA Industry 4.0 dynamic taxonomy will be developed. The results show that this proposal can serve as an international reference guide to designing 2030 educational approaches for active and experiential learning in higher education institutions.

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