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Exploring skill requirements for the Industry 4.0: A worker-oriented approach

Marco Peña-Jimenez[1,3*], Adalgisa Battistelli[1], Carlo Odoardi[2], and Mirko Antino[3]

1 Université de Bordeaux, Laboratoire de Psychologie EA4139, Bordeaux (France).
2 Università degli Studi di Firenze, Dipartimento di Formazione, Lingue, Intercultura, Letterature e Psicologia (FORLILPSI), Firenze (Italy).
3 Universidad Complutense de Madrid, Facultad de Psicología, Madrid (Spain).

Título: Explorando habilidades requeridas para la Industria 4.0: Un enfoque orientado al trabajador.
Resumen: Tecnologías emergentes están dando forma al mundo del trabajo, creando así una industria cada vez más digital, también conocida como "Industria 4.0". Por tanto, examinar el requirimiento de habilidades se vuelve esencial para facilitar la adaptación organizacional a esta revolución tecnológica. El objetivo de este estudio fue explorar la percepción de las habilidades requeridas por los trabajadores de una empresa manufacturera altamente tecnológica. En el Estudio 1 (n = 671), se realizó un análisis factorial exploratorio para identificar grupos relevantes de habilidades. Un año después, en el Estudio 2 (n = 176), confirmamos la estructural factorial a través de un análisis factorial confirmatorio y realizamos un análisis de curva de crecimiento latente para examinar posibles cambios en las habilidades requeridas debido al confinamiento y el trabajo remoto forzado durante la pandemia del COVID-19. Los resultados mostraron que las habilidades cognitivas, funcionales del negocio, estratégicas y de gestión de personas se consideran recursos importantes para la industria 4.0, siendo las habilidades funcionales del negocio más relevantes en el tiempo 2. Además, identificamos diferencias entre gerentes y subordinados con respecto a tales habilidades. Discutimos las implicaciones teóricas y prácticas para el desarrollo de habilidades en la era digital.
Palabras clave: Habilidades. Industria 4.0. Era digital. Preparación laboral. COVID-19.

Abstract: Emerging technologies are shaping the world of work, thus creating an increasingly digital industry, also known as "Industry 4.0". Thus, examining skill requirements becomes essential to facilitate organizational adaptation to this technological revolution. The aim of this study was to explore the perception of skill requirements of workers of a highly technological manufacturing company. In Study 1 (n = 671), an exploratory factor analysis was carried out to identify relevant groups of skills. A year later, in Study 2 (n = 176), we confirmed the factor structure through a confirmatory factor analysis and we conducted a latent growth curve analysis to examine potential changes of the previous skill requirements due to the lockdown and the forced remote working during the COVID-19 pandemic. Findings showed that cognitive, functional business, strategic and managing people skills are considered as important resources for the industry 4.0, being the functional business skills increasingly relevant in time 2. Moreover, we identified differences between managers and subordinates regarding such skills. We discuss theoretical and practical implications for skills development in the digital age.
Keywords: Skills. Industry 4.0. Digital age. Workforce readiness. COVID-19.

Introduction

Technological advancement is considered as one of the most important vectors of the transformation of the world of work and, consequently, of a large number of aspects of the organizational system (e.g., business processes and structures) and the way we work (e.g., work-related tasks and procedures) (Bakhshi, Downing, Osborne, & Schneider, 2017; Battistelli & Odoardi, 2018; Cascio & Montealegre, 2016). "Industry 4.0" is nowadays a term widely used to refer to the integration of advanced and smart technologies within organizations (e.g., additive manufacturing, artificial intelligence, augmented and virtual reality, big data, collaborative robots, cloud computing, drones, 3D printer), which is also associated with the Fourth Industrial Revolution (Salkin, Oner, Ustundag, & Cevikcan, 2018; Schwab, 2017). In fact, many industrial sectors are already experiencing changes due to the adoption of disruptive technologies, take aeronautics (e.g., Durak, 2018), manufacturing (e.g., Zhong, Xu, Klotz, & Newman, 2017), and supply chain (e.g., Tjahjono, Esplugues, Ares, & Pelaez, 2017), for instance.

Within this rapid transformation process, several scholars underline the need to uncover the skills that workforce requires to adapt to organizational demands linked to this new technological revolution (e.g., Kipper, Furstenau, Hoppe, Frozza, & Iepsen, 2020; Oztemel & Gursev, 2020; Pacchini, Facchini, & Mummolo, 2019), as the integration of such technologies with the workforce is a key element to ensure organizational effectiveness (Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019). Over the last decade, there has been a growing interest about the skills in the industry 4.0 as can be noted from recent literature reviews on research in this topic (e.g., Chaka, 2020; Maisiri, Darwish, & van Dyk, 2020; Prifti, Knigge, Kienegger, & Krcmar, 2017). For instance, considerable efforts from psychological research have been made to identify and assess the required skills in the digital age, thus providing valuable information on how relevant are some skills for university students and employees from traditional work settings (e.g., Herde, Lievens, Solberg, Strong, & Burkholder, 2019; Strong et al., 2020). However, the latter poses the need to seek more empirical evidence on skills required by those employees who are already experiencing organizational changes as a result of the use of cutting-edge technologies (Kanfer & Blivin, 2019). To fill this gap, by following a worker-oriented perspective, our first goal in this paper is to explore employees' perception of skill requirements, focusing on those employees who work in a company whose operations and processes are driven by advanced technologies.

*** Correspondence address [Dirección para correspondencia]:**
Marco Peña-Jimenez, Univ. Bordeaux, LabPsy, EA 4139, F-33000 Bordeaux (France). E-mail: marco.pena-jimenez@u-bordeaux.fr
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Our second goal, according to organizational role theory (Katz & Kahn, 1978), we will explore differences in skill requirements depending on different roles that employees have in their organization. Specifically, we will focus on the role differences between leaders (e.g., influencing their subordinates, work distribution) and their subordinates (e.g., performing specific tasks, solving particular problems), a key distinction in organizational change phases (Wickham & Parker, 2007; Vogel, Reichard, Batistič, & Černe, 2020). We consider that this distinction is key, in order to investigate the skills that leaders specifically require for their job, and shed light on those requirements in the specific context of industry 4.0, beyond the more classical view of personal characteristics of the leaders (Mumford, Campion, & Morgeson, 2007; Vogel et al., 2020).

Finally, our third goal, we will explore changes in the skill requirements perception, by two different times, being our second data collection temporally situated in a context where employees have been forced to work virtually due to the COVID-19 lockdown. This is especially relevant to explore potential variations in the perception of skill requirements in an uncertain context where, due to the lockdown, people were forced to interact virtually and adapt many of their work-related activities. Lastly, the theoretical and practical implications for skill research and the industry 4.0 of both studies are addressed in a general discussion.

To meet these three goals, in Study 1 we first explore the clusters of skills that are considered as important resources in a sample of employees who are dealing with the challenges of the current technological revolution, by performing an exploratory factor analysis[1] on a set of indicators, according to the Occupational Information Network content model (Peterson et al., 2001). We consider that the identification of groups of skills can improve our understanding about the skill requirements in the digital age (Ackerman & Kanfer, 2020; Kanfer & Blivin, 2019). Moreover, we investigate group differences between managers and their subordinates regarding their perceived skill requirements. About one year later, in Study 2 we examine the previously identified set of skills that are relevant for a smaller group of the same employees working remotely during the COVID-19 pandemic context, by first conducting a confirmatory factor analysis (to confirm the factor structure) and a latent growth curve analysis to explore potential changes. In addition, we also evaluate between group differences between work roles (i.e., managers, subordinates) to explore specific skill requirements during this uncertain context.

Overall, we consider that this work contributes to identifying skills required by workers from a highly technological firm (from aeronautics sector), through the adaptation and use of a large set of skill descriptors. Moreover, such skills requirements were assessed in two different organizational contexts, during a relatively controlled work environment (c.f., main office location, before the lockdown due to COVID-19 pandemic), and then in an uncertain and complex work environment (c.f., fully remote work, during the lockdown due to COVID-19 pandemic), also evaluating possible differences in the skill requirements both for managers and their subordinates

Theoretical background

The study of workers' skill requirements has been approached from several perspectives (Basoredo, 2011; Campion, Schepker, Campion, & Sanchez, 2020; Sanchez & Levine, 2012). While a *job-oriented approach* provides us critical information to determine occupational requirements based on both *work activities* (e.g., task and duties) and *work context* (e.g., physical and social factors), a *worker-oriented approach* offers us valuable information to explore the workforce readiness, grounded on *worker attributes* (e.g., professional skills) (Peterson et al., 2001). For instance, a financial analyst must perform several work assignments (e.g., gathering reliable data) to achieve a particular goal (e.g., developing a risk analysis report), by following different organizational guidelines. Nevertheless, there are many other informal, implicit and/or undeclared activities (e.g., coordination with other specialists, verification of previous reports), to achieve a high-level work performance (Andrade, Queiroga, & Valentini, 2020; Griffin, Neal, & Parker, 2007). Due to the complexity and the rapidly changing work environment in the digital age, research on industry 4.0 needs to integrate the worker-centered requirements to better understand the skills gap.

This approach finds his theoretical base on a psychological perspective, that clarifies how workers' perceptions regarding their skills are strongly related with organizational outcomes such as work performance and affective states (Ajzen, 1991; Bandura, 1986). The individual's perception in the workplace, as one of the basic components of the cognitive process, is related to the perceived self-efficacy, which in turn affects the capacity to self-regulate their own behavioral intentions and actions (Bandura, 2018; Wood & Bandura, 1989). At the dawn of a technological revolution, perceived skill requirements from employees may provide us a vision of those who must deal with different job demands (e.g., analysis of big data) and job resources (e.g., virtual collaboration devices). Accordingly, we argue that workers' perception of skill requirements is a personal evaluation about how individuals value the importance of having a certain skill to perform their job well, based not only on personal attributes but also contextual factors.

As a result, based on a worker-oriented approach, we explore skill requirements for the industry 4.0 through the workers' perception, an essential source to determine the relevance of skills, especially in a company that is already dealing with the integration of smart technologies. Thus, in ac-

[1]According to recent methodological recommendations (Lloret-Segura, Ferreres-Traver, Hernández-Baeza, & Tomás-Marco, 2014; Zickar, 2020), we adopted an EFA approach in study 1 since we adapted the measure from an English version into a different cultural and linguistic background (Italian), and specific organizational sector (Aeronautics), and then a CFA for study 2.

cordance with the above, we used a comprehensive framework of work analysis, and more specifically, worker-oriented skill descriptors to determine relevant groups of skills.

O*NET Content Model: A comprehensive taxonomy of work descriptors

Occupational Information Network (O*NET, Tippins & Hilton, 2010; Peterson et al., 2001) *content model* is a comprehensive and flexible taxonomy system developed to describe different aspects of work and occupations, and a common classification of descriptors which can be used to work and organizational analysis. Composed by 277 descriptors, *O*NET content model* encompasses six dimensions of analysis, three dimensions related to *worker-oriented descriptors* (i.e., worker characteristics, worker requirements, experience requirements) and three other dimensions related to *job-oriented descriptors* (i.e., occupational requirements, workforce characteristics, occupation-specific information) (Burrus, Jackson, Xi, & Steinberg, 2013). We carried out this study by focusing on *worker requirements* dimension, and more specifically *skills* descriptors. According to O*NET framework, *worker requirements* dimension refers to those work-related resources learned through different experiences and/or training which are evaluated via three subdomains: *Skills*, *knowledge* and *education* (Burrus et al., 2013).

In line with this taxonomy, we define *Skills* as all strategies and procedures used to acquire and work with the knowledge developed through education, practice and experience (Tippins & Hilton, 2010; Peterson et al., 2001). The *Skills* framework proposed by O*NET is classified in two broad categories of skills: *basic* and *cross-functional* skills (Burrus et al., 2013). On the one hand, *basic skills* are defined as skills (i.e., content, process) that allow the knowledge acquisition and facilitate the learning process. As far *basic skills* are concerned, while *content skills* refer to background structures required to develop more specific skills (e.g., active listening, reading comprehension), *process skills* evoke those capacities associated to procedures to rapidly and effectively acquire knowledge and skills (e.g., active learning, monitoring). On the other hand, *cross-functional skills* describe a more complex type of skill used (i.e., complex problem solving, social, technical, systems, resource management) in different work-related activities and occupations.

O*NET is a tool widely used in the scholar and practitioner milieu. By using different descriptors, sub-dimensions or dimensions of this taxonomy, several researchers have conducted studies to analyze skill requirements (e.g., Burrus et al., 2013; Frey & Osborne, 2017). More recently, by using a job-oriented approach and exploiting the O*NET database, Dierdorff and Ellington (2019) conducted a study on six different clusters of skills considered as relevant (i.e., critical thinking and problem solving, communication, teamwork and collaboration, leadership, flexibility and adaptability, creativity) related to different occupational groups. Such finding showed that about 45% of occupations investigated were grouped into two occupational clusters: (1) architecture and engineering occupations (e.g., software developers, electrical engineering technologists) and (2) management and life, physical, and social science occupations (e.g., plant managers, foresters). Two major occupational groups where such skills are more required (i.e., above-average mean importance score).

In order to identify functional and general groups of skills for the industry 4.0, we used and adapted skills descriptors from O*NET Content Model for three reasons. First, from a theoretical perspective, most of the existing proposals on skills research addresses, in one way or another, the most distinctive theoretical aspects of skills evoked in this comprehensive taxonomy (e.g., Sousa & Wilks, 2018; Kanfer & Blivin, 2019). Second, from a practitioner standpoint, O*NET is a framework used by different OB/OP disciplines and labor stakeholders (e.g., firms, consulting, governments, international organizations), thus allowing the use of a common language in order to analyze the current work with other organizational and practical discussions (Guzzo, 2019; Kanfer & Blivin, 2019). Third, from a methodological view, O*NET is considered as one of the most comprehensive and widely frameworks and tools used to evaluate skill requirements in different cultural contexts, take New Zealand, China, Hong Kong, for instance (Dierdorff & Ellington, 2019).

Study 1: Perceived Skill Requirements in the Industry 4.0

Purpose

In study 1, we explored the perceived skill requirements of a sample of workers, in order to explore how specific skills descriptors cluster into valuable groups of skills required by employees working in a 4.0 company. Secondly, we studied the differences in the importance accorded to those groups of skills between managers and their subordinates. To accomplish these goals, we used an exploratory factor analysis (EFA) and an analysis of variance (ANOVA).

Method

Organizational context

Presenting the organizational context is considered an indispensable source to better understand organizational phenomena as well as to integrate well theoretical and practical implications in organizational research (Johns, 2018). Accordingly, we present relevant aspects of the organizational context in the current study. This organization is a leading and multinational manufacturing firm in the aeronautics and industrial sectors with nearly half a century of presence in the market and whose corporate headquarters and main manufacturing floor are located in the central region of Italy.

Further, the different company's subsidiaries are located in America and Europe, but in this study, we surveyed employees working in the Italian facility which has the major technological advancements among all the subsidiaries in the firm.

This company is a representative case of the industry 4.0, thus providing an ideal organizational context for exploring the skill requirements in the digital age for three principal reasons. First, the organization has already integrated cutting-edge technologies in its business processes (e.g., industrial, administrative) and its value chain. Some examples of such technologies include, but are not limited to, 3D printers, additive manufacturing, advanced sensors and actuators, cloud systems, embedded systems. Second, the continuous improvement of products, services and processes is an explicit organizational strategy. In fact, the company's products and services (mainly oriented to clients from the aerospace, industrial and energy sector) are supported by an internal research staff focused on the engineering and organizational development, but also by an external set of manufacturing and organizational experts. Third, due to its technological development, this company has been considered as a highly technological organization by national and international experts. For instance, the organization has been selected to participate as a place of research related to the industry 4.0 in a European project.

Sample

The total population of the multinational company working in the Italian facilities was about 811 employees. In order to conduct the current study, we contacted the company's HR department and line managers to invite employees to participate in this study. Then, taking into account the availability of the employees and the company, the online questionnaire was sent to all the staff. The final sample was composed 671 employees who voluntarily participated in the study 1 (82.74% of the Italian facilities). Within this sample, 92.55% (n = 621) were male, 6.41% (n = 43) were female and 1.04% (n = 7) did not answer. As part of a request from the organization, age and organizational tenure were asked in terms of categories. The age group were as follows: 26.08% (n = 175) between 18 and 35 years old, 51.71% (n = 347) between 36 and 50 years old, 21.16% (n = 142) between 51 and 65 years old, and 1.04% (n = 7) did not specify their age range. The categories of organizational tenure were the following: 29.06% (n = 195) from newcomers to 10 years, 52.46% (n = 352) from 11 to 21 years, 17.44% (n = 117) from 22 to more than 32 years, and 1.04% (n = 7) did not indicate their tenure in the company.

Instrument

Perceived skill requirements. In accordance with our theoretical framework, perceived skill requirements were assessed by using an adapted version of the 30 skill descriptors forming part of the worker requirements domain of the O*NET content model (Burrus et al., 2013; Peterson et al., 2001). Each skill descriptor was presented in the form of the corresponding Italian translated definition. Likewise, taking into account the Italian-speaking context, the scale was initially translated from English to Italian by one translator. Later, another independent translator performed an inverse translation from Italian to English. Lastly, the translation differences were discussed and solved by both translators (Brislin, 1980). Thus, each skill was measured through the same following question: "How important are the following skills to your job?", on 5-point Likert-type scale ranging from 1 (*not at all*) to 5 (*extremely*).

Procedure

The participating organization was selected due to its use of emergent and sophisticated technologies. The data collection was conducted around mid-2019, using a convenience sample of individuals working at the company's Italian facility. The questionnaire was administered via an online survey platform where authors presented the study's aim and characteristics. Furthermore, line managers and HR specialists invited to participate in this study to their staff through internal staff meetings. After completion, descriptive results in the form of aggregated data was presented to employees via both line managers and authors.

Data Analysis

By using Mplus 8 software, Exploratory Factor Analysis (EFA) was conducted to determine the underlying factorial structure of skills following the recent methodological recommendations (e.g., Goretzko, Pham, & Bühner, 2019; Zickar, 2020), by using polychoric correlation matrix and employing Robust Weight Least Square extraction method (WLSMV estimator in Mplus software, which is a recommended technique to be used when variables' responses can be considered as "ordinal" e.g., 5-point Liker-type scales of agreement) instead of "continuous" (Finney & DiStefano, 2006) with an oblique rotation. To determine the number of factors we used several goodness of fit indexes: The Comparative Fit Index (CFI) as well as the Tucker-Lewis Index (TLI) ought be close to or higher than 0.90 (Hu & Bentler, 1998); and the values of the Root Mean Square Error of Approximation (RMSEA) together with the value of the Standardized Root Mean Square Residual (SRMR) should be 0.08 or lower (Browne & Cudeck, 1992). Further, considering the categorical analysis approach to perform EFA (Finney & DiStefano, 2006), we report the Ratio of Maximum-Likelihood Chi-Square to the degrees of freedom (χ^2/df), but such value is not used to determine the model's fit because it becomes inflate as a result of using categorical data and small/medium samples. As part of the analysis, we also presented descriptive data and the reliability was estimated with coefficient omega, by using Jamovi software (McDonald, 1999; McNeish, 2018). Finally, a bivariate analysis was used to evaluate the degree of association among the different clusters of skills, and an analysis of variance was performed to identify between group differences.

Results

The 4-factor model presented the best fit to the data (TLI = .95, CFI = .96, RMSEA = .090, SRMR = .032, χ^2/df = 6.437), compared to the 3-factor model (TLI = .94, CFI = .95, RMSEA = .102, SRMR = .040, χ^2/df = 7.947), the 2-factor model (TLI = .93, CFI = .94, RMSEA = .108, SRMR = .050, χ^2/df = 8.822) and the 1-factor model (TLI = .89, CFI = .90, RMSEA = .133, SRMR = .073, χ^2/df = 12.872). Moreover, each factor showed satisfactory levels of reliability (ranging from ω = .82 to ω = .95). It also has to be pointed out that Item 6, 10, 23 and 30 shared factor loadings in more than one factor. However, considering that they refer to different but related skills descriptors, as well as do not compromise the underlying structure, such items were preserved because of its theoretical value. Table 1 presents the factor loadings of the 4-factor model, and Table 2 reports descriptive statistics, and correlations for each group of skills. We present below the different skills descriptors grouped into four functional groups of skills that are considered as important resources by the employees working in a highly technological work environment.

Table 1.
*Four-Factor Model: Results from an Exploratory Factor Analysis for the O*NET Questionnaire On Skill Requirements Dimensions.*

Skills item	Factor loading			
	1	2	3	4
Factor 1: Cognitive skills				
3. Combining information to form an overall picture and drawing effective conclusions from it	**.81**	.03	.12	-.01
2. Developing unusual or ingenious ideas on a given topic or situation, and developing creative or alternative ways of solving a problem	**.76**	-.08	.04	.01
5. Understanding the implications that new information has for problem solving	**.76**	.20	.11	-.08
4. Understanding when a process/activity does not work or when there is a risk that it will not work in the future	**.71**	.10	.19	-.07
1. Switching from one concept or activity to another and thinking of multiple concepts or activities simultaneously	**.71**	-.03	-.11	.11
6. Transmitting information clearly and effectively	**.56**	**.42**	.01	.04
11. Using logic to identify the strengths and weaknesses of the different approaches	**.52**	.25	-.08	.33
12. Solving poorly defined new work problems in complex contexts even in the absence of time and/or resources	**.49**	.04	.04	.34
10. Listening carefully to what other people say and asking appropriate questions despite the lack of time and/or resources	**.42**	.24	-.09	**.41**
Factor 2: Functional business skills				
7. Understanding all the contents of the company documents for carrying out my work	.29	**.62**	.04	.04
8. Writing useful business documents for managing business activities	.20	**.49**	.16	.12
21. Actively seeking ways to help others and/or performing your tasks by paying attention to quality processes	.08	**.44**	.11	.26
14. Recognizing the appropriate use of equipment, structures and materials needed to perform specific tasks	.08	**.40**	.16	.26
Factor 3: Strategic skills				
26. Defining when major changes will occur in a system or are likely to occur	.04	-.18	**.99**	.02
25. Developing an image of how a system should function under ideal conditions	.06	-.06	**.88**	.02
27. Considering many system performance indicators, taking into account their accuracy	.03	-.02	**.82**	.07
28. Understanding the results of long-term changes in work activities	.03	.02	**.78**	.12
29. Identifying what needs to be changed to achieve a work goal	.02	.31	**.72**	-.08
9. Identifying what needs to be changed to achieve a job goal	.01	.37	**.67**	.03
30. Identifying and understanding the nature of the working problems that you encounter	.03	**.47**	**.61**	-.04
24. Determining how a process should work and how changes in conditions, operations and situations will affect results	.05	.08	**.55**	.31
23. Considering the relative costs and benefits of potential actions before choosing the most appropriate ones	-.06	.07	**.49**	**.43**
Factor 4: Managing people skills				
18. Understanding other people's emotions and reasons for their actions	.30	-.06	-,02	**.63**
19. Bringing others together to reconcile different positions and opinions	.26	-.05	.08	**.60**
17. Regulating your actions according to other people's tasks	.16	-.02	-.00	**.59**
16. Managing your and other people's time efficiently even in critical situations	.00	.22	.23	**.58**
15. Motivating, developing and managing people/colleagues while they work, identifying the most suitable for each specific activity	-.06	.10	.37	**.56**
22. Teaching and/or transferring skills to others to deal with certain situations	.00	.13	.27	**.55**
20. Influencing other people's behavior and ideas	.36	-.41	.07	**.48**
13. Controlling how the money will be spent on completing the job and taking these expenses into account	.00	.04	.37	**.46**

Note. *N* = 671. The extraction method was robust weight least square with an oblique (Geomin) rotation. Factor loadings above .40 are in bold.

Table 2.
Descriptive Statistics, Reliability and Correlations for Skills Factors.

Variable	*M*	*SD*	Reliability (ω)	1	2	3	4
1. Cognitive	3.56	0.70	.93				
2. Functional business	3.65	0.72	.82	.76**			
3. Strategic	3.40	0.79	.95	.76**	.71**		
4. Managing people	3.29	0.72	.89	.74**	.66**	.81**	

Note. N = 671. M = mean; SD = standard deviation; ω = internal consistency reliability estimated by coefficient omega; ** = p < .01.

Cognitive Skills

The first factor refers to cognitive capacities, a set of personal resources to identify, analyze and use different kinds of information and knowledge for combining or grouping things in different ways (e.g., identifying patterns, solving problems). Such skills are as follows: *logical reasoning* (i.e., combining information to form an overall picture and drawing effective conclusions from it), *creativity* (i.e., developing unusual or ingenious ideas on a given topic or situation, and developing creative or alternative ways of solving a problem), *active learning* (i.e., understanding the implications that new information has for problem solving), *sensitivity to problems* (i.e., understanding when a process/activity does not work or when there is a risk that it will not work in the future), *cognitive flexibility* (i.e., switching from one concept or activity to another and thinking of multiple concepts or activities simultaneously), *oral expression* (i.e., transmitting information clearly and effectively), *integrative analysis* (i.e., using logic to identify the strengths and weaknesses of the different approaches), *complex problem solving* (i.e., solving poorly defined new work problems in complex contexts even in the absence of time and/or resources), and *listening* (i.e., Listening carefully to what other people say and asking appropriate questions despite the lack of time and/or resources).

Functional Business Skills

The second factor indicates the capacity to determine how business operates in a given context in order to identify and improve work-related processes (e.g., understanding business processes, identifying business resources). Skills that comprise this category are: *Business report analysis* (i.e., understanding all the contents of the company documents for carrying out my work), *report formulation* (i.e., writing useful business documents for managing business activities), *service orientation* (i.e., actively seeking ways to help others and/or performing your tasks by paying attention to quality processes), and *resource management* (i.e., recognizing the appropriate use of equipment, structures and materials needed to perform specific tasks).

Strategic Skills

The third factor refers to the capacity that enables strategy development and decisional processes from goal-setting to work-related action (e.g., evaluating different aspects of organizational system, improving processes). The skills comprising this category are: *perception of systems* (i.e., defining when major changes will occur in a system or are likely to occur), *visioning* (i.e., developing an image of how a system should function under ideal conditions), *evaluation of systems* (i.e., considering many system performance indicators, taking into account their accuracy), *identification of consequences* (i.e., understanding the results of long-term changes in work activities), *identification of causes* (i.e., identifying what needs to be changed to achieve a work goal), *solution evaluation* (i.e., identifying what needs to be changed to achieve a job goal), *problem identification* (i.e., identifying and understanding the nature of the working problems that you encounter), *process analysis* (i.e., determining how a process should work and how changes in conditions, operations and situations will affect results), and *judgment and decision-making* (i.e., considering the relative costs and benefits of potential actions before choosing the most appropriate ones).

Managing People Skills

The fourth factor denotes to the capacity to understand, guiding, manage and negotiate with others, as well as dealing with different organizational demands (e.g., working with others, allocating resources). Such skills are as follows: *social perception* (i.e., understanding other people's emotions and reasons for their actions), *negotiation* (i.e., bringing others together to reconcile different positions and opinions), *coordinate with others* (i.e., regulating your actions according to other people's tasks), *time management* (i.e., managing your and other people's time efficiently even in critical situations), *people management* (i.e., motivating, developing and managing people/colleagues while they work, identifying the most suitable for each specific activity), *training and teaching* (i.e., teaching and/or transferring skills to others to deal with certain situations), *persuasion* (i.e., influencing other people's behavior and ideas), and *financial management* (i.e., controlling how the money will be spent on completing the job and taking these expenses into account).

Measurement invariance was assessed through a cross sample comparison (managers and subordinates) and as a result, we had no significantly different factor numbers in the study samples ($\Delta\chi^2$ = 23.097, df = 26, p = ns), thus supporting evidence of configural invariance. Subsequently, we assessed difference between factor loadings in our samples where we found no significant differences ($\Delta\chi^2$= 63.293, df = 52, p = ns), thus providing evidence of metric invariance. Then, we found that the indicator intercepts were significantly different between the study samples.

After that and considering the work role, a secondary analysis was conducted to explore differences between managers and subordinates. ANOVA revealed that there are significant differences between managers and their subordinates regarding the relevance of skill requirements. The level of importance accorded to all groups of skills (i.e., cognitive, functional business, strategic, managing people) were higher for managers in comparison to the other employees, as is presented in Table 3.

Table 3.
Means, Standard Deviations, and One-Way Analyses of Variance of Skills by Role.

Skills	Manager		Employee		F(1, 662)	p
	M	SD	M	SD		
Cognitive	3.88	0.56	3.51	0.30	28.05***	.00
Functional business	3.88	0.56	3.62	0.31	12.67***	.00
Strategic	3.76	0.61	3.33	0.34	28.93***	.00
Managing people	3.71	0.55	3.21	0.31	21.58***	.00

Note. N = 664. (n = 110 managers; n = 554 subordinates). 7 participants from the study 1 did not answer the question about the organizational role. M = mean; SD = standard deviation; *** = p < .001.

Study 2: Perceived Skill Requirements during a Complex and Uncertain Context

Purpose

In the study 2, conducted during the COVID-19 lockdown context, we studied the fit of the four factors skills (i.e., cognitive, functional business, strategic, managing people) previously investigated in study 1. In addition, such skill requirements were compared between managers and their subordinates. Lastly, to explore potential changes in the perceived importance of the skill requirements in a milieu where employees must deal, among many other issues, with changes related to a non-traditional way of work (i.e., remote working) and professional relations (i.e., virtual interactions), we carried out a latent growth curve analysis.

Method

Organizational context

The data were collected from the same company's Italian facility whose organizational context was already presented in study 1. However, it is important to highlight some relevant macro-, meso- and micro-level issues that shaped the context of the study 2. At a macro level, lockdown was one of the measures taken by the Italian government to stop the covid-19 spread and, as a result, most of the economic and business activities in the country were impacted (including the participating company). At a meso level, the participating company was one of the little number of companies authorized to operate during the covid-19 pandemic in the Italian region where are located its facilities. At a micro level, the company adopted teleworking as an organizational strategy to ensure essential processes through the use of a diverse range of technological devices (e.g., notebook, cloud and embedded systems, videoconference systems, remote access to internal platforms and servers).

Sample

In the course of the study 2, 192 individuals were designed by the company to perform work activities from home (via teleworking). After inviting them, 176 employees voluntarily participated in the study 2 (91.67% of employees working at that moment) through an online questionnaire. Within this sample, 83.52% (n = 147) were male and 16.48% (n = 29) were female. Likewise, to ensure anonymity, age and organizational tenure were requested to surveyed employees in terms of categories. The age groups were the following: 23.30% (n = 41) between 18 and 35 years old, 51.70% (n = 91) between 36 and 50 years old, and 25.00% (n = 44) between 51 and 65 years old. Categories of organizational tenure were as follows: 32.95% (n = 58) from newcomers to 10 years, 35.80% (n = 63) from 11 to 21 years, and 31.25% (n = 55) from 22 to more than 32 years.

Instrument

Perceived skill requirements. Based on the O*NET framework (Burrus et al., 2013; Peterson et al., 2001), the perceived skill requirements were examined in the study 2 through the version of 30 skill descriptors and specificities presented in the study 1 (e.g., question, scale).

Procedure

Considering the integration of cutting-edge technologies in its business processes but also the active functioning of some business units during the lockdown context (as a result of the health measure imposed by national authorities), we contacted the same company to participate in the current study. The data collection was carried out in April 2020, using a convenience sample of employees who work in the firm's Italian facility. Thus, the study 2 was conducted by using an online survey platform where authors presented the aim and specificities of the research. HR department sent a message to invite all employees working at the company at that moment. After having answered the questionnaire, authors prepared a general report that contained descriptive and aggregated data for the organization and employees.

Data Analysis

CFA was performed, by using Mplus 8 software, to assess the 4-factor solution and following the recent methodological recommendations (e.g., Zickar, 2020). In accordance with our analytical approach in the study 1, CFA conducted in the study 2 used Robust Weight Least Square extraction method (WLSMV estimator in Mplus software) considered as an appropriate technique for scales of agreement's responses (Finney & DiStefano, 2006). The model fit was evaluated by following the same index criteria presented in the data analysis section in the study 1. Reliability was estimated with coefficient omega through the Jamovi software (McDonald, 1999; McNeish, 2018). Likewise, ANOVA was used to determine between group differences related to work roles (i.e., manager, subordinates). Subsequently, in order to explore possible changes in the skill requirements between time 1 (Study 1) and time 2 (study 2), we adopted an analytical strategy based on growth modeling (Bliese & Ployhart, 2002; Ployhart & Vandenberg, 2010) using the software R.

Results

Based on CFA analysis and consistent with our theoretical framework, we compared our four-factor model with a single-factor model. Thus, empirical findings showed that, even in a complex, non-traditional and uncertain context, the 4-factor correlated model presented the best fit to the data (TLI = .92, CFI = .93, RMSEA = .088, SRMR = .07, χ^2/df = 2.368) in comparison with the one-factor model (TLI = .86, CFI = .87, RMSEA = .114, SRMR = .092, χ^2/df = 3.295). Furthermore, the four-factor model presented satisfactory levels of reliability for each factor (ranging from ω = .76 to ω = .93). Table 4 presents descriptive statistics, reliability, and correlations for each of the 4-factor correlated model of skill requirements (i.e., cognitive, functional business, strategic, managing people).

Regarding work role differences between managers and their subordinates, we tested measurement invariance through a cross sample comparison of managers and their subordinates. We found configural invariance which means that we had no different factor numbers in our samples ($\Delta\chi^2$ = 25.937, *df* = 26, *p* = ns). Then, we found significantly differences between factor loadings in the aforementioned samples. Later, analysis of variance showed significant group differences in the importance accorded to two groups of skills. While cognitive skills and functional business skills did not show significant differences between the two groups of workers, strategic skills and managing people skills were significantly higher for leaders compared to other employees, as is presented in Table 5.

Table 4.
Descriptive Statistics, Reliability and Correlations for Skills Factors.

Variable	*M*	*SD*	*Reliability* (ω)	1	2	3	4
1. Cognitive	4.05	0.53	.87				
2. Functional business	3.92	0.65	.76	.63**			
3. Strategic	3.81	0.69	.93	.63**	.61**		
4. Managing people	3.66	0.73	.89	.61**	.60**	.72**	

Note. *N* = 176. *M* = mean; *SD* = standard deviation; ω = internal consistency reliability estimated by coefficient omega; ** = $p < .01$.

Table 5.
Means, Standard Deviations, and One-Way Analyses of Variance of Skills by Role.

Skills	Manager		Employee		*F*(1, 174)	*p*
	M	*SD*	*M*	*SD*		
Cognitive	4.12	0.48	4.01	0.55	1.74	.19
Functional business	3.91	0.54	3.94	0.70	0.72	.79
Strategic	3.95	0.54	3.73	0.76	4.51*	.03
Managing people	3.98	0.53	3.47	0.77	21.58***	.00

Note. *N* = 176. (*n* = 64 managers; *n* = 112 subordinates). *M* = mean; *SD* = standard deviation; * = $p < .05$; *** = $p < .001$.

With respect to possible variations in skill requirements between time 1 and time 2, we found a significant difference in functional business skills (time growth parameter = .15, $p < .05$), differing from other skills (c.f., cognitive, strategic, managing people) where no significant differences were found, as seen in table 6.

Table 6.
Main Results of the Latent Growth Curve Analysis Comparison Between Time 1 and Time 2.

Main DV / Model	Cognitive	Functional business	Strategic	Managing people
Intercept	3.92** (.10)	3.73** (.11)	3.70** (.12)	3.47* (.12)
Time growth parameter	.09 (.06)	.15* (.06)	.11 (.07)	.11 (.07)

Note. *N* = 111 (Those who reported the anonymous code to track participants in both study 1 and study 2). Estimate (Standard errors in parentheses). * = $p < .05$; ** = $p < .01$.

General Discussion

The general aim of the current work was to explore relevant skills as they are perceived by employees working in a 4.0 organization, which can be considered as a representative case of skill requirements in a digital, connected and smart work environment. Based on a worker-oriented approach and a comprehensive framework of skill descriptors (Tippins & Hilton, 2010; Peterson et al., 2001), we investigated the perceived skill requirements in the same highly technological organization but in two different moments (i.e., conventional vs. lockdown) and settings (i.e., company-based vs. home-based). In the study 1, findings showed four groups of skills (i.e., cognitive, business functional, strategic, managing people) perceived as important skills. Likewise, we found that cognitive, functional business, strategic and managing people skills were considered by managers as more important skills compared to their subordinates, which is in line with previous research on leadership skill requirements (e.g., Mumford et al., 2007). In the study 2, results revealed that the previously explored four-factor clusters remains a valuable asset in a smaller sample of employees remotely working at the same company in a non-traditional workplace (i.e., home-based) and less common way of work (i.e., virtual interactions) due to the lockdown. This study 2 also suggests that, in the midst of an unprecedent event, leaders require skills that support their strategic decisions and personnel management, but evidently, all these findings should not be analyzed without taking into account the particular macro-, meso- and micro-levels of contextual aspects inherent to the study 2. Below are presented some specific implications related to the current work. In terms of changes in skill requirements between time 1 (c.f., before lockdown) and time 2 (c.f., during lockdown), findings suggest that functional business skills acquire an additional relevance in time 2 meaning that during the lockdown employees need to adapt quickly to meet the organizational demands and new work-related processes (e.g., remote work, virtual interactions).

Theoretical implications

We consider that our work offers several theoretical contributions. First, based on a worker-oriented approach, the paper focuses on perceived skill requirements rather than organizational demands, expectations or vision. This standpoint finds theoretical support in the social cognitive theory (Bandura, 1986, 2018), which states that the personal belief regarding our self-capacity represents an insightful source of self-regulatory behavior. While other research focuses on job-oriented exploration of skill requirements (e.g., Burrus et al., 2013; Dierdorff & Ellington, 2019; Frey & Osborne, 2017), this study allowed us to identify the perceived skill requirements by those who have to deal with a digital work environment in their everyday work. Likewise, this adds to the increasing body of literature studying perceived skill requirements in the industry 4.0, explored in other labor stakeholders such as university students, consultants and managers (e.g., Motyl, Baronio, Uberti, Speranza, & Filippi, 2017; Sousa & Wilks, 2018; Van Laar, Van Deursen, Van Dijk, & De Haan, 2018). Consequently, the current results extend our understanding about the skills research by focusing on the workers' perception about what is important to perform their job well in a representative case study of the industry 4.0, but at the same time, this complements other approaches (e.g., job-oriented, occupational-oriented) to investigate skill requirements.

As a second theoretical implication, we applied an adapted version the *O*NET framework* (Tippins & Hilton, 2010; Peterson et al., 2001) to investigate functional groups of skill requirements in a highly technological work environment. While O*NET distinguishes two broad clusters of skills (i.e., basic, cross-functional), our findings suggest that it is possible to identify four relevant clusters of skills (i.e., cognitive, functional business, strategic, managing people) within an organizational context of high technological development. These results are consistent with previous research on skill requirements using the O*NET framework (e.g., Guzmán, Muschard, Gerolamo, Kohl, & Rozenfeld, 2020; Mumford et al., 2007) in specific organizational settings, such as the leadership skills strataplex model that proposes four broad categories of skills (i.e., cognitive, interpersonal, business, strategic), and which was an insightful source to the development of the current proposal. Further, despite being a comprehensive framework of work descriptors, O*NET has been mainly used in the U.S. labor market to explore the workforce skills (e.g., Dierdorff & Ellington, 2019; Frey & Osborne, 2017). In the current work, by adapting different skill descriptors, we use the conceptual aspects of the O*NET content model to carry out research on skill requirements in another cultural background. Thus, our study highlights the value of the O*NET framework to identify functional groups of skill requirements for the industry 4.0 and in specific work environments.

As a third implication, the current work addressed the issue of leadership skill requirements. By analyzing the work role differences (i.e., managers, subordinates) regarding the perceived skill requirements, we examine how the importance accorded to the skills required to vary, depending on the organizational roles. According to the results of the study 1, the four clusters of skills were more important for leaders. In study 2, however, only two clusters of skills (i.e., strategic, managing people) were higher in the degree of importance attributed by leaders during the lockdown. Both studies highlight the need for skill frameworks and development adapted to the leadership role, as well other related aspects such as their expertise (e.g., novice, intermediate, expert) and their responsibilities (e.g., middle management, top management), which is consistent with previous leadership research (e.g., Guzmán et al., 2020; Mumford et al., 2007). Therefore, exploring specific leadership skill requirements is an issue that we cannot overlook in the current technological revolution (Lord, Day, Zaccaro, Avolio, & Eagly, 2017).

As a fourth implication, we studied how the perception about the relevance of the groups of skill requirements changed due to the lockdown. This is especially relevant since workers were forced to interact virtually and work remotely by using technological devices during the global pandemic (Collins, Earl, Parker, & Wood, 2020). According to event system theory (Morgeson, Mitchell, & Liu, 2015), organizations are dynamic and structured systems that can also be shaped by external and environmental events. Following this premise, we argue that macro-, meso-, and micro-level context surrounding the organization during the lockdown has the potential to change the workers' perception about the professional skills they need as a result of an unexpected and critical event. We found that the four groups of skill requirements (e.g., cognitive, functional business, strategic, managing people) explored in a conventional context (study 1), were also considered as important set of skills by the same employees about one year later and during the lockdown (study 2), being the functional business skills perceived as a more valuable resource in changing work environments, but it is possible to think that these skills may change in the near future. Accordingly, the current findings provide preliminary evidence of skill sets which remains as important resources by employees working in an industry 4.0 not only in a traditional work context but also during challenging circumstances.

Practical implications

In the fourth industrial revolution, the skills shortage is not only a scholar issue but also a practitioner concern. Our work has two main practical implications that are presented below. The assessment and development of a skillful workforce for the industry 4.0 can be considered as a first implication. The four clusters of skills represent a useful framework to identify the skills gap, but also to create training programs and adopt organizational strategies that enable the skill development. It is possible to consider that many other industrial sectors interested in and/or related to the use of more advanced technologies can benefit from the proposed skill framework, which can be integrated to other/new specific skill frameworks. For example, Van Deursen and colleagues (2016) proposed a technology-related or internet framework which is composed of operational, mobile, information navigation, social and creative skills to promote digital inclusion in the workplace but it seems necessary to develop other personal skills to deal with a changing world of work. Nowadays, new digital information or technological devices (e.g., sensors and actuators, cloud systems, artificial intelligence) are modifying job demands (e.g., monitoring data patterns, analyzing large amounts of data) as well as job resources (e.g., virtual relations with others, a perception of less control/autonomy to make decisions). Accordingly, the development of cognitive, functional business, strategic and managing people skill can contribute to improving the perceived controllability of smart technologies and the capacity to face new and rapidly evolving work environment.

Second, leadership challenges in the digital age is another important practical implication addressed in this study. Currently, new ways of work (e.g., remote working) and organizational dynamics (e.g., virtual teams) require well-trained leaders who facilitate, for example, the acceptance of such technologies by the workforce (Collins et al., 2020). Our results suggest that there are role differences between managers and their subordinates about the importance they attribute to the skills they need to perform their job well. Therefore, leadership development is particularly important for organizations to ensure a successful a sustainable digital transformation and deal with complex work environments (Mumford & Connelly, 1991; Vogel et al., 2020). Besides the exploration the characteristics of the leaders, we suggest that companies must also take into account the leadership skill requirements to develop their own model of leadership. In light of this, the above-mentioned clusters of skills can be an insightful framework to attain that end.

Limitations and future research directions

The current work provides insightful elements about the skill requirements in the fourth industrial revolution; nevertheless, there are some opportunities which may be of interest to future research. First, despite the sample of study was composed of people working for an organization that can be considered as a representative example of the industry 4.0, but it is nevertheless a particular case of the manufacturing firm in the aeronautics and industrial sectors. Therefore, to confirm generalizability of the groups of skills, further research must replicate our research in other industrial sectors and/or cultural contexts. Second, based on a worker-oriented approach, we focused on a general and functional clusters of skills (Mumford et al., 2007; Peterson et al., 2001) that are useful in an individual level. Nevertheless, future research should integrate other approaches (e.g., job-oriented, event-oriented), types of skills (e.g., technical, digital) and a multilevel perspective (e.g., individual, team) to offer complementary views on the skill requirements in dynamic and complex industry. Third, the employees' perception about the skill requirements are not static but rather dynamic evaluations, depending on personal but also contextual factors. For instance, companies are continuously integrating new and more advanced technologies, which require new or different knowledge, abilities but also skills (Battistelli & Odoardi, 2018). Although we offer a first time based comparison, future research must take into account the variations in specific personal characteristics (e.g., knowledge, expertise) and organizational context (e.g., virtual work environment, new business models), to develop a comprehensive skills framework adapted to the organizational strategy over the time.

Conclusion

We are experiencing the transformation of the world of work. Smart, digital and interconnected technologies are shaping a more complex and changing work environment which demand a skillful workforce. This paper provides us a look on perceived skill requirements by employees who are already experiencing such technological revolution in their daily work. Thus, based on a worker-oriented approach, findings suggest that four different but related clusters of skills (i.e., cognitive, functional business, managing people, strategic) are a relevant asset to be developed to face the challenges of the Industry 4.0, which can vary depending on work role differences, and more specifically, between leaders and their subordinates. We hope our work contributes to assisting organizational scholars and practitioners to paving the way for the industry 4.0 and in the long and complex road towards the development of a more realistic, closer and well-integrated model of skills in the digital age.

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