Explicating AI literacy of employees at digital workplaces

Dilek Cetindamar* (a), Kirsty Kitto, Mengjia Wu, Yi Zhang, BabakAbedin (b), and Simon Knight

Abstract: This paper aims to understand the definition and dimensions of artificial intelligence (AI) literacy. Digital technologies, including AI, trigger organizational affordances in workplaces, yet few studies have investigated employees' AI literacy. This paper uses a bibliometrics analysis of 270 articles to explore the meaning of AI literacy of employees in the extant literature. Descriptive statistics, keyword co-occurrence analysis, and a hierarchical topic tree are employed to profile the research landscape and identify the core research themes and relevant papers related to AI literacy's definition, dimensions, challenges, and future directions. Findings highlight four sets of capabilities associated with AI literacy, namely technology-related, work-related, human-machine-related, and learning-related capabilities, pointing also to the importance of operationalizing AI literacy for non AI professionals. This result contributes to the literature associated with technology management studies by offering a novel conceptualization of AI literacy and link it to the employee's role in digital workplaces. We conclude by inviting researchers to examine the effect of employee-technology interactions on employees' AI literacy, which might improve the design and use of AI.

Keywords: AI, AI literacy, dynamic capability, employees, digital workplaces, bibliometrics

I. INTRODUCTION

Artificial Intelligence (AI) holds the potential to create radical changes in organizations, industries, societies, and the work life of individuals. While AI technologies offer the potential for significantly higher productivity and job creation, they could also lead to diminishing employment rates and substantial changes in the roles available to humans in the workplace [1]. However, despite the potential significance of AI's impact on employees, relatively little is currently known about what the employees themselves know of AI [2].

Some studies have focused on the role of digital technologies on the content of employment changes such as roles, workplace designs, specific digital skills, and competencies [3]. For example, Van Laar et al. [4] argue that broader skills such as creativity, collaboration, flexibility, self-learning, ethical awareness, and cultural awareness are essential 21st-century skills. Others, such as Kietzmann and Pitt [5], consider managers' readiness for AI in the workplace. However, to date, most research has focused on the *economic* impacts of AI and treated employees abstractly in that context [6, 7].

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Therefore, in our paper, we focus on AI literacy in the workplace. We aim to understand the state of the art in current understandings about AI literacy and how it might be operationalized in the workplace. This understanding could then be used to develop mechanisms that would enable employees to participate as equals in the design and use of AI in their workplaces. The following two research questions (RQ) will guide our approach:

1) How can emergent themes around AI literacy in the extant literature be unified in an overarching definition of AI literacy?
2) What knowledge is available in the extant literature regarding employees' capabilities in AI literacy?

Following the recent literature perceiving literacy as a capability [8, 9], we will develop a model of the competencies needed to utilize AI technologies for achieving company goals. This study adopts the intelligent bibliometrics method that incorporates advanced data analytics with bibliometric indicators [10]. This method has been recently used in broad practical scenarios to profile scientific and technological landscapes and detect emergences [9]. Intelligent bibliometrics is particularly appropriate for analyzing large-scale scientific textual data with complicated semantics and discover latent relationships among semantic structures, such as association, topic hierarchy, and evolutionary pathways [11]. Aiming to capture the emergent themes around AI literacy in the existing literature bases, we will use this innovative approach to develop an analytic framework showing a set of major capabilities needed for AI literacy as a construct. Then, we put forward future research avenues regarding our research questions.

Overall, our paper contributes to the literature by shedding light on what AI literacy for employees means, and by identifying a set of key future research opportunities to advance knowledge in this topic. These results can inform policymakers and strategists making decisions to ensure future education and employment of workers with social justice in mind, meaning participation and engagement in the digital space [12]. Further, managers could decide about investment in their human capital necessary to fit the employee's profile to the future and engage employees with collaboratively creating and deploying those technologies at workplaces [8, 13, 14].

The paper has six sections. After this introduction, section two presents the key concepts and background information on the importance of AI literacy. Section three reviews the data and research methodology, followed by section four, which includes the findings from our bibliometric and content analysis. Findings are grouped under the two research questions given above. Section five offers a new definition for AI literacy and presents key themes for future studies, while the last section includes a conclusion and recommendations for a research agenda.

II. THEORETICAL BACKGROUND/RELEVANT WORK

Kurzweil [15] defines AI as a set of machines performing functions that would require intelligence if people were carrying out those functions. These machines have been gradually diffusing into all sectors of the workforce, with projections that the overall AI industry will reach a trillion-dollar economy by 2030 [16]. Thus, people in the workforce will increasingly come into contact with AI tools. Some of these tools, such as drones, will work under employee guidance, while others, such as automated vehicles operating in workshops or warehouses, will not need any employee interaction [17]. However, the literature offers very few insights about how employees interact with AI tools [18]. For example, AI applications are now able to detect metastatic foci, count tumor cells, and predict gene mutations, however their use in pathology are limited due to difficulty in developing training data and a lack of explainability for application users, namely pathologists [19].

It is crucial that we improve our understanding of employees' knowledge of AI in order to ensure its rapid and equitable uptake. The extant literature acknowledges how wide the effects of AI on employees are [6, 14, 18, 20]. However, few studies work to map out potential changes in the division of labor and the types of tasks performed by employees at various companies as they start to adopt AI-based digital technologies [8, 21]. Several studies tackled expected technology-based changes in workplace practices, sometimes coined as "the future of work" [3, 20, 22]. For example, AI helps to modularize tasks [23]: specifying the details of inputs and outputs of digital tasks, defining modules of tasks, and building their standardized interfaces. As widely experienced in the Gig economy, such as in the cases of Uber (transportation) and Airbnb (hospitality). Indeed, learning algorithms are already automating administrative coordination by managing task decomposition and integration [20, 24].

The trends on modularization and governance of tasks by algorithms are particularly important given issues regarding ethics and governance of AI where employees are often put at a disadvantage [25]. For example, Bailey and Parley [21, p.10] warn that: "... once an intelligent technology is good enough to be put into place in the workplace, the agendas of its makers will have been too cemented into its features that the degrees of freedom we have to alter the technology and or shape the changes it triggers will become more limited." They call for researchers to develop a comprehensive understanding of two distinct phases of technological creation and adoption: design and use. In other words, researchers must find ways of integrating employees as key stakeholders to the digitalization of workplaces. Following this invitation, our paper further argues that when employees are unaware of AI [20, 26], they cannot effectively engage with the it in their workplaces by using it, for example, in three-dimensional printers and robots [18].

Inspired by the idea of integrating employees into the design and use of AI technologies, this paper considers AI literacy as an organizational-level capability where individual capabilities add up to an organizational level strength to perform a set of coordinated tasks and utilize organizational resources to achieve a particular result [27]. Organizational capabilities constitute ordinary and dynamic capabilities. While the former help carry out routine activities, the latter refer to a firm's capacity to "integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" [28]. Even though AI literacy occurs at the individual level, we argue that employees' collective AI literacy builds an organizational capability. AI literacy has a bundle of capabilities, ranging from technical to soft skills, but eventually building an overall organizational capability over a lifetime of employee learning [29].

Long and Magerko [2] define AI literacy as a set of individual competencies that help them communicate and collaborate effectively with AI. However, despite this acknowledgement of the importance of AI literacy, it seems that the education of students and the general public have been prioritized when compared to employees per se. For example, Lee et al. [30] argue that students should be AI literate: “Through their participation in developing the AI technologies of the future, persons from underrepresented groups in STEM and computing and their allies can work together towards ensuring that the AI industries of the future are founded in principles of inclusivity, provide equitable access, include consideration of multiple stakeholders and potential users, and minimize the potential for bias (p. 191).” Furthermore, there is a global talent gap in AI [31] and a well-established problem of employee inequality, with the gender divide a particularly critical one [32, 33, 34]. Moreover, while school and tertiary education play an essential role in educating young people and the public, the implications of AI for the professional needs and learning of current employees are less clear [2]. By understanding the AI literacy required of employees, we may develop approaches to assessing and developing these capabilities across organizations, which would help to extend employees’ foundational knowledge and skills so that they can effectively interact with, and critically evaluate AI.

The umbrella term AI literacy allows us to capture capabilities instrumental in utilizing the opportunities arising from AI within companies. Even though technologies might offer many affordances, their actualization depends on their enactment within an organization [13]. For example, Google’s designers cannot fully anticipate all possible ways in which Google Maps may be used as a component. A hotel might use it as a service to point out location features to its customers or a car company might use it in a self-driving car to support the navigation of its customers [35]. The employees of companies make sense of any digital component and adopt it in a particular context to capture its affordances for the company [18]. This enactment necessitates investing in employees’ AI literacy that will facilitate the variety of dynamic capabilities at workplaces.

We aim to address the knowledge gap in the literature to understand what employees’ AI literacy is. While clarifying the concept, we aim to identify the capabilities that can form the basis of AI literacy. To do so, we conduct a bibliometric analysis and topic modeling with a set of unique approaches, as described in Section three.

III. DATA AND METHODOLOGY

A. Data collection

Scopus is a comprehensive bibliometric database that collects more than 82 million bibliographic items[1]. As one of the most representative bibliometric sources, Scopus shares a large number of common features with other publication databases (e.g., Web of Science and Google Scholar), such as titles, abstracts, and other bibliographical information. However, we selected Scopus as our database for the following reasons: 1) Compared to Web of Science, Scopus collects not only journal articles, but also conference papers. Considering AI literacy is a relatively new topic, with pilot studies starting to appear in certain conferences, the inclusion of conference proceedings is critical to achieve appropriate coverage; 2) Despite its high coverage of bibliometric documents (e.g., articles, patents, and reports), Google Scholar also includes a significant proportion the grey literature, including brand-new concepts and immature studies,

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[1] More detailed information on Scopus can be found on the website:
https://www.elsevier.com/solutions/scopus/why-choose-scopus

making it quite noisy when compared to Web of Science and Scopus; and 3) Scopus itself has been already well recognized by the bibliometric community and has been widely used in a broad range of bibliometric studies [36, 37]. Given this choice of database, we initially built up the following search strategy in Scopus:

TITLE-ABS-KEY (“AI literac*” OR “artificial intelligence literac*”)
Search date: 12/07/2021

The above search strategy yielded 25 papers, which we call Dataset 1 throughout the paper. Note that this is a markedly small quantity, and reflects the embryonic status of AI literacy research. To uncover more of the related relevant literature, while narrowing the scope of this review to work-related AI literacy with specific subject limitations, we performed a second more detailed search:

(TITLE-ABS-KEY (("literac*" OR "capabilit*" OR "competenc*" OR "skill*") AND ("ai” OR "artificial intelligence" OR "Algorithm")) AND TITLE-ABS-KEY (("worker*" OR "employee*" OR "work*" OR "workplace*"))) AND PUBYEAR > 2009 AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "SOCI") or "BUSI")
Search date: 12/07/2021

We limited our research to social sciences and business. This is because the primary focus of the papers in the technology (software engineering and computing science) and education fields has been on building a curriculum for technical professionals around AI knowledge & skills within educational institutions [38]. That is why they have been inadequate to provide insights into AI literacy of non-technical employees operating in company/business context.

The expanded search strategy returned 246 papers, which we call Dataset 2. Only one duplication was found between the two datasets, since both datasets rely on different academic sources. While the Dataset 1 consists of mainly education-focused journals, Dataset 2 encompasses business-focused journals and conferences. These papers form our dataset 2. Hence, we kept both datasets and utilized Dataset 1 (25 papers) to define AI literacy. We analyzed Dataset 2 (246 papers) to identify the dimensions, challenges, and future directions of AI literacy as it might develop in the workplace.

B. Methodology

Figure 1 illustrates our methodology, which largely relied upon bibliometric, content, and topic modeling analyses. A descriptive analysis adds quantitative data to further our conceptual understanding of the research landscape surrounding AI literacy. We use this to identify the publication trend of AI literacy-related papers, top affiliated countries, and their collaborative patterns.

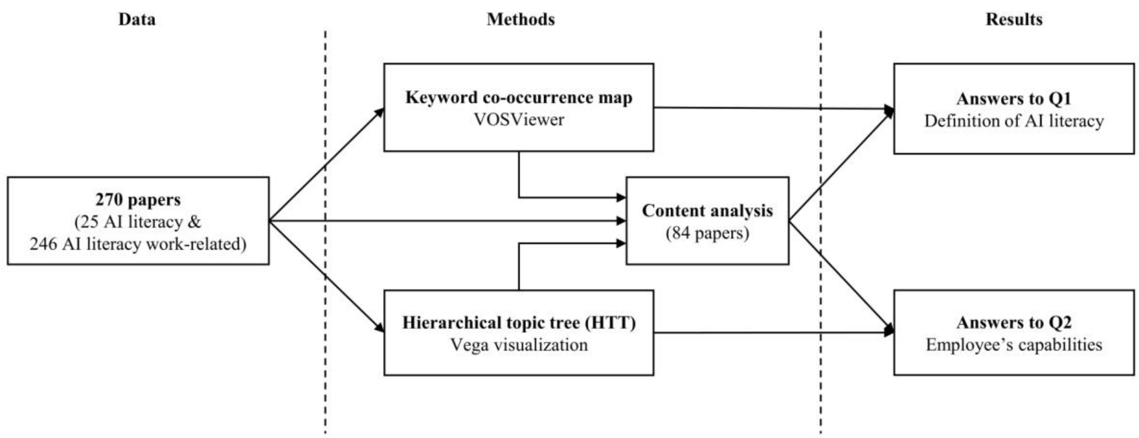


Fig. 1. Research framework

Topic analysis was used to derive the main dimensions of AI literacy. Specifically, a keyword co-occurrence analysis profiled the general topical landscape of AI literacy through core terms retrieved from the titles and abstracts of the collected articles and the co-occurrence relationships among these terms. The hierarchical topic tree (HTT) analysis was then used to further analyze the co-occurrence network, clarify the key topics and their hierarchical relationship.

We applied keyword co-occurrence analysis to the 25 papers collected in Datasets 1 and 2, and HTT analysis to Dataset 2. Keyword co-occurrence assumes that keywords in the same context have close semantic relationships, enabling the discovery of key terms and their composed communities. We used this approach to understand key concepts and terminologies in the definitions of AI literacy made by papers in Dataset 1. The data was then visualized in VOSviewer to detect related communities [39]. While VOSViewer offers a high degree of flexibility to construct networks [40], the co-occurrence network still contains rich information in its topological structure (such as topics consisting of a group of proximate nodes and relationships among these topics). Such information becomes more significant when the data scale increases. Thus, the HTT analysis provides a solution to delve into this topological information and discover meaningful relationships and insights. Dataset 2, with 246 papers covering a relatively broad range of topics in AI literacy, was more difficult to summarize using keyword co-occurrence, which led us to utilize HTT analysis to discover the hierarchical relationships among these topics. This method works to hierarchically profile research topics based on their topological characteristics in a keyword co-occurrence network [9] to identify key terms and discover complicated relationships. It does this by mapping high-density peak nodes in a network to root nodes, while nodes with lower densities are assigned to their closest root or leaf. We employed VEGA grammar toolkits[2] to visualize the results of HTT.

Finally, a content analysis was applied to the most relevant 84 papers identified from our bibliometric and HTT analyses. We chose to focus on papers providing insights into AI literacy of non-technical employees operating in company/business context (listed in the references with an asterisk). After these papers were read in-depth by two authors/experts in the field to guarantee the most semantically meaningful topics are captured in the analysis. Then, all authors

[2] https://vega.github.io/

worked to discuss and categorize the definition, research dimension, challenges, and future directions of AI literacy in a hybrid manner by combining the bibliometric results (quantitative) with the domain knowledge gained from this close reading (qualitative).

C. Data preprocessing

Since the bibliometric analysis, particularly the HTT analysis, requires an input of free terms extracted from combined titles and abstracts of papers, we utilized the natural language processing (NLP) module in VantagePoint to extract 8,393 raw terms from the collected dataset and then conducted a term clumping process [41] to identify 4,669 terms for topic analysis. The stepwise results for the term clumping process are given in Table I.

Table I. Stepwise results for term clumping

Step	Description	# Terms
1	Raw terms retrieved with NLP	8,393
2	Consolidated terms with the same stem, e.g., “digital capability” and “digital capabilities”	7,904
3	Removed spelling variations, removed terms starting/ending with non-alphabetic characters, e.g., “Step 1” or “1.5 m/s”, removed meaningless terms, e.g., pronouns, prepositions, and conjunctions	5,717
4	Removed general single-word terms, e.g., “information” *	5,423
5	Consolidated synonyms based on expert knowledge, e.g., “blockchain” and “blockchain technology”	4,669

Note: Given that most single-word terms take on additional context when used in multi-word phrases, e.g., “information” vs. “information systems”, we opted to remove generic single-word terms. Further, some multi-word terms were consolidated into a single-word form in Step 2 (e.g., “classification method” became “classification”). Non-general single-word terms were retained.

IV. FINDINGS

This section explores our findings from this review, organized into two subsections that each respond to the two research questions listed in section I.

A. The definition of AI literacy and core research themes in the extant literature

Searching on the exact terms of “AI literacy” resulted in a broad definition of education literature related to human-machine interactions [30, 42]. Most of this literature revolves around students [30, 38, 43, 44]. However, two significant studies focus on AI literacy in a manner relevant to organizations. The first is Long and Magerko [2], which focuses on individuals and uses AI literacy, referring to a set of competencies needed to evaluate, communicate, and collaborate with AI. In short, this approach aims to understand what competencies/capabilities are needed for individuals at home and work while interacting with AI technologies. In contrast, the second study, by Mikalef and Gupta [45], treats AI capability as a firm-level construct.

The studies with clear definitions of AI literacy are given in Table II.

Table II. AI literacy definitions

Source	Level	Context	Definition
Long and Magerko (2020)	All	Work.	AI literacy is "a set of competencies that enables individuals to evaluate AI technologies critically; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace (p.2)."
Mikalef and Gupta (2021)	Org.	Work.	AI capability is "the ability of a firm to select, orchestrate, and leverage its AI-specific resources (p.2)."
Hermann (2021)	Ind.	Students	"AI literacy is individuals' basic understanding of (a) how and which data are gathered; (b) the way data are combined or compared to draw inferences, create, and disseminate content; c) the own capacity to decide, act, and object;(d) AI's susceptibility to biases and selectivity; and (e) AI's potential impact in the aggregate (p.13)."
Kandlhofer & Steinbauer (2018)	Ind.	Students	AI literacy is sound knowledge about the principles of AI and its application.
Dai et al. (2020); Lee et al. (2021)	Ind.	Students	AI literacy is a student's ability to access and use AI-related knowledge and skills.

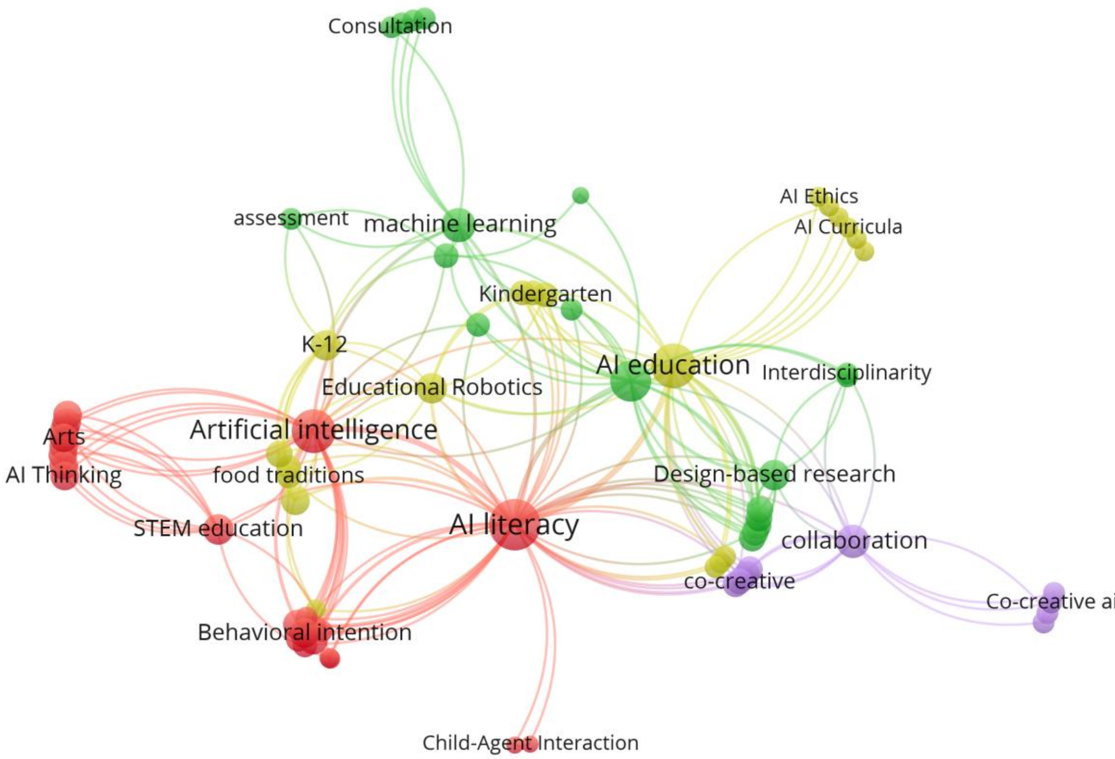
Org.-organization, Ind.-individual, Work.-workplace

Regarding the core research terms in the literature, we generated keyword co-occurrence maps and hierarchical topic trees. The co-occurrence maps of 72 keywords from the core 25 papers and 342 terms (with term frequency above 1) from 246 papers are respectively given in Figures 3a and 3b. Due to the sparsity of research terms/keywords, we set the attraction and repulsion parameters[3] in both figures to 9 and 1 to present compact visualizations. The minimum clustering sizes were set to 10 and 50 to avoid generating trivial clusters. Different colors in each map represent theme clusters identified by VOSViewer.

In Figure 3a, we can observe that the 25 core papers dispersed their attention on four significant aspects: behavior intention (red in Fig. 3a), specific AI techniques (machine learning and deep learning, green in Fig. 3a), AI education (yellow in Fig. 3a), and human-machine interactions (purple in Fig. 3a). In contrast, Figure 3b of 246 papers presents a broader research landscape of AI literacy in work-related backgrounds. AI education (yellow in Fig. 3b) is still one of the major clusters, but its emphasis has changed from K12 education to work-related skills and competencies compared to the core 25 papers. Additionally, three new cluster have emerged: data analytics (blue in Fig. 3b); digital transformation (red in Fig. 3b); and the social impacts of AI (green in Fig. 3b). The clustering patterns in Fig. 3b indicate that: 1) data analytics is a key set of techniques in working-related situations, and 2) the social impacts and significance of acquiring AI-related techniques attract substantial research attention.

Overall, the differences of Figures 3a and 3b reflect that the 25 core papers tended to focus on the definition of AI itself and how people in the general public might work to improve their understanding of this topic. In contrast, the 246 papers extended the boundaries of the discussion to the social significance and industry impacts of mastering AI skills. Hence, we argue that there is a clear gap in defining AI literacy that could apply to the context of a digital workplace. If we drop general topics such as AI education and the social impacts of AI, we see that the literature on AI literacy tends to define this construct with a set of capabilities. We chose a subsequent analysis, based upon HTT to further explore these capabilities in an attempt to understand what they are.

[3] The parameters are used to control map layout in VOSViewer (Waltman and Van, 2013).



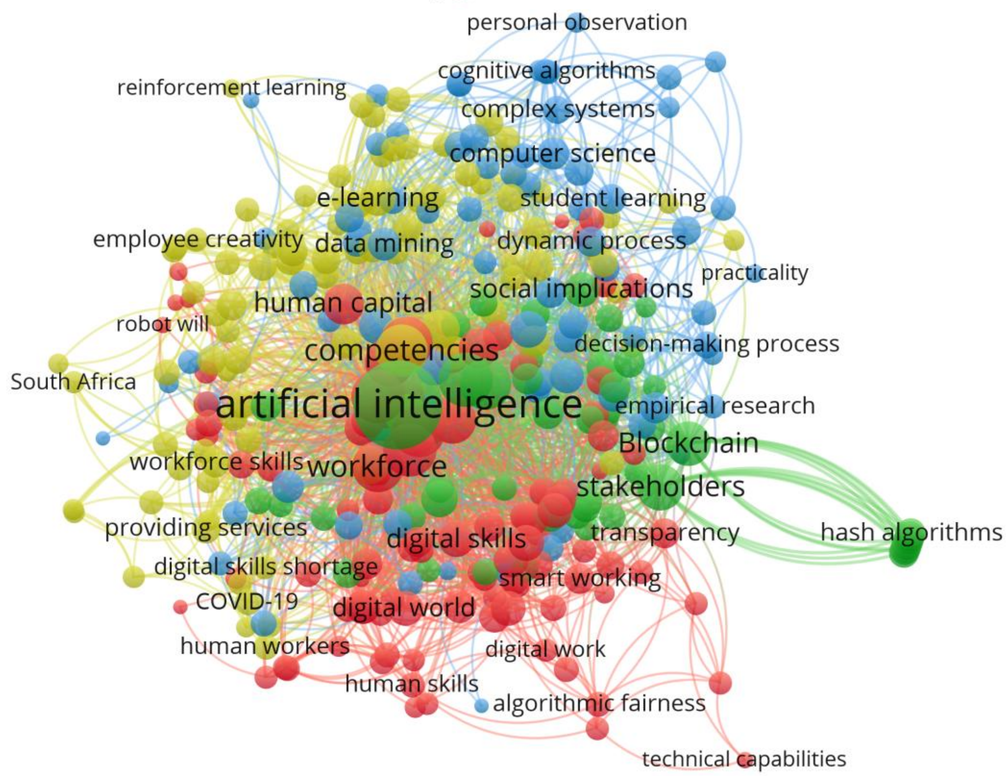


Figure 3. The keyword co-occurrence map of 25 core papers (a) and 246 papers (b)

B. The knowledge in the extant literature regarding employees' capabilities

Feeding the extracted terms from preprocessing step to the HTT algorithm, we generated the HTT result in Figure 4. Stretching from left to right, it profiles a hierarchical structure of the distribution of topics as they occur in the AI literacy research field. The number at the end of each edge indicates the two related terms' co-occurring frequency (i.e., the number of papers). We utilized this result to identify the relationships between research themes and narrow down our content analysis of AI literacy capabilities.

As the root node of the tree, "competencies" indicates that most papers in our collection aim to investigate the specific competencies related to AI literacy and their relevant impacting factors. Another characteristic we can observe from the tree is that its major branch (with a broad line going through the whole tree) consists of terms either describing digital phenomena or specific influential technologies (such as "industry 4.0", "digitalization", "digital transformation" and "big data"). Such terms suggest that the AI technology revolution has provided the primary background and the driving power of AI literacy studies.

We focused on branches that discussed specific capabilities required in the workplace, examining the papers in the branches marked red in Figure 4 with particular care. This included: (1) the root node term "competencies," which covers a broad range of papers discussing multiple competencies functioning in AI literacy increasing [23, 46, 47, 48]; (2) "skills gap" and "required skills" branches under the node of "workforce," papers in these branches typically examine skills requirements in this digital era and existing skill gaps in the current labor market from the individual level [49, 50]; (3) "digital skills," "digital literacy" and "digital education" branches under the node of "digitalization," papers in this set discuss the practice of digital literacy and how it influences working performance and how to improve it through education [26, 51]; and, (4) "digital capabilities" and "digital competencies" nodes branch under the node of "digital technologies." Papers containing those terms concentrate more on digital abilities/competencies to promote digital transformation from the organizational level [31]. (5) "skill sets" branch under the node of "machine learning." These papers uncover the influence of specific AI technologies on the skill sets of conventional sectors [52].

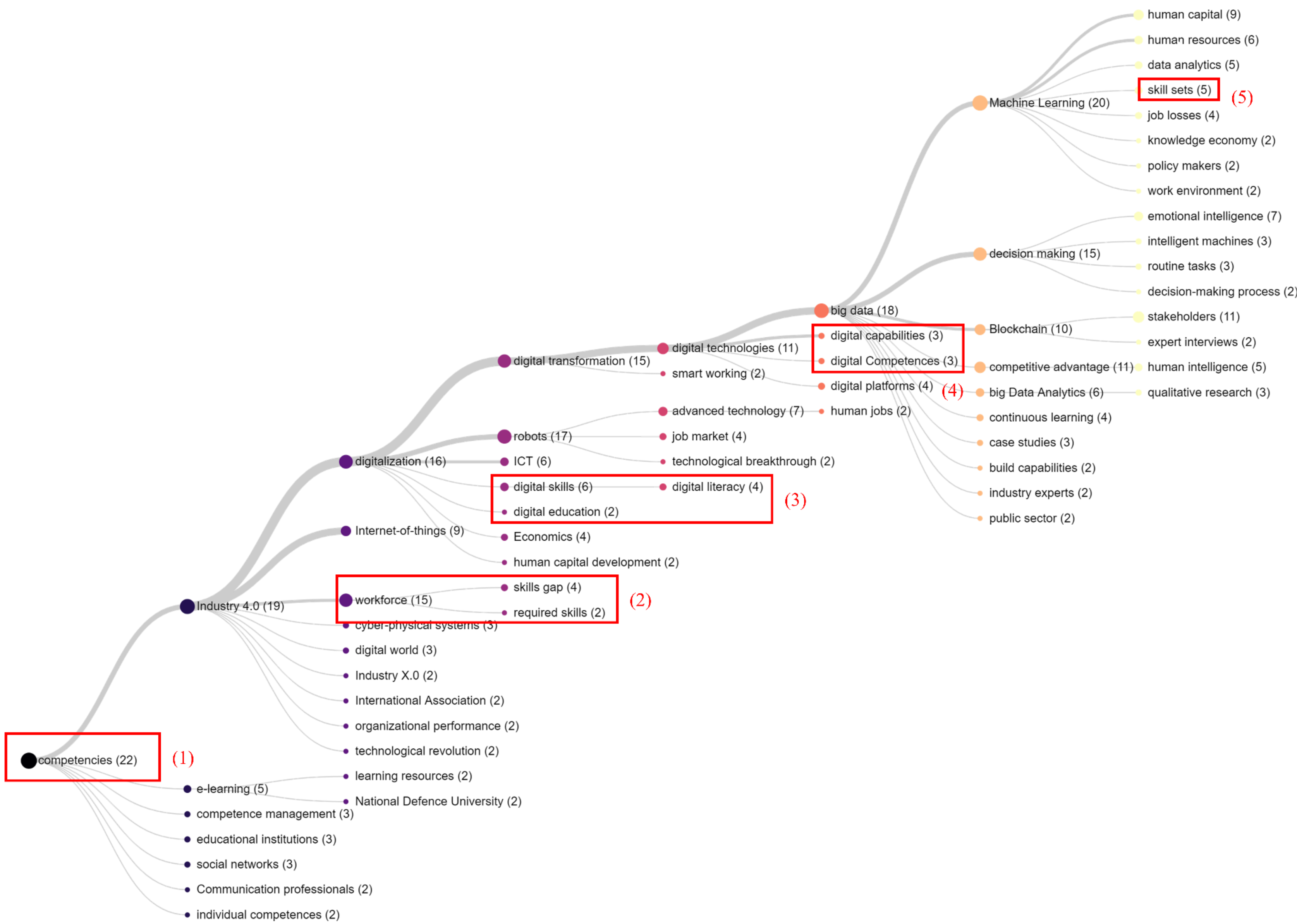


Fig. 4. Hierarchical topic tree

V. DISCUSSION

We iterated several times between theory and the topics resulting from the HTT analysis in order to create new theoretical artifacts, and to build theory with them [53, 54]. Focusing on the differentiation of topics judged by authors as an interdisciplinary team led to a multidimensional construct of AI literacy for employees. In this section, we first introduce our framework, then we propose key themes for future studies.

A. A framework in defining the AI literacy for employees

Figure 4 helped to provide a framework for integrating the dispersed literature that attempts to describe the capabilities needed for AI literacy. Following the HTT analysis, we undertook a detailed content analysis of papers that explicitly mention competencies, capabilities, and skills. This leads us to suggest a new refined definition for the AI literacy of employees (which is depicted in Figure 5). AI literacy is a bundle of four core capabilities as shown in Fig.5: (1) technology-related (generated from HTT 4), (2) work-related (generated from HTT 2), (3) human-machine-related capabilities (generated from HTT 5), and (4) learning-related capabilities (generated from HTT 1 and 3). The names of the first three categories are inspired by the study of Fréour et al. [17], while the last one emerges from our analysis. We now discuss these capabilities in more detail.

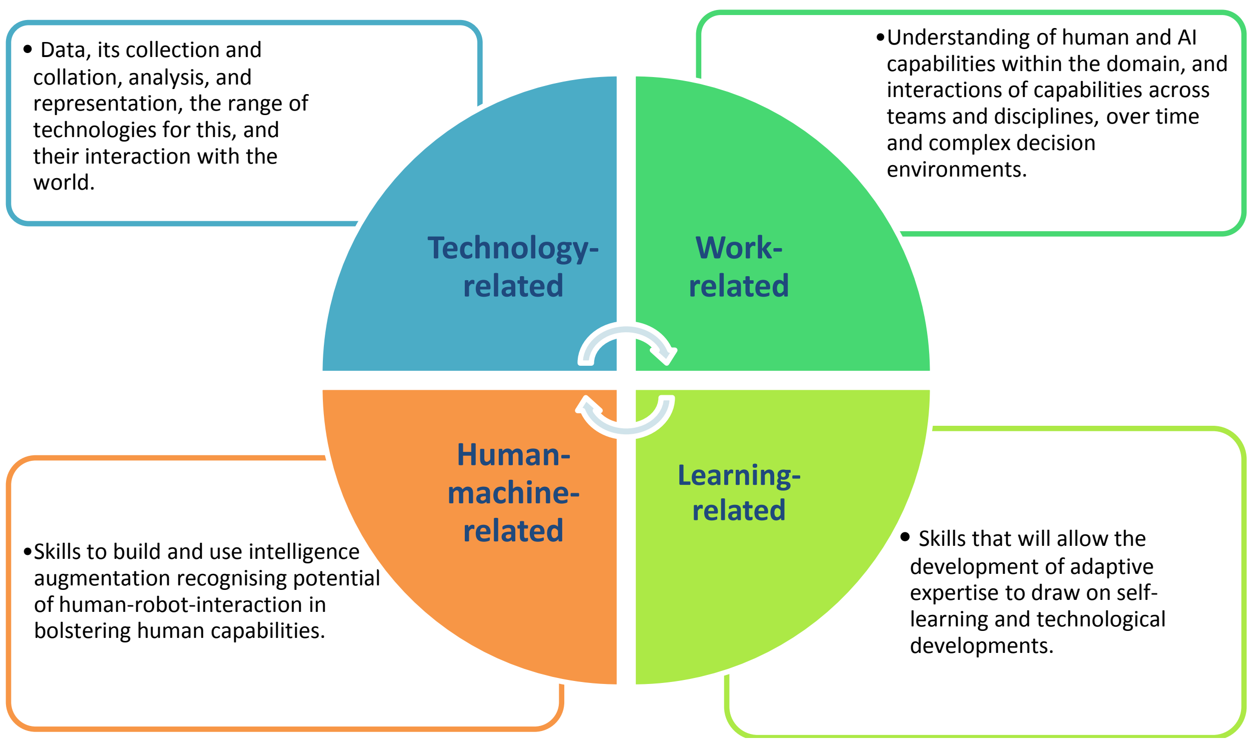


Fig. 5. Capabilities for AI literacy

(1) Technology-related capabilities

Considering that AI literacy is based on technology, it is no surprise to expect that technological capabilities might be one of the critical dimensions of AI literacy.

Mikalef and Gupta [45] are very specific in describing these technological capabilities. They concentrate on three significant capabilities for companies: data, technology, and technical skills. Data, particularly the availability of high-quality data, is a critically necessary input for AI. Once these large, unstructured, fast-moving, and complex data sources are created, companies are expected to build AI applications, a technological infrastructure. An interesting example of a famous designer illustrates how technological capabilities could change engineering and arts. As described in a study [45], Philippe Starck, designer, who introduced a new series of chairs in 2020 by using specific AI specialized software provided by Autodesk that integrated Fusion 360 software package in analyzing large datasets of chairs [45]. Finally, technological capability encompasses the technical skills of employees. While Mikalef and Gupta [45] argue that most employees will need to have a strong background in statistics, probability, predictions, calculus, algebra, Bayesian algorithms, logic, programming, data structures, language processing, and cognitive learning theory, we are not as convinced that these skills will be required across the entire workforce. More investigation is required in this space to determine the distribution of skills needed across different domains and work functions.

Another seminal work is due to Long and Magerko [2], who divide each competency into three key AI technologies: cognitive systems, robotics, and machine learning. They propose two competencies for machine learning. One of them is titled Action and Reaction competency and defined as "Understand that some AI systems can act on the world physically. This action can be directed by higher-level reasoning (e.g., walking along a planned path) or it can be reactive (e.g., jumping back to avoid a sensed obstacle)" [2, p.6]. The second one is called Sensors competency, meaning "Understand what sensors are, recognize that computers perceive the world using sensors, and identify sensors on various devices. Recognize that different sensors support different types of representation and reasoning about the world" [2, p.6].

A wide spectrum of work points out the role of digital skills/digital literacy/digital fluency [51]. For example, some studies (e.g., Johnson et al. [50] mention skills of using Microsoft Excel, SAS, Apache Hive, R, Scala, others highlight highly generic sets of skills such digital skills [24] or Internet security skills [55]. Johnson et al. [50] talk about the skills for necessity of conducting E-business, including dealing with websites, social media, reviews, data collection, data analytics, and data management (including protection, ethics, and cybersecurity). They highlight an emerging skills gap in professions such as tourism which are starting to use AI, virtual reality, and augmented reality-driven technologies to develop unique, customized, and personalized experiences for their customers. A similar approach for health care professionals suggests that they would need data governance principles, basic statistics, data visualization, and the impact on clinical processes as basic AI literacy skills [56].

Kipper at al. [57] carried out a bibliometrics study to list 37 knowledge and skills required for Industry 4.0 technologies. They defined knowledge categories that include industrial automation and IT, whereas skills are defined broadly as, e.g. adaptability/flexibility, data analysis, and continuous learning. Such broad categories might give a general idea of what it takes people to get employed in industries using these technologies. However, they are difficult to apply into a clear training and reskilling program.

(2)Work-related capabilities

We define work-related AI literacy capabilities as those which support either the general use of AI in the workplace or the complementary skills needed to have effective AI deployment. Many studies provide insights into the details of these kind of generic capabilities [2, 23, 45, 60]. For example, Long and Magerko [2] suggested a diverse set of competencies including ethics that supports the use of AI. Based on a literature review, Long and Magerko [2, p.7] defines it as "Identify and describe different perspectives on the key ethical issues surrounding AI (i.e. privacy, employment, misinformation, the singularity, ethical decision making, diversity, bias, transparency, accountability)." Even though ethics is a general capability for all decisions at daily routines of companies, problems arising from the algorithms such as biases bring it forward for the AI implementations.

Another stream of studies underline the importance of complementary skills that could improve the efficient use of AI [23, 60, 61, 63]. Some of them emphasize critical thinking, problem-solving, communication, and teamwork as vital for AI [23, 58]. This is because these skills play the supporting role in the complex cognitive and decision-making tasks in a company context [58]. Other studies [8, 59] add emotional intelligence, judgment, service orientation, negotiating, cognitive flexibility, and other digital skill sets as capabilities helping employees to handle AI. A few studies highlight the importance of sense-making capacity [60, 61, 63]. How and Hung [38] introduce a need for an AI-thinking skill, claiming that it could enable employees to ask better questions to solve problems.

(3) Human-machine-related capabilities

When employees cooperate with colleagues to contribute knowledge to the firm, they increase process improvements or induce several novel products or services [13]. Similar positive impacts are observed in deploying AI such as chatbots in human services where humans increasingly work with them as co-workers in their daily routines [46, 48]. Hence it is no surprise that there is a great deal of interest in understanding likely future collaborations between humans and AI [64]. Some studies are motivated by finding ways to enhance collaboration capabilities [61], while others focus on protecting and highlighting unique human capabilities such as adaptive expertise [65] or complex problem-solving [4].

Some studies emphasize the need for individual and collaborative cognitive skills due to the inevitability of human-robot interactions at workplaces [66]. These skills include geometric reasoning and situation assessment based on perspective-taking and affordance analysis; acquisition and representation of knowledge models for multiple agents (humans and robots, with their specificities); situated, natural and multi-modal dialogue; human-aware task planning; and human-machine joint task achievement.

Another theme is the emphasis on increasing the explainability of AI, a critical improvement for building genuine human-machine practice [67, 68]. As an increasing research focus on explainable AI seeks to clarify how machines make decisions [69], we see a body of work that points out the need for the receivers of AI insights (i.e. employees) to be able to interpret and examine the associated explanations that the system supplies, such that they can design AI-based interventions accordingly [61]. Similarly, there is a need to educate employees as a key stakeholders of algorithmic systems in algorithmic fairness, accountability, transparency, and ethics [34]. Verganti [35, p. 225] points out that “an algorithm that has been created to solve a problem cannot refuse to solve it; it cannot pull the plug (unless this trigger is already incorporated in its code). A human can. She can avoid to create, if it does not make sense, morally, emotionally, or by intrinsic motivation." Hence, the role of human capabilities become critical in facilitating human-machine interactions.

(4) Learning-related capabilities
A handful of other studies focus on learning. For example, studies by Poquet and de Laat [28] and Jaiswall et al. [24] draw attention to the need for continuous lifelong learning, as people are exposed to information, interact, learn and make decisions in a rapidly changing environment. Similarly, Kateryna et al. [63] point out possession of skills related to cognitive processes contributing to the lifelong learning of employees, including a self-learning ability that helps employees dealing with the volatility and uncertainty of the future in digital age. Interestingly, this learning aspect appears in some studies that focus on determining skills needed in specific industries. For example, Carlisle et al. [42] discusses the future digital skills for all tourism subsectors, one of which is self-learning capacities. They argue that permanent education, adaptability, agility, and flexibility are necessary to cope with ongoing digital innovations and disruptive business models in tourism such as the one adopted by Airbnb, accommodation services company holding no assets. In similar fashion, Moll and Yigitbasioglu [70] highlight how AI applications demand from accountants cultivating their skills (such as data analytics, data visualisation, storytelling and strategic management) rather than traditional ones (such as auditing). Hence, extant studies seem to underline the role of building self-learning skills for a lifetime.

Many studies fall into vaguely defined soft skills that might enhance learning [50, 57]. For example, Su et al. [71] point to the need for managerial skills made up of critical and system thinking skills, considering them as inimitable to AI. Another study [58] underlines problem-solving as the primary soft skill for AI. Santos et al. [51] consider skills associated with social, emotion and cognition as an important input in using the digital technologies responsibly for communicating, socializing and learning.

In a few studies [56, 72], researchers suggest some AI tools to help developing employee skills. For example, Shanmugalingam et al. [73] suggest that Gamification and Predictive Analytics increase employees' skill development, while Wan et al. [72] proposes a simulation software to build AI skills.

B. Suggestions for future studies

Most studies on AI literacy have only been completed in the past two years (2019-2021), meaning that this is an exciting new field of research. In this final section we identify four major themes that could guide future studies on the topic of AI literacy.

(1) Content of AI literacy
AI literacy has the potential to be considered as a critical factor for the survival of companies in the rapidly transforming digital age. Thus, future research should work on clarifying the capabilities associated with AI literacy across all affected professions. To date, the main body of work revolves around only a few specific occupations, industries, individual AI technologies,

and countries. The most immediate occupations under threat by encroaching AI solutions need far more investigation, including accounting [70], the legal profession [74], human resources [46, 47, 75], marketing [55], and pathologists [19]. But many sectors will be affected, and it is crucial that we understand both the similarities and the divergences in the AI literacy required across all of them. In-depth analysis of whole sectors is rare, with one exception being tourism [76]. Similarly, the impact of specific AI technologies like intelligent employee assistants [77] are rarely explored. Few studies have attempted to explore the widespread impact of AI on particular countries, with notable exceptions in the Nordic countries [78, 79], and some developing countries, although these are limited to India or China [80, 81, 82, 83]. A final remark regarding the content of AI literacy is the lack of empirical work on capturing diverse perceptions and views of experts, managers, professionals, and non-technical employees. These empirical studies should adopt diverse methodologies such as Delphi method and surveys to enrich our understanding of AI literacy.

(2) Assessment of AI literacy

Most studies are related to curriculum topics. For example, Lee et al. [30] offer a 30-hour "Developing AI Literacy" curriculum grounded in child development, ethics education, and career development. Some studies offer a list of AI literacy competencies but do not give any actual assessment metric [2]. Nevertheless, to our best knowledge, studies attempting to measure the actual AI literacy of students are rare [30], and we have found no studies attempting to measure it in the workplace. Dai et al. [42] offer an AI literacy construct to measure students' basic understanding of AI knowledge and skills, according to the schools' AI curriculum content. However, while claiming to have measured five skills the paper itself only mentions one: the skill of using AI-assisted image search tools. A European Union research theme provides another example of an embryonic AI literacy assessment as part of developing an AI literacy framework for all citizens [84]. Coined "the driving license for AI," this is a professional, internationally accepted, standardized training and certification system for AI.

Few studies offer what individual capabilities in the field of AI might be assessed. For example, Wengjiu et al. [85] analyzed 9,454 patents to classify AI capabilities into groups such as data collection and transmission capability to leverage technologies that collect data from the physical world or transfer data within and between product modules. This scarcity indicates the gap in the literature about findings reliable and solid constructs, indexes, and so on that might help quantify AI literacy. Some of the recent studies in assessing digital literacy [12, 13] might provide a viable way in which to approach this issue.

(3) AI literacy's role in the future of work

The education literature is often most interested in the content and delivery of curriculum around AI knowledge and skills [2]. It could be good to pursue this line of thinking in workplaces to find out the critical factors facilitating the behavior of employees in adopting and implementing AI. As Fréour et al. [17] show, digital technologies such as AI disrupt employees' work by changing the work characteristics.

During our literature review, we observe emergence of a future theme around the existential or philosophical issues in the future of work. We specifically identified some provocative core questions raised in the articles we reviewed. For example, Santos et al. [86] ask, "Should humans work?” Similarly, Nica et al. [87] prompt the question of “A laborless society?” These studies provoke the obscurity of our relationship with technology. Sutton et al. [88] raise the question of “How much automation is too much?” The study draws attention to the deskilling effect of knowledge-based systems. Third, Grønsund and Aanestad [64] bring forward another dimension with their question, “How do configurations of humans and algorithms evolve as firms adopt AI capability.” Based on these intriguing questions, we would like to suggest that a fruitful line of research would seek to understand the shift from automating “workforce” to automating “brain force” with machines [22]. This would require a line of research that seeks to understand employees’ needs and desires, and how these could support them in dealing with technological challenges in the workplace [18]. In a similar vein, Richardson and Bissell [89] remind us that digital skills must be understood as processes that happen across bodies, objects, and environments because of their extensive dispersal beyond contained workplaces, and so points to the need for more in-depth studies to grasp how these changes to any of these aspects of the workplace will influence employees.

A final avenue for future research might be to consider bridging AI literacy with studies on future of work [60, 90, 91]. Studies about student AI literacy openly argue “what type of future society we are preparing the students for and what type of future citizens we want the students to grow into” [42, p.3]. Hence, AI literacy studies might empower employees by including them in envisioning a future with top management to avoid many negative impacts of AI on employees, such as burnout and discrimination [92, 93]. As Miller [91] argues that when people are more skilled at designing the systems and processes used to imagine tomorrow, they (both women and men) become more empowered with the capacity to be free. We believe that AI literacy could contribute to more inclusive and sustainable development by enhancing the affordances of AI technologies for the social good. This is in line with the calls aiming at gender equality and the inclusion of voices from all stakeholders in society [34].

(4) Policy issues around AI literacy

Ernst et al. [6] warn how companies are left disadvantaged in markets due to the concentration of profit and wealth among a few large technology companies. The study points to the risks companies face to open markets, innovation diffusion, enforcement of labor regulation, and the country’s capacity to collect taxes; thus, it calls upon governments to build social protection and taxation policies to tackle inequality and job polarization [6]. A similar policy request invites governments to prevent the damages of the AI divide on gender, inviting them to implement international governance guidelines and frameworks [34].

Studies on inequality call for policy intervention as well [34, 78]. Dai et al. [42] show that female students perceive themselves as less prepared or even not ready for an AI-infused future when compared to male students. Therefore, the study reminds governments to forge a positive culture and send encouraging messages to female students to address gender equity issues in AI education [42]. Another study emphasizes the role of involving diverse stakeholders in policy-making about AI and increasing opportunities to educate citizens by creating public spaces [2]. A broadened perspective of educating citizens could overcome inequalities regarding opportunities to learn about AI by offering them access to technical knowledge.

In addition, Robinson [79] provides a compellingly good example of AI policies designed at the national level in Nordic countries supporting employee development. The study lists how these nations support the development of AI technology in society by providing policies that rest on their cultural values, including trust through clear information and information security and transparency through AI literacy education. In a similar vein, Hines [90] advocates for a serious policy discussion on the post-work future, encompassing the development of programs to manage the transition and personal futures planning. Thus, policy discussions introduce a wide range of issues that could become critical in deciding the design and use of AI technologies across countries. Future research could tap into this line of inquiry.

VI. CONCLUSIONS

This paper aims to develop a conceptual understanding of the AI literacy of employees that could be instrumental in exploring the preparedness amongst employees for the impact of AI on organizations, workplaces, jobs, roles, and competencies. Due to the phenomenon's complexity, there is a need for shared research agenda to cohere research in the direction of AI literacy to support employees in the design and use of AI in the workplace.

This study presents an overview of the extant literature in two dimensions: the definition of AI literacy and its capabilities. Regarding the definition of AI literacy, most of the reviewed studies are inspired by curriculum development and aim to cover know-how on a wide range of topics. This study considers the AI literacy of employees an organizational capability that is shaped within the digital workplace. Regarding the capabilities of AI literacy, the literature is quite patchy and far from any systematic analysis, i.e. it lacks a theoretical approach. We classified the capabilities under four categories: technology-related, work-related, human-machine-related, and learning-related.

Our study offers a framework to define the employees' AI literacy as a collection of technology, work, human-machine, and learning capabilities. These capabilities could allow employees to actively join in on designing and utilizing AI at their workplaces.

Implications for theory

A methodological review of existing literature offers many advantages for scholars in the field [53]. Our study focused on delivering two benefits: investigating the current the state-of-the-art knowledge on the topic of AI literacy, and inspiring future research through the identification of gaps and promising new topics to pursue. In other words, our first contribution to AI literacy is highlighting its importance from the lens of employees. That clarification of the gap helped us offer four significant avenues for future research on AI literacy: its content, its assessment, its role in the future of work, and policy issues. By doing so, our work expands the discussions on work, organization, and technology studies to rethink AI literacy as a collection of capabilities. Further, our study underlines the role of employee involvement and engagement in utilizing AI in workplace. Although the research is exploratory, it brings forward an agenda to advance our understanding of the role of employees in the development and implementation of AI to ensure inclusivity and equity at work.

Implications for practice

In terms of practice, our work invites several stakeholders, mainly employees, managers, and policymakers, to tackle the impact of AI on the workplace deliberately, rather than through ad hoc and case by case responses. Employees need to become informed stakeholders about the future of work, and provided with opportunities to develop their foundational knowledge and skills. Only then could they engage with future endeavors of AI design and use it as AI-empowered workers. This process will only start if employees who are interested in AI become engaged and learn AI. In doing so, employees might start being an active part of their future selves as AI-enabled workers who could build an inclusive workplace.

Managers might be aware that workplaces should embrace human-machine integration to empower employees and support human development. This practical implication is the right thing to do, but also it is in line with the recent studies on advocating human-machine interactions in favor of humans [93]. Poquet and de Laat [29] call for managers to shift their mindset from managing human capital to human development. Managers should consider ramping up their work-integrated learning activities to support the learning needed for employees. Some studies are already focusing on finding out learning needs for employees in general [21] or specifically for industry 4.0 applications [94, 95].

Limitations

This paper has three limitations arising from its descriptive nature, each of which is an opportunity for future research. First, we have presented an overview of the literature focusing on the concept of AI literacy. There is a need for empirical work to develop in-depth knowledge about AI literacy, its assessment, and the benefits it brings to those who possess it in the workplace. Second, the study limits its focus to AI literacy at organizations to highlight the critical need for engaging employees in the design and use of AI. Other studies have already worked to understand other forms of employee literacy, mainly digital literacy [63], and their methods could perhaps be adapted to AI literacy in future work. Three, in our literature review, we identified many papers looking at AI from an economic perspective. However, this paper did not compare how different sub-groups of papers talk about employees. It would be useful to compare these economically driven points of view with those targeted at “curricula” (or arising from a more formal educational context).

The limited knowledge of AI literacy and its capabilities/competencies [2] indicate a gap. Our findings support the recent finding of Wu et al. [85] about the difficulties associated with defining capabilities. Hence, this paper makes a humble contribution to these efforts to understand AI literacy as a bundle of capabilities, deferring these significant challenges for future studies

REFERENCES

* shows the references resulted from the bibliometrics study.

[1] Acemoglu, D. and Restrepo, P., *Robots and Jobs*, NBER working paper 23285: Boston, MA, 2017.

[2] *Long, D. and Magerko, B., “What is AI Literacy? Competencies and design Considerations,” *Proc. of the 2020 CHI Conf. on Human Factors in Computing Systems*, pp. 1–16, 2020. DOI:10.1145/3313831.3376727

[3] Dery, C., Sebastian, I. M., and van der Meulen, N., “The digital workplace is key to digital innovation,” *MIS Quarterly Executive*, Vol. 16, pp. 135-151, 2017.

[4] Van Laar, E., Van Deursen, A.J., Van Dijk, J.A.A., and De Haan, J., “The relation between 21st-century skills and digital skills: A systematic literature review,” *Computers in Human Behavior*, Vol. 72, pp. 577–588, 2017.

[5] Kietzmann, J. and Pitt, L. F., “Artificial intelligence and machine learning: What managers need to know,” *Bus. Horizons,* Vol. 63 No. 2, pp. 131-133, 2020.

[6] * Ernst, E., Merola, R. and Samaan, D., “Economics of Artificial Intelligence: Implications for the future of work,” *IZA J. of Labor Policy,* Vol. 9 No. 4, pp. 1-35, 2019.

[7] * Fossen, F.M. and Sorgner, A., “Digitalization of work and entry into entrepreneurship,” *J. of Bus. Research,* Vol. 125, pp. 548-563, 2021. DOI: 10.1016/j.jbusres.2019.09.019

[8] Cetindamar, D. and Babak, A., “Understanding the role of employees in digital transformation,” *J. of Enterprise Inf. Man,* 2020. DOI:10.1108/JEIM-01-2020-0010

[9] Wu, M. and Zhang, Y., “Hierarchical topic tree: A hybrid model incorporating network analysis and density peaks searching,” *In the 18th Int. Conf. on Scientometrics and Informetrics*, 2021.

[10] Zhang, Y., Porter, A.L., Cunningham, S., Chiavetta, D. and Newman, N., “Parallel or intersecting lines? Intelligent bibliometrics for investigating the involvement of data science in policy analysis,” *IEEE Transactions on Eng. Man.*. DOI:10.1109/tem.2020.2974761, 2020

[11] Zhang, Y., “Intelligent bibliometrics for technological forecasting,” Forecasting the future for Sustainable development, *CEST Workshops*, 2021.

[12] Raffaghelli, E. J., “Is data literacy a catalyst of social justice? a response from nine data literacy initiatives in higher education,” *Edu. Sciences*, Vol. 10 No. 9, 2020. DOI: 10.3390/educsci10090233

[13] Cetindamar, D., Abedin, B., and Shirahada, K., “The role of employees in digital transformation,” *IEEE Transactions on Eng. Man.,* 2021. DOI: 10.1109/TEM.2021.3087724, 2021.

[14] Parker, S. K. and Grote, G. “Automation, algorithms, and beyond,” *Applied Psychology*, 2020. https://doi.org/10.1111/apps.12241

[15] Kurzweil, R., *The Age of Intelligent Machines*. MIT Press: Boston, MA, 1990.

[16] WEF *The Future of Jobs Report 2018*. World Economic Forum: Geneva, 2018.

[17] * Fréour, L., Pohl, S., and Battistelli, A., "How digital technologies modify the work characteristics," *Spanish J. of Psychology*, 2021. DOI: 10.1017/SJP.2021.12

[18] Murray, A., Rhymer, J., and Sirmon, D., "Humans and technology: Forms of conjoined agency in organizations," *Acad. of Manag. Rev.*, Vol. 46 No. 3, pp. 552–571, 2021.

[19] * Uegami, W., Sakamoto, T., Kuroda, K., and Fukuoka, J., "Update concerning digital pathology and artificial intelligence application," *Japanese J. of Lung Cancer*, Vol. 60 No2, pp. 81-89, 2020.

[20] Faraj, S., Pachidi, S. and Sayegha, K., "Working and organizing in the age of the learning algorithm," *Inf. and Org.*, Vol. 28, pp. 62–70, 2018.

[21] Bailey, D. E. and Barley, S. R., "Beyond design and use: How scholars should study intelligent technologies," *Inf. and Org.*, Vol. 30, 2020. DOI:10.1016/j.infoandorg.2019.100286

[22] * Jain, A. and Ranjan, S., "Implications of emerging technologies on the future of work," *IIMB Man. Review*, Vol. 32 No. 4, pp. 448-454, 2020.

[23] Editors, "The digital workforce and the workplace of the future," *Acad. of Man. J.*, Vol. 59 No. 3, pp. 731–39, 2016.

[24] * Jaiswal, A., Arun, C.J.J., and Varma, A., "Rebooting employees: Upskilling for artificial intelligence in multinational corporations," *Int. J. of Human Resource Man*, 2021. DOI: 10.1080/09585192.2021.1891114

[25] * Hermann, E., "Artificial intelligence and mass personalization of communication content," *New Media and Society*, 2021. DOI:10.1177/14614448211022702

[26] * Bhatt, I. and MacKenzie, A., "Just Google it! Digital literacy and the epistemology of ignorance," *Teaching in Higher Edu.*, Vol. 24 No. 3, pp. 302-317, 2019.

[27] Helfat, C. E. and Peteraf, M. A., "The dynamic resource-based view: Capability lifecycles," *Strategic Man. J.*, Vol. 24 No. 10, pp. 997-1010, 2003.

[28] Teece, D.J., "Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance," *Strategic Man. J.*, Vol. 28 No. 13, pp. 1319–1350, 2007.

[29] * Poquet, O. and de Laat, M., "Developing capabilities: Lifelong learning in the age of AI," *British J. of Educational Tech.*, 2021. DOI: 10.1111/bjet.13123.

[30] * Lee, I., Ali, S., Zhang, H., Dipaola, D., and Breazeal, C., "Developing Middle School Students' AI Literacy," *Proc. of the 52nd ACM Technical Symposium on Computer Science Edu.* pp. 191-197, 2021. DOI:10.1145/3408877.3432513

[31] Nair, K., "Overcoming today's digital talent gap in organizations worldwide," *Dev. and Learning in Org.*, Vol. 33 No. 6, pp. 16-18, 2019.

[32] Eubanks, V., *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York, NY: St. Martin's Press, 2018.

[33] OECD, *Bridging the Gender Divide, Include, Upskill, Innovate*. OECD: Paris, 2018.

[34] UNESCO, *Artificial Intelligence and Gender Equality*. UNESCO: Paris, 2020.

[35] Verganti, R., Vendraminelli, L., and Iansiti, M., "Innovation and design in the age of artificial intelligence," *Journal of Product Innovation Management*, Vol. 37 No. 3, pp. 212–27, 2020.

[36] Falagas, M. E., Pitsouni, E. I., Malietzis, G. A., and Pappas, G., "Comparison of PubMed, Scopus, web of science, and Google scholar: Strengths and weaknesses," *The FASEB J.*, Vol. 22 No. 2, pp. 338-342, 2008.

[37] Mongeon, P. and Paul-Hus, A., "The J. coverage of Web of Science and Scopus: a comparative analysis," *Scientometrics*, Vol. 106, No. 1, pp. 213-228, 2016.

[38] * How, M.-L. and Hung, W.L.D., "Educing AI-thinking in science, technology, engineering, arts, and mathematics (STEAM) education," *Edu. Sciences*, Vol. 9 No. 3, 2019. DOI: 10.3390/educsci9030184

[39] Waltman, L. and Van Eck, N. J., "A smart local moving algorithm for large-scale modularity-based community detection," *The European Physical J. B*, Vol. 86 No. 11, pp. 1-14, 2013.

[40] Pitt, C., Park, A., and McCarthy, I. A., "A bibliographic analysis of 20 years of research on innovation and new product development in technology and innovation management (TIM) journals," *J. of Eng. and Tech. Man.*, 61, p.101632, 2021.

[41] Zhang, Y., Porter, A. L., Hu, Z., Guo, Y., and Newman, N. C., "'Term clumping' for technical intelligence: A case study on dye-sensitized solar cells," *Technological Forecasting and Social Change*, Vol. 85, pp. 26-39, 2014.

[42] * Dai Y., Chai C.-S., Lin P.-Y., Jong M.S.-Y., Guo Y., and Qin J., "Promoting students' well-being by developing their readiness for the artificial intelligence age," *Sustainability* (Switzerland), Vol. 12 No. 16, 2020. 10.3390/su12166597

[43] * Druga, S., Vu, S.T., Likhith, E., and Qiu, T., "Inclusive AI literacy for kids around the world," *ACM Int. Conf. Proc. Series,* pp. 104-111, 2019. DOI: 10.1145/3311890.3311904

[44] * Steinbauer, G., Kandlhofer, M., Chklovski, T., Heintz, F., and Koenig, S., "A differentiated discussion about AI education K-12," *KI - Kunstliche Intelligenz*, 2021. DOI:10.1007/s13218-021-00724-8

[45] Mikalef, P. and Gupta, M., "Artificial Intelligence Capability," *Inf. and Man.*, Vol. 58 No. 3, 2021. 10.1016/j.im.2021.103434

[46] * Nankervis, A., Connell, J., Cameron, R., Montague, A., and Prikshat, V., "Are we there yet?' Australian HR professionals and the Fourth Industrial Revolution," *Asia Pacific J. of Human Resources*, Vol. 59 No. 1, pp. 3-19, 2021.

[47] * Poba-Nzaou, P., Uwizeyemungu, S., and Clarke, C., "Patterns underlying required HR and IT competencies," *Int. J. of Human Resource Man.*, Vol. 31 No.16, pp. 2065-2088, 2020.

[48] * Zerfass, A., Hagelstein, J., and Tench, R., "Artificial intelligence in communication management," *J. of Communication Man.*, Vol. 24 No. 4, pp. 377-389, 2020.

[49] * Carlisle, S., Ivanov, S., and Dijkmans, C., "The digital skills divide: Evidence from the European tourism industry," *J. of Tourism Futures*, 2021 DOI: 10.1108/JTF-07-2020-0114

[50] * Johnson, M., Jain. R., Brennan-Tonetta, P., Swartz, E., Silver, D., Paolini, J., Mamonov, S., and Hill, C., "Impact of big data and artificial intelligence on industry: Developing a workforce roadmap for a data driven economy," *Global J. of Flexible Systems Man*, 2021. DOI:10.1007/s40171-021-00272-y

[51] * Santoso, H., Abdinagoro, S.B., Arief, M., "The role of digital literacy in supporting performance through innovative work behavior: The case of indonesia's telecommunications industry, *Int. J. of Tech.*, " Vol. 10 No. 8, pp. 1558-1566, 2019.

[52] * Szabó, I. and Ternai, K., "Process-based analysis of digitally transforming skills," *Lecture Notes in Bus. Inf. Processing*, Vol. 310, pp. 104-115, 2018.

[53] Hannigan, T. R. et al., "Topic modeling in management research: Rendering new theory from textual data," *Acad. of Manag. Annals*, Vol. 13 No. 2, pp. 586-632, 2019.

[54] Haans, R. F. J., "What's the value of being different when everyone is?," *Strat. Man. J.*, Vol. 40 No. 1, pp. 3–27, 2019.

[55] Vlačić, B., Corbo, L., e Silva, S. C., and Dabić, M., "The evolving role of artificial intelligence in marketing: A review and research agenda," *J. of Bus. Research*, Vol. 128, pp. 187-203, 2021.

[56] * Wiljer, D. and Hakim, Z., “Developing an artificial intelligence–enabled health care practice: Rewiring health care professions for better care,” *J. of Medical Imaging and Radiation Sciences*, 50 (4): S8-S14, 2019.

[57] Kipper L.M., Iepsen S., Dal Forno A.J., Frozza R., Furstenau L., Agnes J., Cossul D., “Scientific mapping to identify competencies required by industry 4.0, ” *Tech. in Society*, Vol. 64, 2021. DOI:10.1016/j.techsoc.2020.101454

[58] Wang, Y.-Y., Lin, T.-C. and Tsay, C.H.-H., “Encouraging IS developers to learn business skills: an examination of the MARS model,” *Inf. Tech. & People*, Vol. 29 No. 2, pp. 381-418, 2016.

[59] * Sousa, M.J. and Wilks, D., “Sustainable skills for the world of work in the digital age,” *Systems Research and Behavioral Science*, Vol. 35 No. 4, pp. 399-405, 2018.

[60] * Del Pino, J.S., Gheorghiu, R., and Roman, A., “The rest of me,” *Futures*, Vol. 44 No. 8, pp. 730-734, 2012.

[61] * de Regt, A. and Gagnon, E., “Rethinking how humans and machines make sense together,” *26th Americas Conf. on Inf. Systems*, 2020.

[62] * Julie, H., Alyson, H., and Anne-Sophie, C., “Designing digital literacy activities: An interdisciplinary and collaborative approach,” *Proc. - Frontiers in Edu. Conf.*, 2020. DOI: 10.1109/FIE44824.2020.9274165

[63] * Kateryna A., Oleksandr R., Mariia T., Iryna S., Evgen K., Anastasiia L., “Digital literacy development trends in the professional environment, ” *Int. J. of Learning, Teaching and Educational Research*, Vol.19 No.7, pp. 55-79.

[64] * Grønsund T. and Aanestad M., “Augmenting the algorithm,” *J. of Strategic Inf. Systems*, Vol. 29 No. 2, 2020. DOI: 10.1016/j.jsis.2020.101614

[65] * Holford, W.D., “The algorithmic workplace and its enactive effect on the future of professions,” *Futures*, Vol. 122, 2020. DOI: 10.1016/j.futures.2020.102609

[66] * Lemaignan, S., Warnier, M., Sisbot, E.A., Clodic, A., and Alami, R., “Artificial cognition for social human–robot interaction: An implementation,” *Artificial Intelligence*, Vol. 247, pp. 45-69, 2017. 10.1016/j.artint.2016.07.002

[67] Abedin, B., “Managing the tension between opposing effects of explainability of artificial intelligence: a contingency theory perspective,” *Internet Research*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/INTR-05-2020-0300, 2021.

[68] Alaimo, C. and Kallinikos, J., “Managing by data: Algorithmic categories and organizing,” *Organization Studies*, Vol. 42, No. 9, pp.1385-1407, 2021.

[69] Rai, A., “Explainable AI: from black box to glass box,” *J. of the Acad. of Marketing Science*, Vol. 48 No. 1, pp. 137–141, 2020. https://doi.org/10.1007/s11747-019-00710-5

[70] * Moll, J. and Yigitbasioglu, O., “The role of internet-related technologies in shaping the work of accountants,” *British Accounting Review*, Vol. 51 No. 6, 2020. DOI:10.1016/j.bar.2019.04.002

[71] * Su, Z., Togay, G., and Côté, A.-M., “Artificial intelligence: A destructive and yet creative force in the skilled labour market,” *Human Resource Dev. Int.*, 2020. DOI:10.1080/13678868.2020.1818513

[72] * Wan, X., Zhou, X., Ye, Z., Mortensen, C.K., Bai, Z., “SmileyCluster: Supporting accessible machine learning in K-12 scientific discovery, ” *Proc. of the Interaction Design and Children Conf.*, pp. 23-35, 2020.

[73] * Shanmugalingam, J., Lario, D., and Ma, Y., “Gamification and predictive analytics for the next generation of workers,” *Proceedings - 2020 Int. Conf. on Computers, Inf. Processing and Advanced Edu.*, pp.1-6, 2020. DOI:10.1109/CIPAE51077.2020.00009

[74] * Simpson, B., “Algorithms or advocacy: does the legal profession have a future in a digital world?,” *Inf. and Communications Tech. Law*, Vol. 25 No. 1, pp. 50-61, 2016.

[75] * Waldkirch, M., Bucher, E., Schou, P.K., and Grünwald, E., “Controlled by the algorithm, coached by the crowd,” *Int. J. of Human Resource Man.*, 2021. DOI:10.1080/09585192.2021.1914129

[76] * McCartney, G. and McCartney, A., “Rise of the machines: towards a conceptual service-robot research framework for the hospitality and tourism industry,” *Int. J. of Contemporary Hospitality Man.*, Vol. 13 No. 12, pp 3835-3851, 2020.

[77] * Manseau, J., “AI in the workplace: A qualitative analysis of intelligent employee assistants,” *26th Americas Conf. on Inf. Systems*, 2020.

[78] * Lloyd, C. and Payne, J., “Rethinking country effects: robotics, AI and work futures in Norway and the UK,” *New Tech., Work and Employment*, Vol. 34 No.3, pp. 208-225, 2019.

[79] * Robinson, S.C., “Trust, transparency, and openness: How inclusion of cultural values shapes Nordic national public policy strategies for artificial intelligence (AI),” *Techn. in Society*, Vol. 63, 2020. DOI:10.1016/j.techsoc.2020.101421

[80] * Bhattacharyya, S.S. and Nair, S., “Explicating the future of work: Perspectives from India,” *J. of Man. Dev.*, Vol. 38 No. 3, pp. 175-194, 2019.

[81] * Gong, X., Tang, Y., Liu, X., Jing, S., Cui, W., Liang, J., and Wang, F.-Y., “K-9 Artificial Intelligence education in Qingdao: Issues, challenges and suggestions,” *IEEE Int. Conf. on Networking, Sensing and Control*, 2020. DOI: 10.1109/ICNSC48988.2020.9238087

[82] * Rani, U. and Furrer, M., “Digital labour platforms and new forms of flexible work in developing countries: Algorithmic management of work and workers,” *Competition and Change*, Vol. 25 No. 2, pp. 212-236, 2021.

[83] * Vazhayil, A., Shetty, R., Bhavani, R.R.R., and Akshay, N., “Focusing on teacher education to introduce AI in schools: perspectives and illustrative findings,” *Proceedings - IEEE 10th Int. Conf. on Tech. for Edu.*, pp.71-77, 2019. DOI:10.1109/T4E.2019.00021

[84] * Kandlhofer, M. and Steinbauer, G., “A driving license for intelligent systems,” *32nd AAAI Conf. on Artificial Intelligence*, pp. 7954-7955, 2018.

[85] Wu, M., Cetindamar, D., Min, C., and Zhang, Y., “Unraveling capabilities enabling digital transformation: A data-driven methodology and the case of artificial intelligence,” *Advanced Eng. Informatics*, 2021. DOI: 10.1016/j.aei.2021.101368

[86] * Santos, S., Kissamitaki, M., and Chiesa, M., “Should humans work?,” *Telecommunications Policy*, Vol. 44 No. 6, 2020. DOI:10.1016/j.telpol.2020.101910

[87] Nica E., Manole C., Stan C.I., “A laborless society? ” *J. of Self-Governance and Manag. Eco.*, Vol. 6 No.4, pp. 25-30.

[88] * Sutton, S.G., Arnold, V., and Holt, M., “How much automation is too much? Keeping the human relevant in knowledge work,” *J. of Emerging Tech. in Accounting*, Vol. 15 No. 2, pp. 15-25, 2018.

[89] * Richardson, L. and Bissell, D., “Geographies of digital skill,” *Geoforum*, Vol. 99, pp. 278-286, 2019.

[90] * Hines A., “Getting ready for a post-work future,” *Foresight and STI Governance*, Vol. 13 No. 1, pp. 19-30, 2019.

[91] Miller, R., *Transforming the Future*, UNESCO, Routledge: Oxfordshire, UK, 2018.

[92] * Kellogg, K.C., Valentine, M.A., and Christin, A., “Algorithms at work: The new contested terrain of control,” *Acad. of Man. Annals*, Vol. 14 No. 1, pp. 366-410, 2020.

[93] * Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., and Wang, K., “Influences of artificial intelligence (AI) awareness on career competency and job burnout,” *Int. J. of Contemporary Hospitality Man.*, Vol. 33 No.2, pp. 717-734, 2021.

[94] * Rangraz, M. and Pareto, L., “Workplace work-integrated learning: supporting industry 4.0 transformation for small manufacturing plants by reskilling staff,” *Int. J. of Lifelong Edu.*, Vol. 40 No. 1,pp. 5-22, 2021.

[95] * Richardson, S., “Cognitive automation: A new era of knowledge work?,” *Bus. Inf. Review*, Vol. 37 No. 4, pp. 182-189, 2020.

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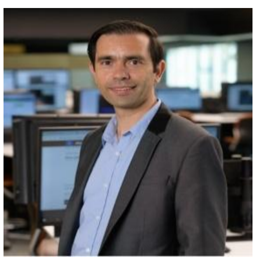

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